LOCATION CHOICES FOR CLIMATE CHANGE AND TRANSPORTATION DECISION MAKING

Phase 1 Report

SPR 745

Oregon Department of Transportation

UNDERSTANDING RESIDENTIAL LOCATION CHOICES FOR CLIMATE CHANGE AND TRANSPORTATION DECISION MAKING

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by

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Abstract: This research aims to fill the gap in the knowledge between residential location decisions and preferences and the resulting travel outcomes. In this first phase, the revealed connections between residential choices and travel patterns are examined using recently collected Oregon household travel survey data. Based on distillation of these data, Oregon households are segmented into policy-sensitive markets defined by their differences in household composition, income, and age. Statistical modeling techniques were then applied to analyze the relationship between each identified market segments, their revealed travel outcomes, and three residential location decisions: housing structure (single family or multifamily), tenure (rent or own), and neighborhood type that were combined into sets of alternatives. Each residential location decision was modeled within a nested multinomial logit framework specified for the sample of households of the Portland and Mid-Willamette Valley metropolitan regions in the OHAS dataset. To further link the household residential location decisions to travel behavior, a set of multivariate regression models were developed and estimated to understand how the socioeconomic characterization and revealed housing, neighborhood, and tenure decisions of a household related to four travel outcomes: vehicle miles traveled, person miles traveled by mode, number of person trips by mode, and vehicle ownership. These estimates were then used to explore travel differences for households in different lifecycle stages with or without access to light rail transit. This first phase provided insight into the connection between the revealed travel outcomes of Oregon households and their neighborhood, tenure, and housing structure decisions.

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APPROXIMATE CONVERSIONS TO SI UNITS					APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	When You Know	Multiply By	To Find	Symbol	Symbol	When You Know	Multiply By	To Find	Symbol
			LENGTH					**LENGTH**	
in	inches	25.4	millimeters	mm	mm	millimeters	0.039	inches	in
ft	feet	0.305	meters	m	m	meters	3.28	feet	ft
yd	yards	0.914	meters	m	m	meters	1.09	yards	yd
mi	miles	1.61	kilometers	km	km	kilometers	0.621	miles	mi
			AREA					**AREA**	
in^2	square inches	645.2	millimeters squared	mm^2	mm^2	millimeters squared	0.0016	square inches	in^2
ft^2	square feet	0.093	meters squared	m^2	m^2	meters squared	10.764	square feet	ft^2
yd^2	square yards	0.836	meters squared	m^2	m^2	meters squared	1.196	square yards	yd^2
ac	acres	0.405	hectares	ha	ha	hectares	2.47	acres	ac
mi^2	square miles	2.59	kilometers squared	km^2	km^2	kilometers squared	0.386	square miles	mi^2
			VOLUME					**VOLUME**	
fl oz	fluid ounces	29.57	milliliters	ml	ml	milliliters	0.034	fluid ounces	fl oz
gal	gallons	3.785	liters	L	L	liters	0.264	gallons	gal
ft^3	cubic feet	0.028	meters cubed	m^3	m^3	meters cubed	35.315	cubic feet	ft^3
yd^3	cubic yards	0.765	meters cubed	m^3	m^3	meters cubed	1.308	cubic yards	yd^3
NOTE: Volumes greater than 1000 L shall be shown in m^3.									
			MASS					**MASS**	
oz	ounces	28.35	grams	g	g	grams	0.035	ounces	oz
lb	pounds	0.454	kilograms	kg	kg	kilograms	2.205	pounds	lb
T	short tons (2000 lb)	0.907	megagrams	Mg	Mg	megagrams	1.102	short tons (2000 lb)	T
			TEMPERATURE (exact)					**TEMPERATURE (exact)**	
°F	Fahrenheit	(F-32)/1.8	Celsius	°C	°C	Celsius	1.8C+32	Fahrenheit	°F

*SI is the symbol for the International System of Measurement

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DISCLAIMER

EXECUTIVE SUMMARY

The residential location decisions of a household have an inherent and complex association with the travel behaviors exhibited by its members. Longer-term decisions regarding neighborhood, tenure, and dwelling type selection vary according to a household's sociodemographic and economic conditions, which taken together influence short-term transportation decisions related to trip generation, mode choice, distance traveled, and vehicle ownership. An evaluation of this multidimensional arrangement has significance to decision makers and researchers who seek a more comprehensive understanding of these connections between residential location and transportation to better inform a range of policy initiatives, improve the realism of modeling frameworks, and guide transportation-land use plan development.

In response, this project has assembled recently-collected revealed preference data on the residential location and travel decisions of Oregon households segmented into policy-sensitive markets defined by their differences in household composition, income, and age. Market segmentation profiles related to a household's activity participation were also explored as an innovative and complementary strategy for categorizing a household based on their actual motivation for travel. Statistical modeling techniques were then applied to analyze the relationship between three residential location decisions of the identified market segments and their revealed travel outcomes under current conditions.

Three residential location decisions: housing structure, tenure, and neighborhood were combined into unique alternative combinations and modeled in this phase of the project. Transferability and computational ease informed an aggregation of housing structure into a binary classification of single-family and multifamily units, while the decision of tenure was logically divided into the household decision to own or rent a housing structure. Neighborhood type was empirically determined by a two-staged principle component and k-means cluster analysis of the built environment resulting in separate regional and statewide area-based typologies. Each residential location decision was modeled within a nested multinomial logit framework specified for the surveyed households of the Portland and Mid-Willamette Valley metropolitan regions. To link household residential location decisions to travel behavior, a set of multivariate regression models were estimated to understand how the socioeconomic characterization and revealed housing, neighborhood, and tenure decisions of a household connected to four travel outcomes: vehicle miles traveled, person miles traveled by mode, number of person trips by mode, and vehicle ownership. Estimates were then used to explore travel differences for households in different lifecycle stages with or without access to light rail transit.

Although a discussion of the findings should be done with the caveat that these data were reflective of a one-day household travel survey, the following represents a selection of notable findings of this analysis:

- Individuals in the most urban neighborhood type exhibited a positive relationship between bicycle miles traveled and light rail access, but the link was non-significant when living elsewhere.

- Household vehicle ownership was lower for households in an outer suburban neighborhood than ownership rates for households in urban areas when the former had light rail access.

- Single and related adult households without children conducted significantly fewer walking and bicycling trips than households in other lifecycle stages, as head of household age increased.

In all, this study has provided valuable insight into the connection between the revealed travel outcomes of Oregon households and their neighborhood, tenure, and housing structure decisions. Nevertheless, the results of this first project phase have highlighted areas for future exploration including an examination of the neighborhood and housing preferences informing the residential location decision process and an improved understanding of the implicit transportation tradeoffs individuals make during this process.

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1.0 INTRODUCTION

Growing populations and the drive for urban expansion are largely responsible for generating transportation congestion and greenhouse gas emissions (GHG). In order to evaluate the future of Oregon's landscape in relation to its growing and changing population, a better understanding of evolving land use patterns and travel behavior is required, particularly because behavioral change will be a significant and necessary component of successful climate changes strategies. Specifically, the connections between residential choices (housing type, tenure, and neighborhood type) and activity/travel behavior decisions (car ownership, mode choices, trip lengths, activity schedules, and vehicle miles traveled) need to be better represented in modeling frameworks, policy goals and transportation and land use plans. Shifting demographics, changing attitudes, and the introduction of new communications and transportation technologies require new knowledge and approaches to complement the traditional research in this topic area.

These connections between residential location and transportation are an important component to tackling the policy issues facing Oregon and its urban areas. Oregon legislation (HB 2001 and SB 1059), passed in 2009 and 2010 respectively, have focused on exploring methods for reducing GHG emissions from the transportation sector, and setting reduction targets for Oregon's metropolitan areas. The bills anticipate that metropolitan areas will perform a detailed analysis of transportation and land use scenarios to meet set targets. Additionally, ODOT is currently charged with developing a statewide strategy for GHG reduction and analyzing policy alternatives. Both require better explicit representation of residential location choices, particularly in the future scenarios where conditions and household choices may depart from current behaviors, given expected and unanticipated demographic, economic and technological changes. How households respond to these changes is a fruitful area of research and one that requires innovation in the methodological approach since one cannot rely on the current patterns in existing data to understand the impact of these changes.

The residential location decisions of households have long been investigated in the travel behavior and land use and planning fields. Studies along this line of inquiry have examined the link between land-use or location choices and travel, focusing mainly on variations of these themes: (i) the issue of resident self-selection into neighborhoods that support desired behaviors (i.e. is the land use-travel behavior relationship causal or associative); (ii) capturing spatial correlations; (iii) representing household taste-variations in models; and (iv) understanding the combined housing-transportation cost burdens. Despite increases in the knowledge base across these areas, questions persist about how applicable past research findings are for the future under different conditions, populations, technologies and policy assumptions. Similar to previous investigations in this area, the fundamental research questions proposed here will investigate how home location decisions such as what type of housing structure, renting versus owning, and neighborhood character are related to household transportation and travel decisions such as vehicle ownership, mode choice, and activity/travel patterns. Unlike other studies, this research will attempt to link current behaviors in this arena with those likely to be exhibited in the future.

The advances in integrated land use and transportation models, combined with the increasing policy questions that these models are asked to address, have placed greater need to better represent these relationships in decision tools. Studies have largely focused on examining choices and behaviors from the past, using data from household travel surveys, home sales, and other revealed preference data. Revealed preference studies add value to understanding how households respond to sets of past conditions and the findings are then used to forecast how these household might respond to future conditions, assuming that future conditions fall within the bounds of those observed in the past. The use of stated preference survey techniques allows researchers to explore the decision process, understand tradeoffs that are made between different factors, and gauge responses to hypothetical situations or policies that cannot be observed from real life situations. Stated preference techniques can go beyond examination of a generation's current choices to try and understand more about how their future lifestyle visions might be realized. This type of inquiry lends itself to the type of scenario analysis being developed in Oregon at the statewide and metropolitan level, where the outlook is over the long term (20-50 years) and considers a range of conditions and policies in play.

This research aims to combine these two approaches, using both revealed preference and stated preference techniques. Revealed preference data will be to understand past location decisions and their relationship to travel behaviors. These data can contribute to understanding the associations between the built environment and travel behaviors. Then, building on the results from the revealed preference survey, survey employing stated preference techniques will be conducted that aims to understand responses to future policy scenarios and link current preferences and behaviors to future ones. The two approaches together provide the possibility of linking current and future behaviors more explicitly in both the decision tools used to guide policy and the policies themselves.

In the first phase of the research, the analysis will rely primarily on OHAS data, collected statewide starting in 2009 and ongoing through 2013 and include information about household members, their home and work locations, number and type of vehicles, their travel for one day, and some information about their rationale for their home location. These data will be augmented with other data and information about the built environment, such as transportation networks and services, housing costs, accessibility measures, neighborhood attributes, and other salient information. This combined data will be used to identify the various housing and neighborhood market segments that exist across Oregon and link these markets to travel outcomes using multivariate statistical analysis.

This report presents the literature review, methodology and findings from this first phase of the research. The second phase of research, building largely on the first, will commence after finalizing this phase, refining the research questions, developing a research approach, and implementing it. The remainder of this document is organized as follows. We begin with a review of the current literature covering: a) the concepts used in this research, including the topics of lifestyle analysis, tenure and housing choices, neighborhood definition and the links between residential choices and travel outcomes; b) the methodological approaches including endogenous correlation in the residential location literature and survey instruments and design.

This is followed by a discussion of our analysis of household market segments where we used several approaches to organizing the complexity of household characteristics to better understand the housing and transportation decisions under investigation. Here we explore the utility of using the duration of activity engagement, lifecycle stages and other combinations of household socio-demographics as a basis to analyze choices.

In order to advance our analysis, we need to explore the theoretical and empirical definition of the concepts of housing type and neighborhood classification. We examine the possibilities and constraints of using various housing types in our analysis of the OHAS data. The empirical definition of neighborhood is not a new challenge in this line of research yet there is no consensus on approach. The geographic scale, build environment characteristics and methods of data reduction used to develop these typologies for this study is outlined in this section.

Next, we discuss the model specification and estimation findings from several different structures of nested residential choice models (tenure, structure and neighborhood). While the model estimations did not yield a model that could be employed in forecasting or policy analysis, the exercise provided useful lessons that could inform future attempts at estimating such a model. The results of these estimations are shown in the Appendices.

In the next section, the connections between residential choices and travel outcomes are examined in a variety of multivariate analysis. Here, vehicle miles traveled, person miles traveled by various modes, and vehicle ownership were associated with residential choices and socio-demographics via the estimation of various multivariate regressions. The results of these estimations were then used to explore the differences across the market segments defined by lifecycle groups and neighborhoods defined in the previous sections.

Finally, we conclude with a discussion of the findings, lessons learned and implications for future work, including additional revealed preference analysis and the next phase of this study.

2.0 LITERATURE REVIEW

The pursuit of a future in which Oregon residents are encouraged to positively shift their travel behaviors toward more environmentally sustainable patterns has been a commendable focus of statewide policymakers. A future change in travel patterns that reduces emissions related to the transportation sector is ultimately reliant upon an improved understanding of the fundamental connection between residential travel behavior and the decisions concerning land use made by these same policymakers. Central to this comprehension of the travel and land use connection is a more developed determination of the phenomenon of residential location choice and the strong interconnection between the three elements *(Van Wee 2009*). In addition to advising policies favoring a reduction in vehicle miles traveled *(Cao et al. 2009)*; a greater knowledge of the residential location choice and travel link informs the extent to which land use factors influence where households choose to reside or their impetus to relocate *(Lee and Waddell 2010)* and provides essential input for integrated transportation and land use models *(Zolfaghari et al. 2012)*.

Traditionally, academic research on this link has examined the influence of socioeconomic attributes of the household, physical characteristics of the residential unit, built environment factors of the neighborhood, and travel decisions of the household members as they relate to their locational choice. From a transportation policy standpoint, the long-term choice by a household of where to reside impacts the effectiveness of an array of strategies ranging from the support of telecommuting programs *(Ettema 2010)* to the promotion of public transit travel *(Cervero 2007)*. Of particular importance to decision makers is the identification of variables related to residential location choice that are particularly sensitive to such emissions-reduction policies and a subsequent understanding of what levers to pull in order to achieve success. From a statewide modeling or methodological standpoint, an ability to account for residential location choice with respect to travel behavior is essential for ensuring that integrated transportation and land use models are adept at providing solutions to the questions of policymakers regarding the link between the two elements, such as does residential location choice impact the effectiveness of telecommuting advocacy or statewide transit improvement programs?

2.1 TOPICS COVERED IN LITERATURE REVIEW

The following literature review examines previous academic research pertaining to a household's decision of residential location with specific respect given to travel behavior. A household will generally select a residence based upon factors related to housing structure, housing tenure, and the surrounding built environment. The outcomes of these three long-term choices are dependent upon a household's economic stature, demographic composition, and orientation toward activity participation; which may be collectively referred to as the household's lifestyle. As such, topics describing the impact of lifestyle, housing structure and tenure, neighborhood and the built environment, and travel in their relationship to residential location choice will be addressed in order to provide a better context for the reader. Additionally, as each of the latter three decision areas will be modeled in order to improve the understanding of how households of different lifestyles choose their residential location, a second section is provided to denote methodological issues of concern when modeling there household choices. Conceptual and methodological topics covered in this review are listed below in addition to a brief description of their relevance to the present study:

2.1.1 Overview of Conceptual Topics

1. Household Lifestyles: Traditionally, household lifestyle has referred to a pattern of behavior that is revealed under constrained resources and conforms to the orientations of a household toward decisions of household formation, labor force participation, and orientation toward leisure *(Salomon and Ben-Akiva 1983)*. The lifestyle preferences shown by a household affect residential location decisions. One example of a revealed lifestyle is a household comprised of two young adults with younger children and low female workforce participation *(Salomon and Ben-Akiva 1983)*, whereas another lifestyle example may be a household of a small size located in an urban setting whose members exhibit a high rate of walking and transit use *(Krizek 2006)*.

2. Housing Structure and Tenure: A household's locational decision is influenced by their preference for specific attributes of a housing structure and their choice as to rent or own their residence. Housing structures range in function and size and, as such, the literature has ranged in its classification scheme from a simple distinction between single family and multifamily housing *(Walker and Li 2007)* to a more complex distinction that differentiates amongst types of single family and multifamily housing *(Hunt 2001)*. On the other hand, the tenure decision has been traditionally modeled as a binary choice to rent or own *(Skaburskis 1999; Ioannides and Kan 1996)*.

3. Neighborhood and Built Environment: Residential location choice is linked to land use patterns and features of the surrounding built environment. The former influence refers to the allocation of land to different purposes, such as the degree of mix between residential, commercial, and industrial areas *(Handy 1996)*, whereas the built environment refers to a dynamic land use, urban design, and transportation system that encompasses human activity within the physical environment *(Handy et al. 2002)*. In the transportation-land use relationship, these built environment attributes are often described as neighborhood characteristics *(Pinjari et al. 2007)*, which introduces an abstraction of how to define neighborhood boundaries. Households within the same neighborhood are likely to exhibit similar travel patterns; however, the limited understanding of the concept in regard to spatial representation and membership has implications for modeling residential location choice.

4. Travel Decisions: A primary focus of this research is the relationship between residential location choice and travel behavior. While the influence of household location decisions on travel behavior seems self-evident, there remains a large gap in understanding the precise nature of this influence *(Bagley and Mokhtarian 2002)*. Travel characteristics are associated with the feasible options available to a household and may be represented by any assortment of measures ranging from vehicle ownership, commute distance or time, and availability of alternative travel options.

2.1.2 Overview of Methodological Topics

1. Endogenous Correlation: Two commonly examined sources of endogenous correlation in the residential location choice literature pertain to a link between residential location choice and housing structure characteristics such as housing price and the self-selection of households into a neighborhood. The first endogenous correlation may be the result of the housing structure's price being correlated with the error term in the choice model *(Guevara and Ben-Akiva 2006)*, whereas the phenomenon of self-selection bias is the "tendency of people to choose locations based on their travel abilities, needs, and preferences *(Mokhtarian and Cao 2008)*." Adjusting for this second endogenous correlation has become imperative in determining the effect of the built environment on travel behavior *(Chen and Lin 2011)*, as not controlling for self-selection in models tends to produce a biased estimate of the built environment's actual influence on travel behavior *(Cao et al. 2010)*.

2. Survey Instruments and Data: A second important methodological topic is the selection of data used for analysis, including the sources of these data. Housing and transportation data are accessible from many public sources, such as the American Community Survey or the National Household Travel Survey (NHTS), both of which are conducted by the United States Census Bureau. However, depending on the questions being asked by the research, supplemental data may become increasingly necessary in order to accurately address some questions.

This literature review will next discuss these listed conceptual dimensions of residential location choice as they have been addressed in past academic research, which will be followed by a discussion of the methodological considerations from this body of work. The literature review will conclude with a synthesis of the important findings and directions for future research.

2.2 CONCEPTUAL TOPICS

The following four subsections provide an overview of how the concepts of household lifestyle, housing structure and tenure, neighborhood and built environment, and travel decision have been studied in regard to their link with residential location choice.

2.2.1 Household Lifestyles

Residential location choice is strongly influenced by the lifestyle choices of household members. This choice of lifestyle refers to the preference an individual, residing in a household dynamic, has toward a particular way of living *(Walker and Li 2007)*. As such, lifestyle can refer to the individual or to the household as a functional unit, in which case there is a distinction between a household's lifestyle and the lifestyle of its individual members. More specifically, lifestyle has been defined as a pattern of behavior under constrained resources which conforms to the orientation of an individual toward three major life decisions that he or she must make: (1) household formation, (2) labor force participation, and (3) leisure orientation *(Salomon and Ben-Akiva 1983)*. These lifestyle choices are viewed as long-term decisions that condition short-term choices such as daily travel behavior *(Kitamura 2009)*. In travel demand modeling, the utilization of the lifestyle concept has been viewed as a theoretical advancement in identifying distinct household activity profiles from past clustering processes based solely on attributes of household income and social class *(Salomon and Ben-Akiva 1983)*. A further expansion of this identification of household lifestyles, which are typically measured by characteristics of these three long-term decisions, is the inclusion of societal roles defined by gender, marital status, and lifecycle stage *(Hanson and Hanson 1981)*.

However, with that stated, the socioeconomic and demographic characteristics of the household still remain a significant determinant of residential location choice. Common socio-demographic household characteristics employed in previous residential location choice research include household size, age, presence of children, and income level. In regard to household size, Bhat and Guo *(Bhat and Guo 2007)* found households with multiple members are hesitant to locate in areas with a high street block density relative to their single member household counterparts. The authors note several plausible motivating factors for explaining this difference including the preference of smaller household sizes to locate in high street block density areas due to their higher potential for social interaction and the desire of single individual households to seek neighborhoods that are more pedestrian-friendly, whereas larger households may prefer the increased privacy of an area characterized by a lower block density. Similarly, Srinivasan and Ferriera *(Srinivasan and Ferriera 2002)*, through their analysis of residential choice in the Boston metropolitan area, found the average household size was larger in suburban areas, whereas more urban areas generally had a higher population density and fewer households. In relation to travel, Rashidi et al. *(Rashidi et al. 2010)* found household size to be positively correlated with trip count and, more specifically, automobile trip count.

Another characteristic of the major lifestyle decision of household formation, which is related to an increased household size, is the presence of children. The aforementioned study by Srinivasan and Ferriera *(2002)* found, in households with children under the age of five, that a one-worker household was more likely to perform a non-work tour in order to carry out a non-work activity, whereas a two-worker household tended to chain the non-work activity to its work tour. Though, the demarcation was not so clear between one-worker and two-worker families with school age children. As for residential location, Wyly's *(Wyly 1999)* examination of the spatial segregation among varying household compositions in the Minneapolis-Saint Paul metropolitan area found that households consisting of adults with children were more likely to be located outside of the urban core in areas marked by lower residential population densities. Also, Bagely and Mokhtarian *(Bagely and Mokhtarian 2002)* found a negative relationship between the number of children in a household and the likelihood of the household being in a traditional neighborhood within the San Francisco Bay Area. In this particular context, the authors described a traditional neighborhood as having high population density and public transit convenience with low household sizes, an absence of any backyard, and limited private parking.

Similarly, Bagley and Mokhtarian *(Bagley and Mokhtarian 2002)* found the average age of a household to be negatively associated with living in a traditional neighborhood. The average age of the household, or head of household, represents another demographic characteristic of the household formation lifestyle decision. Hildebrand *(Hildebrand 2003)*, by using Portland data from the 1994 Oregon Household Activity and Stated Preference Survey, developed an activity-based travel model for senior adults and concluded that the majority of senior adults will have an average trip rate greater than those for the general population while a smaller share will be mobility impaired but automobile dependent. The latter was confirmed by the research of Lee and Waddell *(Lee and Waddell 2010)*, who found households with senior adults to be less likely to relocate than young adult households, who are generally the most mobile segment of the population. Smith and Olaru *(Smith and Olaru 2012)*, in their examination of residential location choice based on household lifestyle preferences, noted the main demographic measures correlated with lifestyle segments were the age of the household head and household income variables.

Household income, in addition to employment, represents a measure commonly associated with the second major lifestyle decision noted by Salomon and Ben-Akiva *(Salomon and Ben-Akiva 1983)* of participation in the labor force. In terms of residential location, Bhat and Guo *(Bhat and Guo 2007)* found that middle and high-income households prefer neighborhoods with a lower employment density, whereas households in the lower quartile of income were indifferent to employment density in their residential choices. Rashidi et al. *(Rashidi et al. 2010),* in their clustering of lifestyles using 2001 NHTS data, produced 11 clusters in which the two lifestyles characterized by high-income households were largely located in suburban areas. This finding parallels the research of Guo and Bhat *(Guo and Bhat 2007)* that found households of a comparable income generally choose to locate near households of a similar income level. One transportation implication of this finding, per the research of Srinivasan and Ferriera *(Srinivasan and Ferriera 2002),* was that households with higher incomes, who generally reside in suburban neighborhoods, were more likely to perform a non-work activity during their daily work tour.

In relation to household income is the employment status of members within the household. Bhat and Koppelman *(Bhat and Koppelman 1993)*, in their examination of the employment status and income of Dutch households as determinants of travel behavior, conceptualized these two characteristics as being subsistence household needs. This abstraction was later operationalized by Wen and Koppelman *(Wen and Koppelman 2000),* who stated that mobility decisions such as household residential location or individual work location were qualified by subsistent household needs, and that these interdependencies were ultimately linked to household maintenance activities. Employment status and the decision to either voluntarily or permanently withdraw from the labor force was found by Habib et al. *(Habib et al. 2011)* to be significantly influenced by the socioeconomic characteristics of age, gender, and educational attainment. Habib et al. *(Habib et al. 2011)*, who estimated job mobility and location choice models for households in Toronto, Ontario, Canada based on major employment events such as this described withdrawal from the labor force, along with a career change, return to school, or short-term employment, also noted that job mobility decisions are important long-term decisions made by households at different lifecycle stages.

An approach toward further segmenting households based upon these long-term decisions attributed to labor force participation and household formation has been to divide individual households via this concept of different lifecycle stages. Lifecycle, which plays a significant role in residential location choice *(Smith and Olaru 2012)*, represents a sequence of social roles assumed by individuals in a household at different life stages *(Chen and Lin 2011)*. These lifecycle stages, which are viewed as indicators of the necessities and constraints governing activity and trip making, are typically defined in terms of the age and marital status of adult members in the household and have long been applied in transportation planning studies *(Kitamura 2009)*. However, there has been an extensive amount of research in the field of marketing that has incorporated the long-term decision of employment into the lifecycle classification process *(Du and Kamakura 2006)*. This historical reliance upon the utilization of lifecycle stages based on household formation and labor force participation has provided an opportune approach toward adequately controlling for many of the major sources of variation characteristically found among households through the construction of one composite variable *(Kitamura 2009)*. Hanson and Hanson *(Hanson and Hanson 1981)*, in their analysis of results from a household travel survey in Uppsala, Sweden, segmented the activity travel patterns of 97 households into six distinct lifecycle classes varied by head of household age and the presence and age of children.

The final major life decision noted by Salomon and Ben-Akiva *(Salomon and Ben-Akiva 1983)* in their definition of lifestyle involves an individual's leisure orientation, which is formed and developed over a long period of time by an individual's life experiences *(Lazendorf 2002)* that may be further divided into out-of-home leisure and home-based leisure activities *(Kitamura 2009)*. Such an approach lends credence to Walker and Li's *(Walker and Li 2007)* research which concluded that socioeconomic variables related to lifestyle have significant explanatory power, but that there are aspects of lifestyle preference that could not be explained by the sole use of these variables. In regard to residential location, Bagley and Mokhtarian *(Bagley and Mokhtarian 1999)* found individuals who self-identified as having a culture-oriented lifestyle (i.e., often attended ballets, theatres, or concerts) were likely to select a residence that was located in a high-density urban core characterized by accessibility to many cultural options. With similar respect to leisure orientation, Holz-Rau and Scheiner *(Holz-Rau and Scheiner 2010)* noted households who prefer a variety of cultural and leisure opportunities were inclined to reside in urban areas, whereas more traditional or reclusive lifestyle groups resided predominately in rural areas. Such leisure preferences appear to be mutually reinforced by the built environment since participation in such leisure opportunities has been exhibited by households who reside in neighborhoods with greater opportunities for these out-of-home leisure activities *(Lazendorf 2002)*. This finding was also observed by Naess *(Naess 2006)*, who reported a certain degree of distance decay in terms of household leisure activity frequency since many leisure facilities are located in the urban core and thus in proximity to urban households.

As for the association between lifestyle orientation and household composition, Kitamura *(Kitamura 2009)* noted that young, single households participated more often in leisure activities, and for a greater duration, than their married counterparts. In complement to this finding, Scheiner *(Scheiner 2010)* found that multi-member households had a low out-of-home leisure orientation, but that their leisure activities generally resulted in longer trips. Schwanen and Mokhtarian *(Mokhtarian 2005)* found longer leisure trips were linked to a heightened probability of utilizing an automobile to perform the activity, as was household membership to a lifestyle category defined by a positive reaction to the belief that an automobile functions as a status symbol. This latter finding was confirmed by Scheiner *(Scheiner 2010)* who found social status to be positively correlated with leisure trip distances, activity frequency, and automobile use.

Determining household lifestyles through the use of long-term life decisions regarding household formation, labor force participation, and leisure orientation had been standard practice until more recent research began to incorporate short-term life decisions attributable to personal daily travel and preference. The inclusion of short-term decisions into the categorization of differing lifestyles rises from the notion that there exists a synergistic effect between short- and long-term decisions that are often mutually informed *(Krizek and Waddell 2002)*. Ultimately, households make a multitude of decisions, including residential location choice and the choice of daily activity travel, as part of a comprehensive lifestyle identification instead of several independent decisions in one successive manner *(Pinjari et al. 2011)*. Accordingly, short-term decisions such as daily travel or activity participation are informed by a household's long-term decisions, and therefore should be considered when examining residential location choice *(Krizek 2006)*.

Krizek and Waddell *(Krizek and Waddell 2002)* classified lifestyle based on travel characteristics, activity frequency, automobile ownership, and neighborhood type for households in the Seattle metropolitan area. This lifestyle classification process was later employed by Krizek *(Krizek 2006)*, who analyzed households in Minneapolis-Saint Paul and suggested that there was little dissimilarity between how urban and suburban residents spent their time on a daily basis. This notion of activity participation has been also used to define lifestyle classifications when examining residential location choice. Applying this classification approach, Bagley and Mokhtarian *(Bagley and Mokhtarian 2002)* found that when attitudinal preferences are incorporated alongside socioeconomic measures to define household lifestyle type, neighborhood type had little influence on travel behavior. In another unique approach to lifestyle definition, Diana and Mokhtarian *(Diana and Mokhtarian 2009)* employed a scheme that strictly utilized travel characteristics to define household segments as opposed to the traditional use of lifestyles based on socioeconomic characteristics.

The inclusion of attitudinal preferences, reflected in the third approach to lifestyle classification, provides a clearer illustration beyond the traditional reliance on observed data toward defining lifestyle. Regrettably, this approach to lifestyle classification has not been used often, since such data are seldom collected *(Lin et al. 2009)* due to the extended effort required of the survey respondent and the expenses associated with additional data collection. Other methods of lifestyle classification, whether based solely on the long-term decisions of household formation, labor force participation, and leisure orientation or a combination of these long-term decisions with short-term household decisions related to travel, are also hindered by their static definitions. This drawback may be overcome by the additional segmentation of these lifestyles into lifecycle stages, where the former grouping is a subset of the latter. Within this conceptual framework, households with similar lifestyles may potentially be found in different lifecycle stages based upon their value toward different household characteristics. A potential next step may then be the incorporation of life course theory, in which a household dynamically crosses through different lifecycle stages, or, specifically, an improved comprehension of how preferences for residential location choices are determined by the past residential experiences of individuals within the household *(Chen and Lin 2011)*.

2.2.2 Housing Structure and Tenure

Intuitively, the household decision of where to locate is dependent upon the type and availability of a desired housing structure, as well as socioeconomic characteristics of the household *(Elder and Zumpano 1991)*. In close relation to the structure decision is the separate choice of tenure, or whether to rent or purchase the desired housing structure. These decisions of housing type and tenure are common to the residential location choice literature, but have been modeled in distinct manners. Ben-Akiva and de Palma *(Ben-Akiva and de Palma 1986)* employed a dynamic nested logit model, in which the two decisions were sequenced with the tenure choice preceding the structure decision. This ordered approach was also used by Skaburskis *(Skaburskis 1999)*, whereas Onaka and Clark *(Onaka and Clark 1983)* and Quigley *(Quigley 1985)* estimated residential location choice with structure as a characteristic of the housing unit and Louviere and Timmermans *(Louviere and Timmermans 1990)* estimated residential location choice with both structure and tenure as a housing characteristic. Independent of the modeling approach, the examination of tenure is typically a two-choice verdict to either rent or own the housing unit; however, variables related to housing structure have been more varied in their representation.

Walker and Li *(Walker and Li 2007)*, in their stated preference survey of household residential location choice decisions for residents of Portland, Oregon, utilized a simplified demarcation where housing nested within the tenure decision to own was either a single house or apartment and housing in the tenure decision to rent was either a single-family attached unit or condominium. Similarly, Quigley *(Quigley 1985)*, in his nested structure of dwelling, neighborhood, and public sector choice for residents of rented housing units in Pittsburgh, Pennsylvania, divided housing structure into the three categories of single-family detached, single-family attached, and apartment. An identical classification scheme was employed by Louviere and Timmermans *(Louviere and Timmermans1990)*, but for both housing tenure decisions, in their analysis of revealed preference survey data for the Roermond region of the Netherlands. Skaburskis *(Skaburskis 1999)*, in his multinomial logistic model for households in Ottawa, Ontario, Canada, extended these three housing structures by dividing the apartment category into two separate categories. One apartment category represented those multifamily complexes with fewer than five floors, whereas those multifamily units located in complexes with five or more floors characterized the other category. Finally, Hunt *(Hunt 2001)* used a similar distinction for apartments in his stated preference survey of residents in Edmonton, Alberta, Canada, but chose to divide single-family attached units into the two separate categories of duplex and townhouse. This wide-ranging classification of housing structure had an option for stated preference survey participants pertaining to a single-family detached unit, two single-family attached units (duplex and townhouse), and two apartment options (low-rise and high-rise).

Perhaps unsurprisingly, Hunt *(Hunt 2001)* found respondents of the survey preferred single-family detached housing structures when offered the array of detached, attached, and apartment options. This preference for single-family detached housing was echoed by the results of Louviere and Timmermans *(Timmermans 1990)* who found the highest utility for residential relocation to be associated with choosing a single-family detached housing unit, preceded by a single-family attached structure in the hierarchy, and an apartment, which was the only structure with an associated disutility. The research of Quigley *(Quigley 1985)* further confirmed this preference for single-family detached housing over single-family attached units and multifamily housing structures. Moreover, a second model by Quigley *(Quigley 1985)* revealed a household preference for structures of an increased size, which helps illustrate the correlation between this housing structure hierarchy and dwelling size. The research of Kim et al. *(Kim et al. 2005)*, who conducted a stated preference survey on residents of Oxfordshire, England to measure their intention to move, found residents living in a single-family detached housing structure tend to have a significantly lower intention to move from their current residence than residents of other housing typologies.

As mentioned, the complementary single-family structure to a detached housing unit, an attached single-family housing unit, was found by Quigley *(Quigley 1985)* and Louviere and Timmermans *(Timmermans 1990)* to be less preferred in comparison, but still more favorable than the choice of multifamily housing. However, Walker and Li *(Walker and Li 2007)*, in their clustering of stated preference survey data, identified a class of urban-oriented households who preferred the duplex option over a single-family detached housing unit. This finding was attributed to the greater influence exacted upon residential location choice by important variables other than structure type such as shortened travel time and proximity to retail. The notion of a hierarchical decision process where neighborhood selection informs structure choice was alluded to by Onaka and Clark *(Onaka and Clark 1983)* and will be discussed in greater detail in the following subsection.

The final housing structure classification relates to multifamily housing complexes with more than two attached units, which have been further subdivided in the literature based on building height *(Hunt 2001)*. Hunt *(Hunt 2001)*, who measured sensitivities of the Edmonton population to a specific set of elements outlined in the city's long range transportation plan, found the greatest aversion for households with children less than 18 years of age to be associated with a high-rise housing structure. In contrast, Hunt *(Hunt 2001)* found retired households to be the age cohort least opposed toward relocation into a high-rise structure, which was preferred to both single-family detached and attached housing types. Yet, Eluru et al. *(Eluru et al. 2009)*, in their examination of long-term household mobility for residents of the Zurich region in Switzerland, found households residing in smaller housing units displayed higher probabilities for shorter durations of stay; presumably because of their interest toward eventually upgrading into a housing structure of a greater size.

The latter finding linking housing structure and residential mobility with the separate household choice of tenure has been addressed at-length in the residential location choice literature. The tenure choice is inherently associated with housing price, whether the decision is to rent or own, and therefore is dependent upon economic characteristics of the household. Ioannides and Kan *(Ioannides and Kan 1996)*, who estimated residential mobility and tenure choice with random effects probit models for households within the Panel Study of Income Dynamics, found an increase in housing price was a deterrent among renting households trying to become homeowners. These households were instead prompted to continue renting their residential units by the increased housing prices. Skaburskis *(Skaburskis 1999)* confirmed this conclusion by noting that homeownership prices, once rent, age, and household size differences were controlled, was associated with a higher inclination to occupy a rental unit; specifically, a demand for high-rise rental apartments. In addition to a negative relationship with homeownership prices, Elder and Zumpano *(Elder and Zumpano 1991)* found the decision to own a house was also negatively related to residential mobility. In this regard, the tenure choice to rent was preferred by households who had relocated in the previous year and thus were presumed to value residential mobility.

Similarly, Eluru et al. *(Eluru et al. 2009)* concluded that households residing in owned housing structures had a lower probability of relocating than their renting counterparts, but that this likelihood was also related to characteristics of the surrounding neighborhood. Meanwhile, Elder and Zumpano *(Elder and Zumpano 1991)* found socioeconomic characteristics describing the presence of children, income, and age of the household head were all positively related to the ownership tenure choice. In relation to the age of the household head, Skaburskis *(Skaburskis 1999)* also found an increase in this socioeconomic attribute to be positively associated with an increased propensity to select the homeownership tenure option for all tested housing structures. This partiality toward homeownership was also noted in the research of Walker and Li *(Walker and Li 2007)* who reported a preference of condominium ownership over apartment renting in each of their three class-specific choice model estimations. The significance of this preference toward ownership is synthesized in the research of Clark and Onaka *(Clark and Onaka 1983)* who noted housing tenure, along with the aforementioned choice in structure size, were the largest components in traditional residential location modeling. An adjustment in these housing characteristics related to tenure and structure were the largest category of reasons noted in their review of seminal research on residential mobility, which was followed by changes in the lifecycle of the household, and alterations in neighborhood characteristics.

2.2.3 Neighborhood and Built Environment

Neighborhood, as it relates to residential location choice, represents a significant dimension since it often defines the geographical space that both incorporates and immediately surrounds the housing structure. The concept of neighborhood has been extensively discussed in the literature, as has the notion behind how to best operationalize it through boundary delineation. As such, researchers have used a wide range of methodological approaches for defining the neighborhood boundaries that have sought to support their conceptual definitions of this spatial dimension. Once the neighborhood boundaries have been established, built environment measures may be used to compare one neighborhood from the next. In this context, the built environment represents a composite of characteristics encompassing land use patterns, the transportation network, and features of urban design found within a neighborhood *(Handy 1996)*.

While previous studies have often used a definition of neighborhood boundaries that was either too restrictive or too broad, most research has been conceptually correct in using a multilevel spatial view *(Guo and Bhat 2007)*. A multilevel spatial view related to neighborhood composition has justified the common practice of using census geographies as a proxy for the neighborhood. Lin and Long (Lin and Long 2008), in their national study of household travel and neighborhood characteristics, performed a k-means cluster analysis of census block group data to define ten separate neighborhood types with similar socioeconomic, built environment, and travel characteristics. From their research, Lin and Long *(Lin and Long 2008)* posited that households of an identical neighborhood would exhibit similar travel characteristics, whereas households in different neighborhoods will exhibit distinct travel characteristics. The researchers confirm this assumption by stating that the ten neighborhood types were substantially different when measuring household trip rate, travel distance, travel time, and mode share. Guo and Bhat *(Guo and Bhat 2007)*, in their development of three models to estimate residential location choice, specified neighborhood boundary through the utilization of socioeconomic and built environment measures in addition to commute-related and regional accessibility measures. One finding of the model employing the first approach, which was to utilize census geographies, was that households intuitively located in census block groups characterized by high population density, but nuclear families were less likely to locate in these high residential density neighborhoods.

A second type of neighborhood depiction found within the residential location choice literature was the use of a political boundary to reflect a neighborhood's perimeter. The utilization of a political boundary classification has been conceptually correct, as it offers a multilevel spatial representation, but remains limited by its more aggregate interpretation of neighborhood. This spatial representation of a neighborhood was used by Salon *(Salon 2009),* who defined the separate boroughs of New York City as unique neighborhoods when estimating a multinomial logit model of the combined decision of residential location, automobile ownership status, and commute mode based on household travel data from New York City. Similarly, Chen and McKnight *(Chen and McKnight 2007)* in their study of different travel behaviors among homemakers residing in different neighborhoods in the New York City metropolitan area divided households based on the borough or county boundaries within which the household was spatially located. This aggregated use of jurisdictional boundaries to represent a neighborhood was also utilized by Schwanen and Mokhtarian *(Schwanen and Mokhtarian 2005),* who examined the impact of a neighborhood's physical structure on commute mode choice for three communities in the San Francisco metropolitan area. The researchers designated these three neighborhoods as being either traditional or suburban in nature based on their spatial structure and layout. For instance, North San Francisco was classified as a traditional neighborhood, because of its high residential density and land use diversity together with its grid street pattern and strong access to public transportation facilities. Their research indicated that differences in commute behavior between residents of traditional neighborhoods with suburban preferences and residents of suburban neighborhoods with urban preferences do not appear to be as large as the differences in travel patterns between traditional and suburban neighborhoods. Related research by Bagley et al. *(Bagley et al. 2002)* of five neighborhoods in the San Francisco and San Jose metropolitan regions, which selected neighborhoods through a similar visual inspection of the built environment, found that residents within the same neighborhood, either traditional or suburban, had vastly different values in regard to neighborhood preference. This result foreshadows the previous research of Schwanen and Mokhtarian *(Schwanen and Mokhtarian 2005)* by finding that there were households residing in traditional neighborhoods with both pro-urban preferences (e.g., favor non-automotive travel) as well as pro-suburban preferences (e.g., favor more parking spaces) and that the same was not true for the preferences of suburban neighborhood residents, which were largely pro-suburban.

Aside from the use of census geographies or political boundaries, research on residential location choice has also delineated neighborhood boundaries through spatial proximity. An application of this method was found in the research of Cao et al. *(Cao et al. 2010)* in which households were classified into four locations based on the network distance between the households' residence and a single point in the center of the Raleigh metropolitan area. This delineation of neighborhoods has a sense of arbitrariness similar to the utilization of census geographies, as it implies that the surrounding environment within a chosen distance from a specified point in the study area, radiating in all directions, was somehow more similar than an area slightly farther from the specified point *(Cao et al. 2010)*. Concerning the location of a residence and its connection to a household member's travel behavior, Cao et al. *(Cao et al. 2010)* found that an individual residing in an area farther from the city center drove more miles than an individual with a residence in a neighborhood closer to the city center and that this impact was greater than the influence of self-selection on the individual's vehicle miles driven. However, as mentioned, this research has the potential limitation of defining residential location by a single linear distance variable, which likely has failed to reflect the wide variation of built environment features found within different neighborhoods.

Another method described in the literature for neighborhood identification, related to the use of a distance measure, was the use of a spatial transect. This approach for defining a neighborhood was summarized in the research of Song and Knaap *(Song and Knaap 2007)*, who discussed the subjective nature of demarcating a neighborhood based on visual analysis of maps and images rather than quantitative built environment measures. One utilization of the transect approach, which has become increasingly uncommon due to the growth of Geographic Information Systems (GIS) and other technical capabilities, has been described by Talen *(Talen 2002)*. In this research, a six-zoned system for organizing the built environment of neighborhoods in a region was established, which began in the urban core and fanned out to a rural preserve zone. The creation of this continuum emphasized the coding of built environment elements in order to spatially locate a discrete number of neighborhood types.

As for measuring the impact of built environment measures across segments of a neighborhood, Crane and Crepeau *(Crane and Crepeau 1998)* examined the impact of neighborhood design on travel behavior by employing a circular-unit operationalization of neighborhood that described the network of the neighborhood through a visual inspection of the street layout within a half-mile distance of the household. Similar to the caveat inherent in the research of Cao et al. *(Cao et al. 2010)*, Crane and Crepeau *(Crane and Crepeau 1998)* suggested previous research had failed to disaggregate neighborhood design elements, which limited their conclusions about the transportation effects since neighborhood design features were not independent of any other built environment features. In their research, Crane and Crepeau *(Crane and Crepeau 1998)* addressed this gap with the application of a trip demand function to vary built environment elements by neighborhood and concluding that neighborhood street pattern did not have a significant effect on automobile or pedestrian travel when statistically controlling for land uses and population densities around the trip origin, trip costs, and traveler characteristics. Lastly, to improve the faults of this circular-unit representation of a neighborhood, Guo and Bhat *(Guo and Bhat 2007)* employed a network-band representation. This sophisticated approach to defining a neighborhood's boundary used the street network configuration and, consequently, accounted for natural or artificial barriers that are disregarded by the circular-unit representations used in the research of Cao et al. *(Cao et al. 2010)* and Crane and Crepeau *(Crane and Crepeau 1998)*.

Finally, the demarcation of the boundaries for a neighborhood may be determined through the use of a uniformed geography. This approach was employed by Krizek *(Krizek 2003)*, who measured both neighborhood and regional accessibility throughout the Seattle metropolitan area by using uniformed grid cells to examine household travel behavior and its relationship with different urban form settings. Moreover, the characteristics of these grid cells were not solely determined by the attributes within their own grid cell, but were also influenced by features found inside the adjoining cells. Ultimately, the values for each grid cell were used to determine a neighborhood and regional accessibility measure, which was used in a series of models aimed at determining whether residents change their travel behavior when they move from one neighborhood type to another. This research found that households who relocated to neighborhoods with both higher neighborhood and regional accessibility reduced their vehicle miles traveled, and that an increase in both of these accessibility measures led to a decline in the number of trips per tour.

The concept of neighborhood definition has been operationalized in a variety of manners in the literature, which range from approaches that place the household within a fixed neighborhood representation such as a census geography, political boundary, or uniform transect to approaches that place the household in the centroid of a neighborhood and define the boundary by uniformed distances radiating out from the residence. While no single consensus on how to consistently define a neighborhood existed in the literature, there seemed to be an acknowledgement that the neighborhood should represent a homogenous entity reflective of its built environment measures. Therefore, past research has typically employed a fixed neighborhood representation, such as a census geography, in which aggregate data are made readily available to the analyst. These data include the built environment measures that characterize the neighborhood. Cervero and Kockelman *(Cervero and Kockelman 1997)* introduced a classification scheme for these built environment measures, the 3Ds, which has been frequently used in research of travel demand and the built environment.

The first element of this classification scheme, density, has been found to be significantly linked with a household's locational choice. Pinjari et al. *(Pinjari et al. 2007)*, in their research into the impact of the built environment on mode choice for households in the San Francisco metropolitan area, found that households were less likely to reside in neighborhoods with a high employment density, except for lower income households who may be bound to choosing the less expensive housing typical of such areas. Confirming this conclusion, Bhat and Guo *(Bhat and Guo 2007)* found the effect of employment density to indicate that middle and high-income households preferred neighborhoods with a lower employment density. As for the origin side, Weisbrod et al. *(Weisbrod et al. 1980)*, in their analysis of residential location choice tradeoffs at a national scale, noted that residential density has a significant effect on the location decision of a household. As such, Bhat and Guo *(Bhat and Guo 2007)* found that households comprised of older adults tended to locate in neighborhoods characterized by a lower residential density, whereas households without older adults were inclined to locate in neighborhoods with a higher household density. Kitamura et al. *(Kitamura et al. 1997)* described a higher residential density as being associated with smaller housing units, smaller household sizes, lower incomes, increased accessibility, and diversity in land use types.

Diversity, the second element in the built environment classification scheme, pertains to the number of different land uses in a neighborhood and the degree to which they are represented in land area, floor area, or employment *(Ewing and Cevero 2010)*. One methodological approach for portraying a mixture of land uses in which the existence of commercial, industrial, residential, and other land use types are measured and a variable expressing this mixture was calculated was introduced by Bhat and Gossen *(Bhat and Gossen 2004)*. This method was utilized by Guo and Bhat *(Guo and Bhat 2007)* as a built environment variable in their estimation of residential location choice in the San Francisco metropolitan area. One finding from their application of diversity was that households without an automobile were more likely to reside in a neighborhood characterized by a balanced mix of land uses. However, Bhat and Guo *(Bhat and Guo 2007)* found that this diversity in land uses did not have a significant impact on a household's locational choice after controlling for other socioeconomic and built environment variables. Moreover, Sener et al. *(Sener et al. 2011),* in their modeling of residential location choice behavior in the San Francisco metropolitan area, also found that households had no significant tendency to reside in neighborhoods with a greater degree of land use mix, and instead had a proclivity to locate in neighborhoods marked by a large proportion of residential land use with little mix of other land uses.

The final element in the 3D built environment classification scheme, design, has a more unclear relationship to travel behavior than the first two elements, but generally reflects street network characteristics within the neighborhood *(Ewing and Cevero 2010)*. Bearing in mind the previous findings alluding to a household's locational decision to reside in low density neighborhoods that are predominately residential, Sener et al. *(Sener et al. 2011)* also found that residential location choice was negatively associated with an increase in highway density. In regard to travel behavior, Pinjari et al. *(Pinjari et al. 2007)* found a higher block density positively contributed to the use of nonmotorized travel modes, while Rajamani et al. *(Rajamani et al. 2003)* noted that traditional neighborhoods marked by a grid-like street design with high block density were potentially encouraging of nonmotorized travel. In contrast, Crane and Crepeau *(Crane and Crepeau 1998)* examined network density in the San Diego metropolitan region and found no evidence that the street network had a significant role in mode choice.

2.2.4 Travel Decisions

Even if the difficulty in operationalizing the concept of neighborhood has been achieved, the relationship between the built environment and travel behavior remains very complex for reasons affiliated with the multidimensionality of the two elements and the moderating influence of the decision maker in the context of the relationship *(Bhat and Guo 2007)*. The latter element refers to the lifestyle characteristics described in a previous section; whereas the difficulty accredited to the multidimensional nature of the relationship refers to the notion that the built environment is measured in regard to density, diversity, and design, while travel decisions are represented by measures such as vehicle ownership, travel distance or time, and availability of alterative travel options. Accordingly, an improved understanding of this multifaceted relationship between the built environment and travel behavior will ultimately lead to an informed comprehension of household residential location choices *(Boarnet 2011)*.

The long-term travel decision of vehicle ownership, especially automobile ownership, has been researched at length in the residential location choice literature largely because researchers have sought to encourage land use policies to help negate consequences of automotive dominance, such as congestion, air pollution, and global warming *(Zhou and Kockelman 2008)*. However, Badoe and Miller *(Badoe and Miller 2000)* in their comprehensive review of the interaction between the built environment and travel decisions concluded that past research results have been somewhat mixed, with some suggesting land use policies promoting high density, rich diversity, and quality urban design resulted in declined automobile ownership levels and use, while increasing the use of alternative transportation modes. In regard to residential density, Salon *(Salon 2009)* noted neither automobile ownership nor automotive use was significantly influenced by the measure, whereas Shay and Khattak *(Shay and Khattak 2007)* found automobile ownership was less sensitive to measures of the built environment than automotive use. Bhat and Guo *(Bhat and Guo 2007)* found a decrease in automobile ownership to be only marginally influenced by an increase in residential or employment density, although lower income households residing in neighborhoods described by high employment density were significantly less likely to own an automobile than their counterparts. In contrast, Giuliano and Dargay *(Giuliano and Dargay 2006)* found that built environment variables were important determinants of automobile ownership; specifically for households in high residential density neighborhoods, which may be unsurprising since automobile ownership is itself a function of population density.

As for proximity of residential location to retail, Chatman *(Chatman 2009)* in his attitudinal survey of California residents found that pro-automotive travel households located in neighborhoods with higher retail density within one mile of their household were significantly associated with greater automotive trip frequency than their pro-transit neighbors. Pinjari et al. *(Pinjari et al. 2011)* found that a higher modal accessibility related to improved transit and bicycle accessibility was associated with lower automobile ownership levels. Correspondingly, Pinjari et al. *(Pinjari et al. 2011)* also found levels of bicycle ownership to increase as household commute time decreased. Unsurprisingly, Naess *(Naess 2005)* in his research of residential location and travel behavior for residents of the Copenhagen metropolitan region in Denmark found that higher automobile ownership levels and longer distances from the housing unit to the downtown led to an increase in daily automotive travel.

Aside from vehicle ownership, this last finding also highlights a second travel decision measure as it relates to residential location choice: commute distance and/or time. Cao et al. *(Cao et al. 2010)*, after controlling for residential self-selection also found that the farther a household resides from the city center, the greater the amount of vehicle miles driven. Bagley and Mokhtarian *(Bagley and Mokhtarian 2002)* previously described this finding who found longer commute distances and more vehicle miles driven to be associated with households in suburban locations throughout the San Francisco metropolitan region; additionally, an increased transit distance was also associated with households located in suburban neighborhoods. Moreover, Brownstone and Golob *(Brownstone and Golob 2009)* in their research examining the influence of residential density on national automobile use found that households located in less dense neighborhoods are more likely to consume greater amounts of fuel and commute longer distances than households in neighborhoods characterized by a higher residential density.

Bhat and Guo *(Bhat and Guo 2007)* connected these two major travel decisions with the intuitive finding that a household whose members had a longer automotive commute time had a higher propensity for automobile ownership and, similarly, a household whose members had an increased commute cost were less likely to own an automobile. Understanding this link, Salon *(Salon 2009)*, who found New York City residents were more sensitive to changes in travel distance than travel cost, suggested that the most effective policy goal would be to employ a strategy which reduces both automobile ownership and commute distance by altering the relative travel times for automobiles and transit. Specifically, the implementation of strategies to increase the frequency and travel speed of transit services while allowing congestion levels for automobile users to rise would serve this intention *(Salon 2009)*. Unsurprisingly, Guo and Bhat *(Guo and Bhat 2007)* reported that households tended to locate themselves in proximity to the workplaces of working household members; however, of greater interest, may be their finding that these households located themselves closer to the workplace of the female working household members. This finding supports the household responsibility hypothesis, which states "women shoulder greater household responsibility than men and, as a result, choose shorter journey-to-work commutes *(Turner and Niemeier 1997)*." As for travel costs, Tillema et al. *(Tillema et al. 2010)*, who conducted a stated preference experiment of Dutch households examining the influence of travel costs in household residential location decisions, concluded from their research that households would have preferred higher housing costs and accepted longer travel times in order to avoid high travel costs.

The third travel decision measure relates to the utilization of alternative transportation modes that are associated with the accessibility of facilities enabling the use of these alternative travel modes. Kitamura et al. *(Kitamura et al. 1997)* found differences in travel decisions of San Francisco households could not be solely explained by differences in socioeconomic characteristics, but that their decisions were also influenced by the household's accessibility to public transit. Srinivasan and Ferreira *(Srinivasan and Ferreira 2002)* found that households with increased accessibility to public transit facilities were significantly more likely to select non-automotive commute modes, which was in-line with previous research arguing that people who reside in transit-oriented developments used public transit more frequently than households in lower residential density neighborhoods. Similarly, Cervero *(Cervero 2007)*, utilizing results from a survey of transit-oriented development residents in California, found that households working within one mile of their residence were induced to reside near a rail transit station. Transit access was also described in the research of Cao *(Cao 2010)*, who found households residing in inner-ring suburbs were more likely than outer-ring suburban households to consider transit accessibility when they were looking to relocate. However, Schwanen and Mokhtarian *(Schwanen and Mokhtarian 2005)* noted that suburban residents with a preference toward transit use over automobile use might ultimately feel that they had no choice but to commute via personal automobile since many suburban neighborhoods lacked a realistic transit option for those with a stated proclivity toward using the alternative transportation mode.

While the relationship between the built environment and travel decisions has been extensively studied over the past three decades, the impact of travel decisions as they relate to residential location choice has not drawn adequate attention from researchers. Only recently has the concern of endogenous correlation begun to receive due attention. One such methodological concern related to travel decisions is the residential self-selection of households into a neighborhood, which was first suggested by Cervero *(Cervero 1994)* who found that a high use of rail transit among residents in a neighborhood with a rail station may be due to the inclination these residents have to use rail transit due to habit or personal taste. In contrast, Choocharukul et al. *(Choocharukul et al. 2008)* in their examination into the psychological effects of travel behavior on the residential location choice by commuters in Thailand, found households who preferred automobile use were less likely to stay in a neighborhood characterized by convenient transit access. This occurrence of residential self-selection and approaches toward accounting for such an endogenous correlation will be given further attention in the following methodological section of the literature review.

2.3 METHODOLOGICAL TOPICS

The literature on methodological consideration in residential location choice modeling can be broadly assembled into two bodies of literature. The first body is concentrated almost exclusively on endogeneity in residential location choice models for all of the aforementioned dimensions of residential choice. The phenomenon of endogeneity refers to a misspecification of choice models where a correlation between the error term of the utilities and the observed component has been detected, which induces non-independent errors and leads to biased coefficient estimates in the model *(Louviere et al. 2005)*. An endogenous correlation may occur as a consequence related to the creation of an incorrect choice set, a simultaneous determination, or the exclusion of relevant attributes that are correlated with the characteristics of the observed choice *(Guevara and Ben-Akiva 2006)*. The general approach toward this concern has been to identify the source of the endogenous correlation, for example self-selection in the observed choice, and correct for this endogeneity in the model estimation process. The second body of literature in regard to methodological concerns addresses survey instruments and data issues related to residential location choice studies. In regard to this latter methodological topic, the central concern has involved the collection of locational information for both the housing structure and locations related to the household's activities, such as workplace, in addition to other built environment factors used to describe the household's surrounding neighborhood.

2.3.1 Endogenous Correlation

In the context of residential location choice research, endogeneity has most commonly arisen due to the correlation between residential location choice and characteristics of the residential unit *(Guevara and Ben-Akiva 2006; Petrin and Train 2010)*. With respect to the relationship between residential choice and the residential characteristic of housing price, endogeneity may occur since the price of a residential unit is dependent on the demand for residential units in a specific neighborhood, while this demand is concurrently dependent on the housing price *(de Palma et al. 2005)*. This interdependent relationship between housing price and demand has been one potential source of endogeneity found in estimated residential location choice models. The decision to disregard this endogenous correlation in a choice model has led to unidentified, biased, and statistically insignificant model estimates. Past empirical research has reported insignificant parameters for housing price in their residential location choice models, which may be attributable to the failure of these studies to not account for the methodological concern of endogeneity *(Bhat and Guo 2004)*. However, most models do not allow for the possibility of endogeneity through an assumption that the methodological concern was not present, which negates any approach toward testing for its effects within these empirical models.

An illustration of another potential endogenous correlation may exist in the relationship between residential location choice and age of the housing structure. In a residential location choice model where structure age was not observed in the data, but has likely been considered by the household decision maker, there has been an assumption that this housing characteristic was correlated with the price of the housing unit, but not with other observed factors, such as structure type or size. In this circumstance, the analyst may observe that some households select residences with a higher price although the observed factors are the same or even worse than other alternatives. Since the age of the housing structure has been considered by the household decision maker, but not estimated in the choice model, an endogenous correlation will occur that leads to an estimated parameter or sensitivity of housing price, which may be potentially inconsistent and biased towards zero.

Furthermore, recent attention in the residential location choice literature has been devoted toward an improved understanding of an endogenous correlation referred to as residential self-selection bias. Residential self-selection has been defined as the "tendency of people to choose locations based on their travel abilities, needs, and preferences *(Mokhtarian and Cao 2008)*." The confounding notion being that households may choose their residential location in order to realize some set of travel patterns desired by the members of the household, which may lead to the differences in observed travel patterns for residents of varying neighborhoods being related to preferences or other data aside from built environment measures *(Zhou and Kockelman 2008)*. This existence of self-selection does not necessarily signify these built environment measures are irrelevant to travel behavior, but does imply that the impact of the built environment on travel behavior may be overestimated unless this endogenous correlation has been accounted for in the methodological approach *(Cao et al. 2009)*. An improved understanding of this endogenous correlation will help inform whether built environment attributes and travel behavior are a true reflection of some underlying causality, or whether the link is a spurious correlation that is attributable to the intervening relationship between the built environment and the characteristics of the households who choose to reside in the neighborhood *(Bhat and Guo 2007)*.

Methodological approaches to treating endogeneity have relied on the identification of the source of the endogenous correlation and treating its existence through the specification and estimation of the choice model. For example, in regard to the endogenous correlation between housing price and housing demand, one conceptual solution may be for the analyst to control for one of the attributes and observe the response of the related attribute. Applying this approach to a stated preference study, a set of experiments may be designed to vary housing price in accordance to a relationship defined a priori in which the analyst may then observe housing demand.

The treatment of endogeneity in discrete choice models, such as those found in residential location choice literature, could not be pursued directly by using instrumental variables, which had been the customary methodological approach for linear models *(Guevara and Ben-Akiva 2006)*. As such, innovative methods have been explored for addressing endogeneity in a discrete modeling approach; however, while the popularity of the approach has risen in the econometric community, their application has not been explored much in regard to residential location choice. Within the discipline of econometrics, three proposed methodological approaches have been described in the literature.

The first econometric method toward addressing endogenous correlation in discrete choice models was proposed by Berry et al. *(Berry et al. 1995)*, who developed and applied an approach using product-market fix effects to provide consistent estimation under endogeneity resulting from omitted product (alternative-specific) attributes. This econometric procedure may be summarized in the following three steps:

1. Estimate a discrete choice model with alternative-specific constants (ASC) for each product on each market. By accomplishing this step, all the parameters, except for those contained in the ASC (fixed effects), are obtained consistently.

2. Regress the housing unit or product price as a function of exogenous instruments.

3. Regress the ASC (fixed effects) on housing characteristics and price through the use of predicted prices rather than actual prices.

An advantage of applying Berry et al.'s *(Berry et al. 1995)* approach in residential location modeling would be that the error structure would not need to be specified as long as the researcher accepts the assumption of endogeneity occurring in the unobserved market characteristics of markets that are disjointed. Nevertheless, this perceived advantage may also prove to be a barrier toward applying this approach since it is unclear how one would define geographic housing market segments who only share unobserved characteristics.

The second econometric method may be viewed as the application of a control function approach *(Heckman and Navarro-Lozano 2004)* within a discrete choice environment *(Petrin and Train 2010)*. In this method, the estimation equation would include an additional variable that conditions out the part of the error correlated with the observed variables (regressors). This procedure may be performed in two straightforward steps.

1. Regress the housing structure price as a function of exogenous instruments.

2. Estimate a choice model where a function of the residuals from the price equation is included as an additional explanatory variable.

The control function approach may be applied in cases where the fixed effects approach may simply not be feasible; in example, when housing price varies endogenously over each household rather than across all market segments. Such a circumstance would lend to the control function methodology being more promising for a residential location choice analysis where each housing unit may be expected to have unique unobserved attributes. However, the control function method has an impediment related to its requirement of either understanding or assuming the error structure in the system of equations to determine the theoretically correct function of the residuals to include as the additional explanatory variable.

The third econometric method, proposed by Matzkin *(Matzkin 2004)*, has been termed the unobservable instruments approach. The unobservable instruments approach is based on the inclusion of an extra endogenous variable in the model that is correlated with the original endogenous variable (i.e., housing price in the case of a residential location choice model) only through exogenous factors. One practical application of this method was performed by Train and Winston *(Train and Winston 2007)*, who modeled the choice of automobile brands. Train and Watson *(Train and Watson 2007)* claimed that the retained price of an automobile was expected to be uncorrelated to the error terms yet correlated to price only through unobservable characteristics. By using this approach, the retained price may be used as an extra variable that will lead to the inclusion of unobservable instruments similar to the approach suggested by Matzkin *(Matzkin 2004)*. However, this application of the unobservable instruments approach to residential location choice models is not entirely clear since the category of additional variable to include has not been explored.

2.3.2 Survey Instruments and Data

The development of a stated preference survey for residential location choice will serve many purposes as this research progresses, but from a methodological standpoint, the application of a stated preference survey represents a beneficial tactic for collecting data that are necessary for treating the endogenous correlations found in the estimated residential location choice model based solely on revealed preferences. Presently, stated preference surveys of residential location decisions are few in the literature, which is both due to the complexity in understanding a household's decision making process *(Hensher and Bradley 1993)* as well as a general controversy surrounding the technique *(Hunt 2001)*. Whereas more traditional household survey instruments present participants with an array of questions aimed toward obtaining household demographic and socioeconomic characteristics, housing tenure, housing structure, and other characteristics of the residential unit in addition to more spatially-related information, a stated preference survey may complement these data by also measuring characteristics desired by the decision maker that are related to school quality, neighborhood safety, etc. *(Walker and Li 2007)*. The objective of the stated preference experimental design in this project will be to collect data to generate a model with valid parameters for household attributes, both observed and unobserved in the models estimated from revealed preference survey data, which are significant in determining household residential location decisions. Relevant issues to consider include the replication of realistic scenarios and reproduction of a realistic decision making process that captures how households weight their unique interests in regard to a common residential location decision.

Similar to the use of stated preference survey data, the augmentation of the revealed survey dataset through the addition of built environment measures will produce a more comprehensive dataset. Regrettably, while many of these data discussed in the section on the neighborhood and built environment are available, there will need to be consideration given to the use of potentially important neighborhood variables to a household's residential location choice such as school quality and neighborhood safety. In regard to the former neighborhood measure, since school district boundaries and census neighborhoods are not typically spatially concurrent, attention will need to be given to this inexact aggregation process that may potentially lead to spatial error dependence, which would need to be accounted for in the neighborhood choice model *(Bayoh et al. 2006)*. As for the influence of criminal activity, Sermons and Koppelman *(Sermons and Koppelman 2001)* used city-level crime data in their examination of commuting differences between males and females in residential location choice models. While these data may have been significant in their statewide examination of California residents, their more aggregated definition of neighborhood may not provide an appropriate amount of variation if the household residential location choice within a metropolitan region is examined.

2.4 SYNTHESIS OF LITERATURE REVIEW

An assessment of contextual topics within the residential location choice literature revealed that although this area of research has been ongoing since the late 1970s, several new dimensions may be examined through a more disaggregate and thorough examination of residential location decisions. In this body of literature, four broadly defined dimensions have been examined: (i) household lifestyle, (ii) housing structure and tenure, (iii) neighborhood and built environment, and (iv) travel decisions. The second and third dimensions represent choices made by households defined by the first dimension that influence the actions described within the fourth dimension.

In light of recent improvements in travel demand forecasting and the rise of activity-based models, the linkage between activity participation and residential choice has not been examined explicitly, outside of looking at accessibility *(Hagerstrand 1970; Lenthorp 1976; Pirie 1979; Burns 1979; Pendyala et al. 2002)*. Many studies on the accessibility of individual households have alluded to the potential or existing set of opportunities presented to a particular household. However, these accessibility measures merely connect household location to the potential for activity engagement and not the actual observed participation in an activity. A household may be able to access several activity opportunities, but may participate in relatively few activities due to influences on the decision of residential location that went unobserved. Additionally, the link between activity participation and residential location choice is realized through its relationship with travel decisions. Under the activity-based paradigm of travel demand modeling, travel has been derived from activity participation; a suggestion that researchers may model the connection between activity participation and travel behavior to make the additional connection between activity behavior and residential location choice. However, this indirect relationship may not account for this residential location choice being directly influenced by activity participation *(Ben-Akiva and Bowman 1998)*. Thus, in addition to the four broad relationships examined in this literature review, more attention must be directed toward understanding the connection between activity participation and residential location choice.

With respect to household lifestyle and lifecycle class membership, the literature suggested that while observed socioeconomic and demographic characteristics help to explain the residential location decisions of households such characteristics are often not independent of one another. Their collective effect, expressed through the concept of household lifestyle, may better explain the residential location decisions of a household concerning neighborhood selection, housing structure, and housing tenure; and how these separate decisions ultimately inform household travel decisions. The lifestyle approach for relating individual and household characteristics with residential location choice has been favored for several reasons. First, lifestyle preferences are not simply reflective of observed socioeconomic and demographic characteristics, such as household size or income level, but are also representative of observed behaviors, such as activity participation and transit use, making the link between lifestyle and residential location choice more policy sensitive. For example, policymakers are less likely to influence income levels of households relative to improved accessibility of transit than they may be in promoting a lifestyle favoring transit use through an improvement in accessibility to the alternative transportation option. Second, lifestyle classifications within defined lifecycles are more intuitive than individual socioeconomic and demographic categorizations since the lifecycle approach comprehensively considers a multitude of socioeconomic and demographic attributes within a defined household composition. However, a significant methodological barrier to employing the lifestyle approach relates to their definition and the process of assigning membership. As opposed to the use of discrete socioeconomic and demographic observations, such as income level or gender, lifestyle membership may not be as clear in its description or subsequent assignment; a process further complicated by the potential for a large number of lifestyle categories within a specific lifecycle. For instance, two households may belong to the same lifecycle segment and have similar income levels, but differ in their proclivity toward transit use, whereas another pair of households in a different lifecycle segment may have a similar proclivity toward transit use, but have different income levels. Employing a discrete approach based on socioeconomic and demographic observations may simply produce two segments, defined by household income, whereas the utilization of a lifestyle and lifecycle approach may produce four unique segments.

The second dimension within the literature review relates to the relationship between residential location choice and the independent decisions of housing structure and tenure. There has been extensive research seeking to model how households make these discrete housing decisions; however, there have been a variety of approaches to address these characteristics of the housing unit and the tradeoffs undertaken by relocating households. In the literature, the decision of housing tenure is generally represented as a clear decision with two options, while the decision of housing structure is not as cut-and-dry and is generally dependent on the survey instrument and availability of data. In regard to the former dependency, contrasted by a revealed preference survey instrument, a stated preference survey instrument will expectedly limit the variety of housing structures offered to the respondent due to the inherent trade-offs they must make with other decisions related to tenure, neighborhood selection, or travel. In terms of the availability of data, a difficulty akin to the aforementioned lack of disaggregate built environment data exists when trying to examine the finer housing structure classifications that distinguish different types of attached single-family or multifamily housing units. Furthermore, the availability of data that are related to the interior of the housing unit (e.g., number of rooms) or parcel-specific (e.g., lot size) would undoubtedly enhance the understanding of household residential location choice.

A review of literature related to the choice of neighborhood selection revealed a major obstacle related to data availability and measurement. In the discussion regarding neighborhood boundary delineation, the frequent use of a fixed geographic boundary to represent a neighborhood and measure a household's surrounding built environment has been likely selected more for the availability of data at this particular geographic level rather than theoretical soundness. A more accurate operationalization of the neighborhood concept is related to the use of a geographic boundary extending from the household's specific location, which takes into account natural barriers and accessibility along the street network; however, disaggregate built environment data are not as widely available as the more familiar aggregate data available at a fixed geographic boundary. A commonly held belief within the reviewed research pertaining to measures of the built environment and transportation is that more disaggregate data of density, diversity, and design are necessary toward gaining a more informed understanding of a household's residential location choice and the decision's effect on travel behavior. This notion becomes evident when considering density measures of the built environment, which are ubiquitous to the literature and completely dependent upon the selection of neighborhood boundary. For instance, two households that are located in different fixed geographies may have the same number of retail opportunities located within a quarter-mile network distance, but the retail density measures for the households would vary dependent upon the area of the fixed boundary in which they reside.

In respect to the relation with travel decisions, much of the literature examined has recognized that the relationship of residential location choice with travel decisions has been confounded due to the observed phenomenon of residential self-selection and other endogenous correlations. The key barrier in correcting for these correlations is deciding the correct mechanism for correction, which largely depends on the endogenous correlation that needs to be controlled. In order to fully understand the relationship between residential location choice and automobile ownership, commute distance, or access to alternative transportation options, such endogenous correlations need to be accounted for jointly in order to gage their effects relative to each other.

3.0 SEGMENTING HOUSEHOLD MARKETS

In this application, the decision maker faced with the multifaceted choice of residential location was exemplified as the household unit. Being that the household unit is a unique entity that may be segmented in any variety of ways, it was important to classify this decision maker with an approach stringent enough to efficiently model in a complex framework, but sensitive enough to capture the heterogeneity in household attributes that differentiated their decision making processes. Likewise, this segmentation of households needed to be accomplished within a range that was both interpretable and meaningful to policymakers. In an effort to achieve this balance, the research team explored an empirically-driven and an a priori segmentation approach; eventually settling on the latter application due to a stronger capacity for incorporation with established regional modeling approaches.

3.1 HOUSEHOLD ACTIVITY PROFILE CLASSIFICATIONS

The aforementioned empirically-driven method toward classifying the household unit sought to produce activity profiles representing household respondents to the Oregon Household Activity Survey *(Oregon Modeling Steering Committee 2013)*. The fundamental principle informing this activity-based strategy was that travel has been traditionally viewed as a demand derived from the necessity for households to engage in their selected activities. This linkage between household activities and subsequent travel behavior provided the impetus for a distinctive approach toward the market segmentation of the decision-making unit in which classes of households were distinguished from or aligned with other households according to their revealed time allocation for one-day of discretionary and mandatory activities. The following paragraphs describe the methodological approach utilized in order to produce these activity profiles and provide an overview of the classifications developed by this empirically-driven strategy to market segmentation.

The methodological approach utilized for discretizing households into mutually exclusive activity profiles ultimately culminated in the delineation of five activity profiles from disaggregate activities reported by OHAS respondents. In order to classify households into activity profiles based upon their observed one-day activity profiles, a two-stage procedure was employed. The first stage of this approach involved a manual accumulation of the diverse household activity types recorded by the statewide survey; whereas the second stage took the time spent by households on these aggregated activity types and performed a factor analysis in order to assemble them into activity profiles generated by the statistical process.

A preliminary subjective classification of the reported activities placed 21 disaggregate activity types excluding those activities without specification or that resulted in a loop trip, into a more manageable combination of 12 different activities. Table 3.1 provides a breakdown of this initial manual grouping of household activity types, which in certain instances involved the collection of three reported activities into one aggregated household activity.

Table 3.1: Manual Aggregation of Household Activity Types Reported in OHAS

Aggregated Activity	OHAS Activity Type 1	OHAS Activity Type 2	OHAS Activity Type 3
Work-at-Home	Working at Home		
Other Home-Based	At Home Activities		
Work-Related	Work/Job	Other Work Activities	Work/Business Related
School-Related	Attending Class	Other School Activities	
Pick-up/Drop-Off	Change of Mode	Dropped Off Passenger	Picked Up Passenger
Service Vehicle	Service Private Vehicle		
Routine Shopping	Routine Shopping	Household Errands	
Specialty Shopping	Major Purchase Shopping		
Out-of-Home Dining	Eat Meal Outside of Home		
Personal Maintenance	Health Care	Personal Business	
Civic/Religious	Civic/Religious Activities		
Recreation/Entertainment	Outdoor Recreation	Indoor Recreation	Visit Friends/Relatives

Upon assembling these aggregated activity groups, the next step in the development of activity profiles was to conduct a factor analysis using principle component extraction on the time allocation provided to these 12 aggregated activities by each household. To account for the differences in household size and the subsequent implication of larger households having a greater cumulative time budget, a strict budget constraint of 1,440 minutes, or 24 hours, per household member was assumed. An artifact of this assumption was the creation of a measure for the percentage of time allocated to different activity types.

A summary of this measure of household time allocation percentage for residents of the Portland metropolitan region and the entire statewide study area is provided in Table 3.2. Per the results of this descriptive overview, Portland households spent a greater proportion of their day on work- and school-related activities, whereas residents from the remaining stretches of the state spent a larger percentage of their observed day on routine shopping, personal maintenance, and other home-based activities, on average. Overall, the average Oregonian spent approximately one-quarter of their daily time allocation on activities outside of their residence.

Table 3.2: Percent of Household Time Allocation per Aggregated Activity Type

Aggregated Activity	Portland metro*	Outside of Portland metro*	Oregon
Work-at-Home	2.43%	1.68%	1.86%
Other Home-Based	71.4%	75.86%	74.40%
Work-Related	15.45%	11.86%	12.74%
School-Related	3.48%	2.74%	2.92%
Pick-up/Drop-Off	0.45%	0.24%	0.29%
Service Vehicle	0.06%	0.08%	0.07%
Routine Shopping	1.04%	1.29%	1.23%
Specialty Shopping	0.10%	0.11%	0.11%
Out-of-Home Dining	0.87%	0.70%	0.74%
Personal Maintenance	1.20%	1.66%	1.54%
Civic/Religious	0.40%	0.44%	0.43%
Recreation/Entertainment	3.37%	3.36%	3.36%

*Does not include Clark County, WA

The aforementioned factor analysis was then performed using these activity allocation percentages to uncover any bundling of seemingly disparate household activity types that may not be evident or easily observed through sole consideration of individual activity durations. This representation of household activity time allocation through a factor analysis borrowed from the research of Hanson and Hanson *(Hanson and Hanson 1981)*, who introduced this strategy in their representation of activity patterns within a space-travel time context. Descriptive results of the principle component factor analysis, which produced five unique components or activity profiles, are denoted in Table 3.3. The decision to collect five activity profiles was informed by the eigenvalues produced by the principle component extraction, where a component with an eigenvalue greater than 1.0 was preserved.

Table 3.3: Principle Component Analysis of Aggregated Activity Types

Aggregated Activity	Component 1	Component 2	Component 3	Component 4	Component 5
Work-at-Home	-0.13	-0.08	-0.05	0.85	-0.13
Other Home-Based	0.80	0.17	-0.16	-0.04	0.05
Work-Related	0.44	-0.53	0.15	-0.24	-0.08
School-Related	0.84	-0.06	-0.05	0.13	-0.06
Pick-up/Drop-Off	0.30	0.09	0.03	0.18	-0.26
Service Vehicle	-0.01	0.22	0.16	0.04	0.51
Routine Shopping	0.08	0.68	-0.15	-0.06	-0.12
Specialty Shopping	-0.02	0.36	0.28	-0.12	0.03
Out-of-Home Dining	0.08	0.46	0.42	-0.07	-0.13
Personal Maintenance	-0.02	0.27	-0.64	0.04	-0.18
Civic/Religious	0.19	0.04	-0.15	0.19	0.76
Recreation/Entertainment	0.18	0.09	0.51	0.35	-0.07

The aggregated activities within the activity profiles with the strongest correlations, which were noted as those factor scores with values greater than 0.30 or less than -0.30, reflect the activities that provide the greatest weight in defining the activity profile. The complexities of these five activity profiles do not lend themselves to a clear and immediate interpretation. For instance, an examination of the factor scores contributing to the first component detail a strong positive influence of the school-related and home-based aggregated activity types on this bundle and a more modest positive influence of the work-related and pick-up/drop-off aggregated activity types in designating this complex market segment. The following bulleted points provide a brief description of the five activity profiles that resulted from this factor analysis with principle component extraction.

1. Activity Profile 1: Defined by school-related and home-based activities in addition to those activities related to transporting other individuals.

2. Activity Profile 2: Defined by shopping and out-of-home activities with a negative association with work-related activities.

3. Activity Profile 3: Defined by discretionary activities such as recreation/entertainment and out-of-home dining with a negative association with personal maintenance activities.

4. Activity Profile 4: Defined by the home-based activity of working-at-home and complemented by the discretionary activity of recreation/entertainment.

5. Activity Profile 5: Defined by the performance of civic/religious activities and those activities associated with private vehicle service.

In total, the above five activity profiles represent complex interactions and tradeoffs that exist among household members. For instance, the first activity profile in which four distinct aggregated activities were noted as having strong contributions toward the development of a single activity profile illustrates that school activity engagement from a household perspective does not simply entail the time spent as a student, but also includes the time spent by parents transporting school-aged children. Nevertheless, the caveat that these potential market segments are reflective of a single-day observation of activity time allocation should be reiterated before making too many inferences.

Although this technique for segmenting housing units based on activity allocation showed initial promise as an approach toward segmenting households, the strategy was ultimately abandoned due to this limitation attributed to reflecting a household unit's typical activity profile centered on the results of a household travel survey that only captured activities from a single weekday. Guidance from members of the Technical Advisory Committee suggested the sampling bias inherent to this one-day assumption may lead to future complications in estimating annual travel outcomes resulting from a household's revealed residential location choice. However, consideration toward the use of these five activity profiles proved encouraging and should be revisited in future examinations attempting to link one-day travel outcomes to these activity profiles in the context of a household's residential location choice. One such application would be the utilization of these empirically-driven activity profiles within market segments designated by an a priori approach.

3.2 LIFECYCLE STAGE CLASSIFICATIONS

The segmentation of households according to their cumulative activity profile was discontinued in favor of a top-down classification process that incorporated sociodemographic attributes of the household. Similar to the preceding segmentation approach, the classification of households by their lifecycle stage had the intended goal of placing households with a similar composition into the same grouping in order to enable an exhaustive description of household types across the state. In contrast to the creation of activity profiles, the characterization of households into lifecycle stages has a rich tradition in the residential location choice literature and a widely understood meaning to policymakers, who may envision the potential for household to progress through a number of lifecycle stages over a forecasted period. Accordingly, one important aspect to the organization of households into lifecycle stages, which has been exemplified in this approach, was the development of a parsimonious segmentation scheme that produced a manageable number of lifecycle stages. An inclusion of more than a handful of different household attributes, allocated to several subdivisions, would quickly increase the complexity of this classification scheme and cloud any interpretation. Moreover, an intricate division of households in the OHAS dataset would have caused limited sample sizes for certain stages, which would have biased or otherwise restricted any subsequent statistical analysis.

Accordingly, while the residential location choice literature has also taken into account the household attributes of workforce status and income, this lifecycle stage classification was solely based on three components of the decision-making unit: household size, age of household members, and relationship status among household members. After several iterations were examined, the seven lifecycle stages denoted below were settled on as the strategy for segmenting households.

1. Lifecycle Stage 1: Defined as a household with one occupant who is less than 65 years of age.

2. Lifecycle Stage 2: Defined as a household with one occupant who is 65 years of age or older.

3. Lifecycle Stage 3: Defined as a household with one occupant who is 18 years of age or older and at least one related occupant who is less than 18 years of age.

4. Lifecycle Stage 4: Defined as a household with two related occupants who are 18 years of age or older and at least one related occupant who is less than 18 years of age.

5. Lifecycle Stage 5: Defined as a household with two or more unrelated occupants.

6. Lifecycle Stage 6: Defined as a household with two or more related occupants who are all less than 65 years of age.

7. Lifecycle Stage 7: Defined as a household with two or more related households where at least one occupant is 65 years of age or older.

Noting this lifecycle stage organization, while not listed in any particular order, one may easily imagine an individual transitioning through several of these lifecycle stages over the course of his or her lifetime. For instance, an individual may begin his or her life as a child in a household at Lifecycle Stage 4, transition to a household at Lifecycle Stage 5 upon reaching adulthood, and back into a household in Lifecycle Stage 4 as a parent over the course of one generation. Table 3.4 provides an overview of the percentage of households in the OHAS sample within each of the distinct lifecycle stages.

Table 3.4: Percent of Households in OHAS Sample within Seven Lifecycle Stages

Lifecycle Stage	Portland metro area*	Outside of Portland metro*	Oregon
Lifecycle Stage 1	11.97%	12.79%	12.57%
Lifecycle Stage 2	15.66%	11.58%	12.70%
Lifecycle Stage 3	3.12%	2.81%	2.90%
Lifecycle Stage 4	23.01%	19.77%	20.66%
Lifecycle Stage 5	2.68%	3.51%	3.28%
Lifecycle Stage 6	34.55%	35.08%	34.94%
Lifecycle Stage 7	9.01%	14.46%	12.96%

*Does not include Clark County, WA

An examination of the lifecycle stage shares noted in this descriptive synopsis reveals that sampled households were far more likely to fall within the second or fourth lifecycle stages when compared to those observed households residing in other metropolitan or rural areas of the state. Households within the former stage reflect those individuals who live by themselves and are of retirement age, whereas the latter stage represents those households where a married couple is rearing one or more children. In contrast, households sampled outside of the Portland metropolitan region were on average much more likely to be composed of two or more related members with at least one member being or retirement age. Overall, approximately one-third of households observed in the OHAS dataset were segmented as being in the sixth lifecycle stage which encompasses those households of related adults who either chose not to have children or whose children have reached adult age. Those households within the third and fifth lifecycle stage possessed the lowest share of households in the OHAS dataset with households in the former stage reflecting single parent households and other in the latter stage reflecting shared residential arrangements where all household members are unrelated.

3.3 ALTERNATIVE MARKET SEGMENTATION STRATEGIES

As previously mentioned, the seven lifecycle stages represented the culmination of an iterative top-bottom process of segmenting households based on the collective sociodemographic attributes of their members. Nonetheless, two variations of this established classification scheme received additional consideration as potential ways in which to further discretize households. The first of these alternative grouping schemes represented a hybrid of the two aforementioned segmentation processes, whereas the second strategy involved the adoption and modification of a recognized approach. While in the end neither strategy for market segmentation was adopted as a way to detect variation across households in their residential location decisions, each strategy has the potential to contribute toward future analyses into the revealed residential location choices of Oregon residents. As such, each method is given a brief overview in the following paragraphs.

The first alternative segmentation strategy explored by the research team embodied a combination of the activity profile and lifecycle stage methodologies. In this segmentation strategy, the five principle components outlined in Table 3.3 are denoted as activity bundles instead of activity profiles and a series of clustering analyses are performed within each lifecycle stage using the observed activity bundles. The results of the clustering approach may then be thought of as the imaginable activity profiles observed within each lifecycle stage. Similar to the discussion pertaining to the selection of a suitable number of lifecycle stages, careful consideration must be given to the adoption of a particular statistical clustering approach since a further parsing of lifecycle stages with smaller sample sizes will hinder future analyses. Furthermore, the combination of the clustering methodology to the factor analysis, while prevalent in the literature as a more than viable tactic for defining a typology, adds a second statistical strategy to the market segmentation process with an element of subjective selection. Consequently, results of this this approach must be thoughtfully analyzed before being adopted as a way to segment households.

The other alternate market segmentation strategy more closely resembles the adopted lifecycle stage approach in its a priori manner that characterizes the household by its observed sociodemographic and economic attributes. In place of the household relation attribute used in the lifecycle stage classification scheme, the alternate strategy incorporates a household income measure and instead of the household age variable, a measure for age of household head would be utilized. Thus, each household in Oregon would be classified by these two qualities in addition to the household size measure in a segmentation strategy similar to the HIA classification scheme adopted by Metro in their Housing Assignment Model (HIA) for the Portland metropolitan region.

In exploratory work applying the HIA classification scheme, the decision maker was initially categorized into one of five classes based on household size, with any household having five or more members lumped into the fifth household size class. The households were then assigned to one of eight income brackets representing the combined income of all members. These income brackets were based on the eight categories reported in the OHAS dataset and have flexibility in their capability to potentially align with an eight-tiered adaption of the income brackets used in the aforementioned Housing Assignment Model. Finally, one individual in each household unit was denoted as the head of household through an iterative process that at first denoted the household head as being the individual who responded to the survey and subsequently assigned the household the age of its eldest individual in the instances where the respondent information was incomplete.

The outcome of this three-step categorization process was an HIA classification that segmented households into discrete analysis units. In this exploratory work, the classification of household units into HIA segments provided greater control in the modeling structure than the abandoned activity profile approach since the resulting segments may easily be collapsed across any of the three dimensions to either bolster sample size for a particular segment or adapt to aggregate lifestyle stages more sensitive to policy-related efforts. While a decision among the research team and Technical Advisory Committee was made to pursue the lifecycle stage classification described in the previous subsection, the age of household head variable would be used in latter analyses of travel outcomes related to residential location decisions.

4.0 DEFINING HOUSING STRUCTURE AND NEIGHBORHOOD

In the context of residential location choice, the household unit is faced with unique decisions pertaining to the type of housing structure and neighborhood in which they would like to reside. Each household, which the research team has segmented based upon their collective lifecycle stage, must consider the inherent tradeoffs that exist within these fundamental choices to residential location. For instance, a household comprised of a young married couple, classified here as belonging to Lifecycle Stage 6, may presently be suited for a multifamily structure in a more urbanized setting, but may transition in the future into a related adult household with a child, classified here as belonging to Lifecycle Stage 4. The household experiencing this potential shift in lifecycle would undoubtedly have to consider tradeoffs in the residential location decisions of housing structure and neighborhood type, with a natural option leading the household to select a larger structure alternative that is located in a different neighborhood.

This hypothetical scenario underscores a couple of themes related to defining housing structure and neighborhood. The first of which is the abstract nature of each central component to the residential location decision, where one may ascertain that a wide spectrum of alternatives define a household's choice set of housing structure and neighborhood types. This notion similarly situates the forthcoming description of how to discretely represent these choices with the previous explanation of segmenting household markets. A second theme related to the definition of housing structures and neighborhood types encompasses the concepts of data availability and transferability. Often, these seemingly separate ideas must be considered in tandem, as the transferability of any housing or neighborhood typology is in direct relation to the universal availability of datasets. Each of these themes will be given further attention in this section, which describes the methodological strategies implemented by the research team and the resulting typologies for housing structure and neighborhood.

4.1 HOUSING STRUCTURE CLASSIFICATION

As with the selection of a market segmentation strategy for discretizing the household, a handful of approaches were considered for defining the housing structure alternatives within the decision maker's universal choice set. Each of these tested combinations in housing structure type was rooted in the self-reported reply of household respondents to OHAS, who were asked, "Which best describes your home?" The respondent was presented four potential housing structure types as potential answers to this question in addition to the option to refuse a response or state that their home is an alternative not designated by the first four options. Table 4.1 provides a breakdown of the housing structure types reported across the greater Portland metropolitan region and State of Oregon.

Table 4.1: Percent of Households in OHAS Sample within Self-Reported Housing Structure Types

Housing Structure	Portland metro*	Outside of Portland metro*	Oregon	Clark County, WA
Single-Family Unit	77.72%	84.73%	82.75%	87.03%
Duplex	3.23%	2.80%	2.91%	2.00%
3 or More Apartments	18.11%	6.56%	9.60%	7.94%
Mobile Home	1.31%	5.81%	4.62%	2.67%
(Something Else)	0.08%	0.03%	0.04%	0.18%
(Refused)	0.04%	0.07%	0.07%	0.18%

*Does not include Clark County, WA

A glimpse of this descriptive summary of the housing structure types reported in the OHAS sample helps to illustrate two overarching results that steered the development of a housing structure classification. The first outcome pertains to the dominance of single-family housing units across Oregon, the three-county Portland metropolitan region, and Clark County, Washington. The second result, which also had an influence on the specification of the residential location choice models to be later described, was the low share of multifamily structure types, defined in this study as either duplex structures or apartments within complexes of more than two units. In the end, two classification schemes of ranging complexity were examined in the context of this study. The first approach provided additional complexity in the housing structure choice set through augmentation of the dataset with a secondary source, whereas the second approach strictly relied on the reported observations in the OHAS dataset mentioned above. The following paragraphs outline these two strategies for classifying housing structure type.

Being provided with the limited variation in housing structure type offered by the self-reported OHAS dataset, the research team sought to augment this household travel survey dataset with secondary housing data in order to expand the observed choice set of the decision maker. Adhering to the abovementioned results, the most obvious expansion of the housing structure type choice set would be a further parsing of the single-family housing category into multiple categories. The strategy to refine this aggregate classification had the advantage of not only increasing the variation in the single-family structure type, but also the benefit of not further reducing the sample size of those multifamily housing categories already marred by a relatively low percent share. Regarding the first advantage, one may easily imagine the wide range of housing forms encompassed by this common subgroup of housing structure type. For instance, according to the OHAS classification scheme, a single-family housing unit may range in representation from a two-bedroom, single-story Bungalow-style home to a five-bedroom, multistory English Tudor home. A household making a decision between these two housing structures would seem likely to view these housing types as distinct choices.

To account for this range in structure types found within the single-family housing unit category, the research team utilized spatial information provided by Metro's Regional Land Information System (RLIS) dataset. This secondary data source provided parcel-level information on structure size for the majority of tax-assessed single-family housing units in the Portland metropolitan region, which was conveniently linked to the physical address of the structure. By using Geographic Information Systems (GIS), many of those OHAS households residing in single-family housing units within the Portland metropolitan region were able to have their housing structure information augmented with a measure of building footprint. Consequently, the research team investigated the expansion of the single-family unit alternative for those households where this additional data on housing structure were available. This strategy for expanding the single-family housing alternative divided the decision into three separate choices based on the size of the housing structure: small single-family unit, medium single-family unit, and large single-family unit. The initial quantification of the three structure sizes denoted a compact unit as being 1,500 square feet or less, a moderate unit as being between 1,501 to 2,200 square feet, and a large unit as any single-family structure greater than 2,201 square feet in size (Burge and Ihlanfeldt 2006). Table 4.2 shows a summary of the subdivision of the single-family unit category for the Portland metropolitan region and Clark County, Washington.

Table 4.2: Percent of Portland Region Households in OHAS Sample Residing in Single-Family Structures

Single-Family Housing Structure	Clackamas County, OR	Multnomah County, OR	Washington County, OR	Clark County, WA
Compact	12.94%	34.97%	21.73%	32.62%
Moderate	23.80%	37.64%	34.02%	31.86%
Large	35.83%	25.11%	36.33%	19.03%
(Missing Data)	27.43%	2.29%	7.93%	16.48%

Overall, the use of the three divisions in single-family housing structures appeared to provide ample shares of observations within each subcategory, with the majority of single-family units in Clackamas and Washington Counties being larger in area than those single-family units in Multnomah and Clark Counties. However, an examination of the results of this augmentation strategy revealed a new set of challenges. One technical challenge pertains to the ability to adequately supplement the original dataset in a GIS environment with the parcel data provided by Metro's RLIS dataset without having to drop or impute a large share of observations in the OHAS dataset. While the share of households within Multnomah County that cannot be enriched by the supplementary data appears is under five-percent, the share of households in the other three counties of the greater Portland metropolitan region appears to be a severe limitation in using these additional data. A second disadvantage to the expanded single-family alternative approach was the inability to use the added measure of structure size for those households outside the Portland metropolitan region since the measure is only provided within the RLIS dataset. This second disadvantage had the larger consequence of restricting the transferability of this research to regions outside of Portland, which was a guiding principle of this study into residential location choice.

Faced with these limitations and the desire of the Technical Advisory Committee to have the residential location choices of regions outside of Portland studied, the research team opted for a more aggregated approach to classifying housing structure type that strictly relied on the reported observations in the OHAS dataset. In this strategy, to balance out the dominance of the single-family unit structure as an observed choice in the OHAS dataset, those households who reported as residing in a duplex or an apartment unit in a complex with three or more units were lumped together as being attached single-family or multifamily units. Those households who reported as living a housing structure other than the detached single-family or attached single-family dwellings were excluded from this study. The result of this aggregation process was the development of a choice set for housing structure that consisted of two alternatives.

While the aggregation of single-family housing structures into one collective choice has the potential of limiting the policy sensitivity of this housing type since these residences may range considerably in their building footprint, there are a number of advantages to using this aggregated classification scheme. One such advantage is the computational benefit of a confining the housing structure choice set to two alternatives when estimating residential location choice based on additional attributes of neighborhood and housing tenure. This advantage will become more apparent following the discussion on developing a neighborhood typology and estimating the residential location choice models. A second advantage of the more aggregate strategy is the ease of potential integration with established modeling frameworks. Concerning the latter advantage, the utilization of a scheme exclusively separating single-family and multifamily housing structure represented a commonly employed approach for cataloguing housing structure types, which will increase the likelihood of being able to compare future model estimations to regional forecasts of housing structure (e.g., MetroScope) or the prospect of augmenting these structure data with additional attributes (e.g., housing price).

4.2 NEIGHBORHOOD CLASSIFICATION

In conjunction with the choice of housing structure type, the household faced with a residential location decision must deliberate over the type of neighborhood in which they would like to reside. While a standard protocol for defining household choice sets related to housing structure type has been more or less established, the creation of a uniformed neighborhood classification scheme appears to be further from consensus due to the abstract nature of representing the concept of neighborhood with a general typology. When defining neighborhood type, careful consideration must be given toward the selection of indicators to best capture the variation across different neighborhoods as well as the delineation of geographic boundaries to measure the occurrence of these indicators and the methodological approach for operationalizing this theoretical concept of neighborhood type. Moreover, as with the strategies chosen for segmenting household lifecycle class and housing structure type, the research team reflected on the theme of transferability when settling on a preferred approach to defining neighborhood type. The following subsections describe this selected methodology in addition to the results of its application to the Portland metropolitan region and State of Oregon.

4.2.1 Methodological Approach to Defining Neighborhood Type

The first component in the construction of a neighborhood classification scheme was the selection of indicators to utilize in order to distinguish one neighborhood type from another. Adhering to the guiding principle of transferability, the selection process for a set of indicators was contingent upon the public availability of any measure and its coverage across the entire study area. The importance of this notion was previously described in the decision to select the more aggregate tactic for classifying housing structure and centered on the availability of a universal data source. Also informing the selection of indicators was whether the type of measures chosen for this approach to neighborhood classification had the potential of being sensitive to changes in transportation and land use policies and varied regardless of household income or housing price. In defining a neighborhood typology, four general categories of indicators were examined, which included measures describing the built environment, accessibility, neighborhood quality, and collective socioeconomic or demographic attributes of the neighborhood. Many measures found within the latter two categories have a direct association with a household's income or housing price and consequently were not considered in the choice of indicators to represent neighborhood type. Furthermore, indicators of neighborhood quality such as prevalence of property crime or measures describing the educational institutions in a neighborhood were passed over in this classification scheme because of a lack in potential policy-related actions that may be offered in lieu of any finding of quality-related deficiency.

In terms of the built environment and accessibility indicators, a number of different measures were examined. However, presented with the limitation of universal data availability, most measures within the accessibility category (e.g., proximity to transit) were ruled out as potential statewide neighborhood indicators due to their sole availability to Portland or other metropolitan areas within the study area. As for indicators of the built environment, many of the measures considered and those eventually selected for defining a statewide neighborhood typology originated from the 2010 US Census. This decision to use built environment measures provided by this national dataset, which will be described in greater detail in the forthcoming discussion of the methodological strategy used in producing a neighborhood typology, ultimately informed the decision of how to spatially define the boundaries of a neighborhood.

This delineation of geographic boundaries representing the neighborhood unit comprised the second component in the development of a classification scheme for the abstract concept of neighborhood. As mentioned above, the selection of a geographic scale to accurately measure neighborhood indicators was predicated on the utilization of US Census data. These data are provided at a fixed geographic scale of neighborhood based on census units, which inherently has a number of theoretical weaknesses as a spatial representation of the neighborhood unit despite its popularity in application. Central among these limitations is the arbitrary nature in the demarcation of boundary lines, which often fail to account for elements of the physical environment beyond transportation infrastructure and water features. A related weakness in a fixed neighborhood representation, whether based on census units or grid cells, is the lack of sensitivity provided to the placement of the decision maker. In a fixed representation of the neighborhood unit, the analysis unit, which in this case is represented by the household, may be located anywhere within the census boundary, whether in a centrally located position or in close proximity to a boundary line. When the household is located near the boundary of a census-based geography, one may find it reasonable to believe that the household's built environment is more comparable to the built environment of a household across the arbitrary boundary than a household located across the census geography. Finally, the fixed neighborhood representation possesses a potential limitation related to the wide variation in geographic area depending on whether the neighborhood is found in a more urban or rural context. This disadvantage is directly related to the residential population of the neighborhood and is an artifact of the intent of census geographies to encompass a minimum number of households in order to preserve respondent anonymity.

While the fixed scale operationalization of the neighborhood concept may not be as conceptually strong as the sliding scale neighborhood representation, which places the household at the center of an aerial buffer or band based on the street network, the advantages supporting the choice of this spatial scale extended beyond the availability of many built environment measures at this geography. A related advantage of using a fixed neighborhood representation based on 2010 census units is the convenience of being able to provide data that matched the collection period of the OHAS dataset. An arguably more important advantage of using census geographies is the complete coverage of this spatial scale across the entire study area, which permitted a universal representation of all neighborhood typologies for the State of Oregon. The estimation of a residential location choice model that employed a sliding scale neighborhood representation would have the complexity of having to determine a way to represent the neighborhood of a household that was unobserved in the OHAS dataset. This weakness is related to a third advantage of using a fixed neighborhood representation that is based on the improved ease of computation accredited to a representation of neighborhood at this geography since the boundaries are mutually exclusive from one another with no overlap and do not require the generation of a unique neighborhood for all households across the state. As such, a fixed neighborhood representation based on the US Census block group geography was selected as the preferred approach to operationalizing the built environment indicators of neighborhood type.

Having determined the use of built environment measures to reflect distinction in neighborhoods and the spatial representation of US Census block groups at which to quantify these variations, the final decision for operationalizing the concept of neighborhood concerned the selection of a methodological approach. The decision of how to catalog the assortment of neighborhood categories perceived to exist across Oregon received a great amount of attention by the research team. In the end, a factor and clustering approach similar to the strategy proposed in the alternative market segmentation discussion was chosen as the preferred strategy to distinguish neighborhood typologies. The application of this two-staged approach to classifying neighborhood types, which was informed by the literature *(Krizek 2006; Song and Knaap 2007)*, had several advantages. First, akin to the creation of activity bundles, the application of a factor analysis enabled a reduction in the potential for multicollinearity in built environment measures by combining many neighborhood indicators into a set of composite factors that were subsequently clustered into varying neighborhood types. The typology produced by this selected methodological approach also had an added advantage of the potential to guide the forthcoming stated preference research or possibly inform policies promoting the development of certain land use patterns.

The two-staged approach began with the selection of a principal component analysis factor extraction method to arrange the built environment measures into uncorrelated linear combinations. Fundamental to this factor analysis strategy was the choice of a factor in the linear combination that explained the maximum amount of variation. This factor, termed the principal component, was used to derive the initial selection of components to be later incorporated in a clustering strategy. A varimax rotation was applied prior to this determination of a principal component to simplify the interpretability of the factor structure through a reduction in the number of overall factor loadings. Analogous to the explanation of the alternative market segmentation strategy, the resulting components were then used in a k-means clustering analysis to define a universe of neighborhood typologies across Oregon.

An important aspect of this two-staged approach was the unique treatment of neighborhoods that reside within the Portland metropolitan region versus those neighborhoods in other stretches of the state. For those neighborhoods within the Portland region, where Metro's RLIS dataset provides richer land use data than those produced by the US Census, auxiliary built environment measures were added to the factor analysis portion of the classification process. This feature to the construction of a scheme represented a revision to the initially produced statewide classification, as a second factor and clustering analysis using the extra built environment measures was conducted on two neighborhood types within the Portland metropolitan region. By employing this additional step, a subset of neighborhood types for the Portland region was established within each of these two statewide neighborhood types. This ability to nest these additional neighborhood types, which will be illustrated in the next subsections, allowed greater disparities in the built environment to be described in the Portland metropolitan region and was a necessary condition in preserving the capability of transferring this typology across the state.

The development of a neighborhood typology for Oregon using this methodological approach, the results of which will be discussed in following subsections, has the potential to enrich the understanding of neighborhood effects in the future stated preference research and may prove beneficial for statewide transportation models (e.g., GreenSTEP), which presently offer a limited depiction of the variation that exists across different neighborhood types. Moreover, the use of supplementary built environment measures not available across Oregon may be of interest to Portland land use models (e.g., MetroScope) that do not presently account for this central aspect of residential location choice. For that reason, the typologies produced in this factor and cluster analysis may be integrated within the structure of these models and, accordingly, expand the representation of neighborhood within these modeling efforts.

4.2.2 Neighborhood Indicators and Results of Factor Analysis

As alluded to in the previous subsection, producing the fine gradation that enabled the parsing of one neighborhood from an alternative consideration situated in a similar setting was largely predicated upon the availability of rich built environment measures. This requirement directed the development of a typology that had the flexibility to provide an expanded representation of neighborhood type for the Portland metropolitan region without impacting the more aggregate statewide typology. This ability to extend the potential neighborhood consideration set of a household was credited to the use of a more detailed built environment dataset made available at the regional scale. In addition to this guiding principle of scalability in neighborhood representation, the theme of transferability was also addressed since the typology established for the residential location decision of neighborhood type was produced using publicly accessible, built environment measures. The consideration of this strategy was intended to increase the likelihood of existing or future modeling efforts to utilize or replicate the neighborhood typology established for our residential location choice framework.

A number of combinations of built environment measures were examined throughout the development of a statewide and regional neighborhood typology using the two-staged approach. After a spatial examination of the results from the initial factor and cluster analyses produced unsatisfactory groupings of neighborhood types, a decision was made to separate out those neighborhoods residing in urban areas from those located in more rural contexts, as defined by the 2010 US Census. After segmenting based on whether the block group resided in an urban or rural context, the results of the amended factor and cluster approach produced components and subsequent classifications that met both the more objective criterion related to component extraction and the admittedly subjective spatial uniformity requirement. The built environment measures selected for the adopted iteration of the statewide factor analysis for neighborhoods in an urban context as well as the resulting factor scores for the components are detailed in Table 4.3. The four selected components were constructed from five different built environment measures and explained 96% of the variation across Oregon's 1,772 urban neighborhoods.

Table 4.3: Statewide Principle Component Analysis of Built Environment Measures in Urban Contexts

Built Environment Measure	Component 1	Component 2	Component 3	Component 4
Intersection Density	0.442	0.374	-0.164	0.151
Employment Density	0.086	0.051	-0.063	0.989
Population Density	0.956	0.100	-0.106	0.089
Average Year Built	0.106	0.957	-0.154	0.051
Distance from CBD	-0.105	-0.147	0.976	-0.065

The same five built environment measures were also used for the final iteration of the factor analysis for neighborhoods in rural contexts. As displayed in Table 4.4, the use of the five measures resulted in four components explaining 98% of the variation across Oregon's 1,135 rural neighborhoods, represented as census block groups.

Table 4.4: Statewide Principle Component Analysis of Built Environment Measures in Rural Contexts

Built Environment Measure	Component 1	Component 2	Component 3	Component 4
Intersection Density	0.794	0.386	0.241	0.065
Employment Density	0.318	0.934	0.157	0.028
Population Density	0.970	0.209	0.096	-0.006
Average Year Built	0.158	0.150	0.959	0.175
Distance from CBD	0.015	0.025	0.159	0.987

As was also evident in the results from the urban-specific factor analysis, the first component of the rural-specific analysis was strongly influenced by the population and intersection density neighborhood measures. The second component in the rural-specific analysis was also impacted by intersection density, but more so by the measure of employment density. A comparable component in the urban-specific analysis may be found in the fourth component, which was also predominately influenced by the measure for employment density and influenced to a lesser extent by intersection density. The third component in the rural-specific factor analysis was also somewhat impacted by intersection density, but was strongly influenced by the measure representing average structure age across the neighborhood. The average year built measure also dictated the second component in the urban-specific analysis, which was also largely influenced by the intersection density measure. Finally, the fourth component resulting from the rural-specific factor analysis was strongly influenced by the accessibility measure of distance from the central business district. The third component resulting from the urban-specific factor analysis possessed a similar composition, but had factor scores of an opposite direction from the distance measure for the remaining neighborhood measures.

Whereas the factor analysis for the statewide model strictly relied on built environment measures supplied by the US Census, the factor analysis informing the neighborhood typology for the Portland metropolitan region was able to also draw upon measures made available from Metro's RLIS dataset. After attempting several iterations of the factor and cluster analysis for this regional representation and performing a spatial examination of the neighborhood types produced by this methodology, the decision was made to preserve three of the five neighborhoods within the urban area of Portland. Conversely, as mentioned in the previous subsection, two neighborhood types were further segmented by carrying out a second factor analysis bolstered by the addition of two built environment measures to the previous five measures used in the statewide analysis.

Whereas a greater conversation pertaining to the resulting neighborhood typologies will be provided in the following subtopic, the following paragraphs provide an overview of the factor scores comprising the components used in the subsequent clustering analysis. Table 4.5 describes the six components that explained 97% of the variation across the 341 block groups characterized as belonging to the more centrally located subdivided urban neighborhood (Neighborhood Type B). These six components were produced from a factor analysis of the seven built environment measures, which included the additional measures related to the percent of commercial development and average lot size within Portland block groups. Table 4.6 provides the same information for the other subdivided class (Neighborhood Type C) that was typically located a greater distance from the city center. In contrast to the neighborhood explained in Table 4.5, the same seven measures yielded five components explaining 92% of the variation across the 393 block groups noted as being slightly farther from the city center.

Table 4.5: Portland Principle Component Analysis of Built Environment Measures in Neighborhood B

Built Environment Measure	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6
Intersection Density	0.352	-0.269	-0.193	0.357	0.046	0.098
Employment Density	0.043	0.029	-0.149	0.093	0.378	0.905
Population Density	0.953	-0.188	-0.082	0.087	-0.017	0.034
Average Year Built	0.098	-0.101	-0.319	0.901	0.024	0.090
Distance from CBD	-0.088	0.017	0.937	-0.282	-0.027	-0.135
Percent Commercial	-0.018	0.065	-0.020	0.018	0.944	0.321
Average Lot Size	-0.185	0.963	0.016	-0.089	0.064	0.028

Table 4.6: Portland Principle Component Analysis of Built Environment Measures in Neighborhood C

Built Environment Measure	Component 1	Component 2	Component 3	Component 4	Component 5
Intersection Density	0.474	-0.248	0.256	-0.197	0.083
Employment Density	0.064	-0.010	0.019	-0.085	0.938
Population Density	0.914	-0.238	0.138	-0.141	0.064
Average Year Built	0.127	-0.053	0.980	-0.037	0.015
Distance from CBD	-0.128	0.028	-0.038	0.976	-0.079
Percent Commercial	0.038	0.036	-0.008	-0.115	0.326
Average Lot Size	-0.213	0.964	-0.055	0.027	-0.006

The first component in both Neighborhood Type B and Neighborhood Type C produced by the Portland regional factor analysis was strongly influenced by the population and intersection density built environment measures. Similarly, the second component to be used in the upcoming cluster analysis developing the two unique neighborhood types was strongly dictated by a positive association with the average lot size measure and a negative association with an increase in intersection density. The third component in the Neighborhood Type B analysis and the fourth component in the Neighborhood Type C factor analysis were predominately influenced by the built environment measure denoting the distance of the block group center from the central business district. In turn, the fourth component of the Neighborhood Type B factor analysis was largely driven by the average year built measure, with notable influence also arising from the intersection density measure. This component has a similar composition to the third component described in the Neighborhood Type C component matrix. Finally, the fifth and sixth components in the factor analysis related to Neighborhood Type B were both strongly influenced by the percent commercial and employment density measures, with the fifth component being more influenced by the former measure and the sixth component more strongly impacted by the employment density built environment measure. This sixth and final component in the Neighborhood Type B matrix most resembles the fifth component in the factor analysis related to Neighborhood Type C. The components produced from a factor analysis of the various built environment measures noted above were next incorporated into a k-means clustering analysis that provided the nested neighborhood typologies referred to in previous sections.

4.2.3 Neighborhood Typologies and Results of Cluster Analysis

A cluster analysis, introduced in previous discussions, was next performed on the components produced by the factor analyses of select built environment measures. The prior application of a factor analysis enabled a reduction in the potential for multicollinearity in built environment measures by combining many measures into a set of composite factors that may be clustered into a classification scheme. This methodological strategy led to the creation of an objective neighborhood classification scheme to be used in the development of models depicting residential location choice and related travel outcomes. As mentioned, the neighborhood typology developed for the entire study area was expanded within a nested structure for two neighborhood classes found in the urban portions of Portland. The following subsection provides a narrative detailing these neighborhood categories as well as a description of the observed association of built environment measures within each of the neighborhood classes.

During initial iterations of the factoring and clustering approach that ultimately led to a finalized neighborhood classification scheme, a decision was reached to distinguish those neighborhoods residing in an urban context from those located within a more rural context. This screening process safeguarded the methodological approach from generating a neighborhood in the heart of a metropolitan area from being clustered with a neighborhood in the outlying hinterland. Having established this initial filter, a k-means cluster analysis was performed separately for the components derived from the urban-specific factor analyses. The results from the clustering processes led to the production of five neighborhoods found in urban areas across the state and eight neighborhoods in the urban context of Portland. The five neighborhoods found in the urban stretches of Oregon, which were given generic names to remove any bias related to a subjective naming scheme, echoed the variation in the four selected components that existed across urban-situated block groups. These urban area neighborhood types found across Oregon, as well as their rural counterparts, are spatially represented in 9.0, while Table 4.7 provides a descriptive overview of the statistical means of the different built environment measures used to inform the factor analysis that discretized these urban area neighborhood types.

Table 4.7: Mean of Built Environment Measures for Statewide Neighborhoods in Urban Areas

Built Environment Measure	Neighborhood Type A	Neighborhood Type B	Neighborhood Type C	Neighborhood Type D	Neighborhood Type E
Intersection Density (Intersections/Sq. Mile)	423	273	135	162	105
Employment Density (Jobs/Sq. Mile)	41,167	1,934	1,562	1,224	1,261
Population Density (Persons/Sq. Mile)	16,891	6,689	3,532	6,274	2,205
Average Year Built (Years from Present)	54	62	32	24	12
Distance from CBD (Miles from Centroid)	1.2	3.8	2.5	10.0	18.3
Sample Size (Count)	34	503	696	388	151

The block groups classified as belonging to Neighborhood Type A were characterized as having the highest employment, intersection, and residential densities among the five urban area neighborhoods, as well as the shortest average distance from block group centroid to the central point of the nearest metropolitan planning organization (MPO). Neighborhood Type B tended to have an average structure age that was slightly older than the other neighborhood classifications and the second highest magnitude for the density measures. Aside from intersection density and average year built, the statistical mean for the measures in Neighborhood Type C were comparable to those block groups in the Neighborhood Type B classification. Block groups in the fourth category (Neighborhood Type D) had an average population density closely resembling those in Neighborhood Type B, but were located an average distance of over ten miles from the closest downtown and contained far newer structures than the aforementioned neighborhood types. Neighborhoods in Type E had a similar employment density to those neighborhoods classified as Type D, but had structures that were, on average, recently built. Block groups classified as Neighborhood Type E were also generally located the farthest from the nearest MPO downtown area.

As previously mentioned, the block groups in Neighborhood Type B and C were additionally segmented by a supplemental factor and cluster analysis for those neighborhoods located in the urban areas of Portland. The sequential clustering process divided Neighborhood Type B into three unique categories and bisected those block groups in Neighborhood Type C into two categories. The result of this second application of the two-staged methodological approach was the construction of an eight class typology for neighborhoods located in the urban areas of Portland. Regarding this extra segmentation, Table 4.8 offers a summary of the statistical averages for the seven built environment measures across the five nested neighborhood categories.

Table 4.8: Mean of Built Environment Measures for Nested Portland Neighborhoods in Urban Areas

Built Environment Measure	Neighborhood Type B1	Neighborhood Type B2	Neighborhood Type B3	Neighborhood Type C1	Neighborhood Type C2
Intersection Density (Intersections/Sq. Mile)	353	241	124	148	130
Employment Density (Jobs/Sq. Mile)	2,348	1,408	3,586	1,013	5,405
Population Density (Persons/Sq. Mile)	8,185	6,346	3,186	3,811	3,196
Average Year Built (Years from Present)	72	55	58	32	34
Distance from CBD (Miles from Centroid)	3.2	5.0	3.6	6.2	5.9
Commercial Land Use (Percent)	13	11	35	6	32
Average Lot Size (Square Feet)	6,688	10,972	60,230	22,800	77,353
Sample Size (Count)	187	189	17	268	73

An examination of the three Type B neighborhoods reveals that the first type (Neighborhood Type B1) has a relatively high intersection and population density, as well as an older average structure age and lower average lot size. In contrast, the third type (Neighborhood Type B3) was characterized by a high proportion of commercial land uses, increased employment density, and high average lot sizes when compared to the other block groups within Neighborhood Type B classification. Likewise, Neighborhood Type C2 differs from the other nested Neighborhood Type C class by being characterized as having a higher employment density, share of commercial land uses, and average lot size. 9.0 illustrates the spatial allocation of those neighborhood types found in Portland region. The next paragraphs will briefly discuss the results from the clustering of neighborhoods located in rural areas across the state.

The clustering of the four components produced by the factor analysis of neighborhoods in rural areas generated two rural clusters in the statewide typology. Referencing 9.0, the spatial distribution of the neighborhoods in rural areas of the state is exhibited, while Table 4.9 provides the mean of the five built environment measures, used in the factor analysis, across rural area neighborhood types.

Table 4.9: Mean of Built Environment Measures for Statewide Neighborhoods in Rural Areas

Built Environment Measure	Neighborhood Type F	Neighborhood Type G
Intersection Density (Intersections/Sq. Mile)	200	19
Employment Density (Jobs/Sq. Mile)	1,682	112
Population Density (Persons/Sq. Mile)	3,974	356
Average Year Built (Years from Present)	49	36
Distance from CBD (Miles from Centroid)	44.1	39.2
Sample Size (Count)	223	912

On average, block groups associated with Neighborhood Type F have a higher intersection, employment, and population density than those block groups in the other rural area neighborhood type. The built environment measure of average distance to the nearest MPO central business district are comparable when considering the distribution of these classifications across the state, while the block groups classified as Neighborhood Type F tend to have more established housing structures than the other rural area neighborhood type.

The development of a statewide neighborhood typology consisting of these two rural and the previously mentioned five urban neighborhood types provided the set of alternatives available to a household making their residential location decision. The selection of the described methodological approach was steered by the desire to produce a neighborhood typology that was transferable in terms of application within alternative study areas and modeling platforms. In regard to the first condition, the selected classification scheme for the statewide typology was developed exclusively on publicly available built environment data with the capability to further subdivide those neighborhoods where more detailed regional data are available. As for the latter benefit concerning integration within alternative modeling platforms, the chosen neighborhood typology was decidedly not linked to any spatial representation. While one of the selected built environment measures represented an attribute of spatial pattern, distance to the nearest downtown, this indicator used in the factor analysis and the chosen geographical scale for operationalizing the concept of neighborhood did not result in the development of a spatially linked typology. Therefore, a neighborhood type found in one urban area of the state may be identical to another neighborhood of a different urban area. This characteristic of the typology formation has enabled the potential to integrate the produced classification scheme in other modeling platforms. Moreover, a conscientious decision was made by the research team to only include those neighborhood indicators that are viewed as being responsive to transportation and land use policy. This attractive attribute of the neighborhood typology described in this section is important when considering the travel outcomes tied to a household's residential location choice. The following sections will describe these two facets.

5.0 RESIDENTIAL LOCATION CHOICE MODEL

Having identified a strategy for segmenting the decision maker based on their lifecycle stage and developed a classification scheme to represent the more abstract dimensions of housing structure and neighborhood type, the research team moved toward developing a framework in which to model the complex decision of where a household chooses to locate. An improved comprehension of these household residential location choices is fundamental toward apprising long-term transportation and land use planning models forecasting short-term travel outcomes. Accordingly, a three-level nested logit model structure, which accounted for housing structure and neighborhood type as well as tenure, was selected in an effort to better understand the multitude of decisions associated with a household's residential location choice. The model framework changed during the course of this phase, including the testing of various model structures, spatial segmentation schemes and specifications with input of the Technical Advisory Committee and others. The following section provides a summary of these frameworks. Model estimation results are shown in the Appendices.

5.1 MODEL STRUCTURE

Several residential location choice model structures were devised and examined by the research team, which ranged in study area selection and division, nesting order of the dimensions reflecting residential location choice, and aggregation of alternatives within the housing structure and neighborhood type choices. The following paragraphs briefly expound upon the actions taken at these decision points, while providing an overview of the final model structure resulting from this iterative process.

The first decision point concerned the selection of a study area to observe residential location choices. Original efforts, as explained in the previous sections, were aimed toward developing a statewide model with a regional component for the Portland metropolitan region. Preliminary work toward this goal, which was educated by the development of a choice set for the housing structure and neighborhood alternatives across the state, led the research team to the decision that a statewide residential location choice model should be segmented based on the location of a neighborhood in an urban or rural area. Succeeding model structures sought to further segment the urban areas and rural stretches of the state based on regions classified by the Oregon Department of Transportation, so as to improve the ability to differentiate between regional differences across similar neighborhood types. However, a final decision was made to draw together a statewide version of the residential location choice model scaled down to the Portland metropolitan region that pooled together urban and rural areas. Results of the subsequent model estimation for the four-county Portland region were then to be compared against a regional choice model for the Mid-Willamette Valley, which had the consequence of not enabling the more detailed neighborhood typology for the Portland metropolitan region to be utilized.

A second point in which the research team requested advice from the technical advisory committee pertained to the nesting order of the three modeled dimensions of residential location choice. The initial three-tiered model structure had considered the decision of tenure to have the highest ranking of correlation, which was followed by the decision of whether to reside in a single-family or multifamily housing structure and the final residential location decision related to neighborhood type. The decision to rank these choices in the described order was an artifact of early research that only considered the choices of tenure and housing structure type, but was later determined to be theoretically flawed. As a result, the research team settled on a final three-tiered nested logit model structure where the choice of neighborhood type was noted as having the highest ranking of correlation, followed by the decision to rent or own and the housing structure type decision.

Once the final study area and nesting framework of the residential location choice model was decided, the research team had to address the statistical limitation of small and disproportionate sampling sizes for certain combinations of neighborhood, tenure, and housing structure alternatives. The decision to proceed with a choice set for housing structure type that only included alternatives for single-family and multifamily or attached housing structures led to an imbalance of housing types that transcended across neighborhood types. The decision was made to continue with this division of the residential location choice in housing structure type; however, the result was that many alternatives had to be collapsed in order to provide an acceptable sample size for certain combinations of residential location choices. This collapsing of alternatives ultimately restricted the conclusions drawn from the estimation of the model that concerned ownership of multifamily units.

The culminating outcome of the research team's actions informed by the technical advisory committee's guidance at these decision points was the three-tiered nested logit model structure for the Portland metropolitan and the accompanying structure for the alternative Mid-Willamette Valley region displayed in Appendix B. These model structures, which were settled on through an iterative process, served as the basis for the specification and estimation of the residential location choices observed by households in the Portland metropolitan region, which were then compared to the observed choices of households in the alternative region.

5.2 MODEL SPECIFICATION AND ESTIMATION RESULTS

Proceeding with the model structure described in the previous subsection, a residential location choice model was specified and estimated for the pooled urban and rural areas across the four-county Portland metropolitan region. The specification of the Portland regional model, which denoted the observed decision to own a single-family residence in Neighborhood Type A as the base alternative, included the constants of the remaining collapsed alternatives and four attributes of the household. Concerning the latter set of explanatory variables, a decision was made to forego the strictly binary representation of a household's lifecycle stage classification in favor of the use of the sociodemographic variables that comprised the development of these lifecycle stages. The following paragraphs will discuss the process surrounding this decision of how best to represent household characteristics as well as a description of the household price sensitivity measure and the reason for its exclusion from the regional model as an alternative-specific variable. Finally, a brief account of the estimation results for the Portland model will be described, with a summary of some intuitive takeaways to this model and the Mid-Willamette Valley estimation provided in Appendix B.

Previous iterations to the final residential location choice model specified household sociodemographic and economic attributes as lifecycle stages as an approach to represent differences across households in terms of size, age, and relationship status among household members. However, complications arose with the inclusion of these market segments as binary explanatory variables in the choice model, as the advancement of this modeling approach would limit the number of parameters that could be included in the final specification. The specification of one binary variable representing lifecycle stage classification drastically increased the number of parameters in the final residential location choice model, which further complicated the interpretability of the model. For instance, provided with a model having 17 alternatives, the addition of one binary variable would require the addition of 16 more parameters. One alternative strategy to somewhat sidestep this issue was to simply specify only a handful of the lifecycle stages; however, this incomplete strategy provided a less than adequate representation of households and failed to provide a meaningful illustration of the observed variation in sociodemographic and economic attributes that existed between the residential location choices of households. As such, the joint decision between the research team and the technical advisory committee was made to proceed with the use of sociodemographic variables as opposed to the previously accepted lifecycle stages.

In order to distinguish between housing preferences related to the cost of the housing across alternatives, a set of housing cost regressions, developed similar to Cho *(Cho 1997)* and Skaburskis *(Skaburskis 1999)* were estimated to attempt to capture the variation in housing costs in the residential choice model Housing price data was not available to capture the range of prices for different types of housing types (single-family at different scales of housing, multifamily), tenure (rent, own or mortgaged) and neighborhood types (central business district, suburban, inner urban). Instead, Public Use Microdata Sample data set at the Public Use Microdata Area level[1] from the 2009-2011 American Community Survey's (ACS) three-year survey was used to develop a set of regressions to estimate the amount of money spent renting and owning across the state. Since the characteristics of the housing unit for each household surveyed in the ACS were not captured, household size was used as a proxy to determine the scale or size of housing required for each household. Four regressions were estimated: using median home value costs for single-family detached or multifamily/attached single-family dwellings (see Equation 1 for the similar formulation) and using the median rental cost for single-family detached or multifamily/single-family attached dwellings (see Equation 2 for the similar formulation).

Equation 1: Linear Regression Results Estimating Home Value Cost

$$\ln(median\ home\ value\ cost) = \beta_0 + \beta_1 * Household\ Size + \beta_2 * Age\ Category + \beta_i * PUMA\ geography_i$$

Equation 2: Linear Regression Results Estimating Renting Cost

$$median\ rent\ cost = \beta_0 + \beta_1 * Household\ Size + \beta_2 * Age\ Category + \beta_i * PUMA\ geography_i$$

[1] There are 30 PUMA geographies in Oregon, similarly sized to the 36 counties.

Where for each regression,

$\beta_0 \equiv$ Constant
$\beta_1 \equiv$ Coefficient estimated for household size
$\beta_2 \equiv$ Coefficient estimated for the age category of the head of household
$\beta_3 \equiv$ Coefficient estimated for the age category of the head of household
$\beta_i \equiv$ Coefficient matrix estimated for each of the PUMA geographies, *i*

For each household in the OHAS sample, the equations provided by the regression above were run considering the household size2 and the respective PUMA geography in which the household was located. The costs derived from the four equations (median cost of owning a single-family home, median cost of owning a multifamily/attached single-family home, median cost of renting a single-family home, median cost of renting a multifamily/attached single-family home) were then applied within the residential choice model to explain variation in the cost of renting or owning a single-family detached or multifamily/single family attached home for each of the PUMA geographies. This cost value was then normalized by the households income to describe the households ratio of income spent on (the estimated) housing cost for each tenure and housing type alternative.

The main limitation of this approach for our application of analysis was the large PUMA geographies, which line up similarly across county boarders. Neighborhood type was one of the main components of the three alternatives (the others being tenure and household type) considered within the discrete choice model. This approach accounting for variations in housing cost, which satisfied the need to account for price variation in earlier iterations of the residential choice model (Chen et al. 2013), was not sensitive to variations in neighborhood type provided at the block group level. When the model formulation was restricted to Region 1 (and the corresponding mid-Willamette Valley model), this housing cost approach (described in this section) to accounting for housing cost could only be included within the model as a generic cost coefficient[3]. Determining variation in housing price across neighborhoods was determined to be a critical part of specifying the model. Additionally, when the model formulation was applied to the mid-Willamette Valley to investigate transferability of findings, the coefficient sign, significance and effect size were called into question due to the limitations of the housing cost regressions approach for the two-county area. Instead of applying the housing cost regressions normalized by household income within the model which captured limited variation across three (Region 1) and two (mid-Willamette Valley) counties, income was simply applied as a household-specific variable. Furthermore, by restricting the sample to the Portland metropolitan region (instead of Region 1 and Clark County which includes a vast amount of rural land and household observations), more detailed housing cost data may be applied in a similar fashion to allow for housing cost to vary across neighborhood alternatives.

[2] The age category was kept constant at 25-34 despite variation in head of household age observed in OHAS survey "to eliminate the effect of homeowners trading-up as they acquire equity and increase their earnings" (Skaburskis 1999).

[3] Aggregation of neighborhood type/housing type and tenure alternatives prevent the use of this variation to be included as a generic attribute across neighborhoods and alternative-specific across tenure and housing type, hypothesizing that the coefficients for tenure and housing type would be alternative-specific, but generic across neighborhoods.

Noting the significant limitation regarding the absence of a housing price variable, the results of the estimation process for the Portland regional and mid-Willamette Valley residential location choice models are displayed in Appendix B.

6.0 MULTIVARIATE ANALYSIS OF TRAVEL OUTCOMES

After investigating the relationships between residential choice and neighborhood selection, we investigated the relationships between household level residential choices, socio-economic and demographic characteristics and travel outcomes. While this analysis is limited to describing the one-day travel survey diary from the Region 1 Oregon Household Activity Survey, these results punctuate average differences in each of these travel outcomes based on the lifecycle decisions and characteristics observed in the one-day survey.

There are four household level transportation outcomes that are investigated and discussed within this section – vehicle miles traveled, person miles traveled by mode, number of person trips by mode and vehicle ownership. The resulting model estimates provide average person trip rates and person miles traveled for each mode, as well as overall, at the household level. The aim of these multivariate analyses was to partial out the effect of neighborhood characteristics (incorporated through the neighborhood classifications developed in Section 4.2), housing type and tenure, as well as socio-economic and demographic characteristics. All household-level regressions employed appropriate sample weighting in order to represent the population of interest. The same households analyzed in the previous section were included in this analysis (e.g., ODOT Region 1 and Clark County households).

6.1 HOUSEHOLD PERSON TRIPS, BY MODE

To investigate the relationship between household person trips taken by each mode and the characteristics of the households socio-economic, demographic and neighborhood characteristics, four negative binomial regressions were estimated for each of the following transportation outcomes measured at the household level: total person trips, person trips taken by automobile, person trips taken by bicycle, and person trips taken by walking[4]. Two few observations, as well as issues sorting out the multimodal nature of certain trips, limited the ability to account for transit travel at the household level.

These negative binomial regressions predicted the natural log of the count of trips made by each household. The unobserved factors were assumed to have mean value that was statistically different from the variance of the distribution, which accounted for the over-dispersion of the unobserved factors due to the count-based, negative binomial distributed nature of the unobserved factors[5]. The four regressions are presented in Table C.4 and Table C.3 in Appendix C: Travel Outcomes - Regressions. Each coefficient in these regressions represents the change in the natural log of the trip counts for each unit change in the independent variable considered.

[4] For trip types that observe a large number of zero-values, more sophisticated model structures, such as zero-inflated Poisson or negative binomial regressions, may be investigated to increase the explanation, specifically around households that have zero-trip values, reducing standard errors and exposing additional significance.

[5] Chi-square tests showed large statistical improvement when controlling for over-dispersion in Poisson regression using negative binomial, rejecting Poisson assumption that the mean and variance of unobserved components were statistically equal for each of the four regressions presented in this section.

Additionally, to improve the interpretation of these models, the lifecycle stages developed in Section 3.2 (Lifecycle Stage Classifications) were used to deepen the understanding of how the average household trip rates vary across neighborhood types and socio-economic or demographic characteristics. For each of these examples, the models presented in Table C.2 and Table C.3 were used to predict the average household trips (for each of the four models) using the average socio-demographic and economic characteristics observed in the seven lifecycle stages presented in Table 6.1. Each model run was estimated for each lifecycle class, considering these average characteristics, across each neighborhood type (from the most urban neighborhood A to the most rural neighborhood G) with and without access to MAX transit. The resulting trips estimated account for the average estimated trips expected to occur for each lifecycle class in each area-type. These values were placed in bar charts and presented throughout this section to enrich the interpretation of the models and improve our understanding of how different household types function compared to each other across the region.

Table 6.1: Average Socio-Economic and Demographic Statistics for Each Lifecycle Class

Lifecycle Class	Percent of Households Renting	Percent of Households in Multifamily Housing	Household Size	Household Workers per Household Size	Household Children (<17 years) per Household Size
Non-related Households	29.4%	24.4%	3.1	0.6	0.1
Parents	13.4%	8.9%	4.0	0.5	0.4
Related Adults, No Children (<65years)	12.6%	12.8%	2.3	0.8	0.0
Related Adults, No Children (>=65years)	6.2%	10.0%	2.2	0.4	0.0
Single Households <65 years	45.1%	46.6%	1.0	0.8	0.0
Single Households >=65 years	33.1%	40.1%	1.0	0.5	0.0
Single Parents	39.8%	33.1%	2.8	0.4	0.4
Lifecycle Class	**Head of Household Age**	**Household Income ($10,000/year)**	**Household Vehicles Owned by Licensed Drivers**	**Transit Pass Available to Household**	**Household Bicycles Owned by Household Size**
Non-related Households	49.8	6.3	0.9	0.5	0.4
Parents	44.3	8.9	1.0	0.3	0.6
Related Adults, No Children (<65years)	53.1	8.4	1.1	0.3	0.5
Related Adults, No Children (>=65years)	73.1	7.0	1.0	0.2	0.3
Single Households <65 years	50.4	4.8	1.2	0.4	0.6
Single Households >=65 years	73.7	4.4	1.1	0.2	0.2
Single Parents	46.7	5.4	1.2	0.4	0.7

The following sections discuss the results from each of four models estimated and include a discussion of the findings presented from the expected lifecycle class household person trips estimated.

6.1.1 Total Household Person Trips

The first model presented in Table C.2 investigated the relationship between the total person trips observed for each households with the household characteristics. Using the lifecycle classes developed in Section 3.2 (Lifecycle Stage Classifications) and the process described in the previous section, the data supporting Figure 6.1 and Figure 6.2 were estimated.

When comparing with and without access to light-rail facilities (MAX), areas in more urban locations (A,B,C) had slightly more person trips in areas with MAX than without. The reverse was true for less urban areas. Households observed, on average, larger positive effects to light-rail facilities in neighborhoods A than B, generating higher trip rates in the more urban A with the addition on this high quality transit. Conversely, households observed larger negative effect sizes in neighborhoods E than D, observing lower trip rate deductions for areas with access to MAX transit facilities in E compared with D.

Total person trips per household were estimated to be similar, on average, across most neighborhood types within each lifecycle stage. In general, households in more urban neighborhoods (A, B and C) tended to have slightly higher trip rates than areas in less urban areas, except for neighborhood F. Neighborhood F, representing areas with more rural towns, had, on average, more person trips than other neighborhood types.

In general, families with kids made more trips per household than families (related adults) without kids. Households with adults over 65 years of age tended to make fewer trips than their respective households without adults over 65 years of age. Households with children and more than one adult made more trips, in general, than single parent households. These households tended to have a larger household size (approximately 4.0 compared with 2.8), which was estimated to have a positive and significant relationship with the total person trips per household. The variable representing household workers per number of members was not significant in explaining the variation in total person trips.

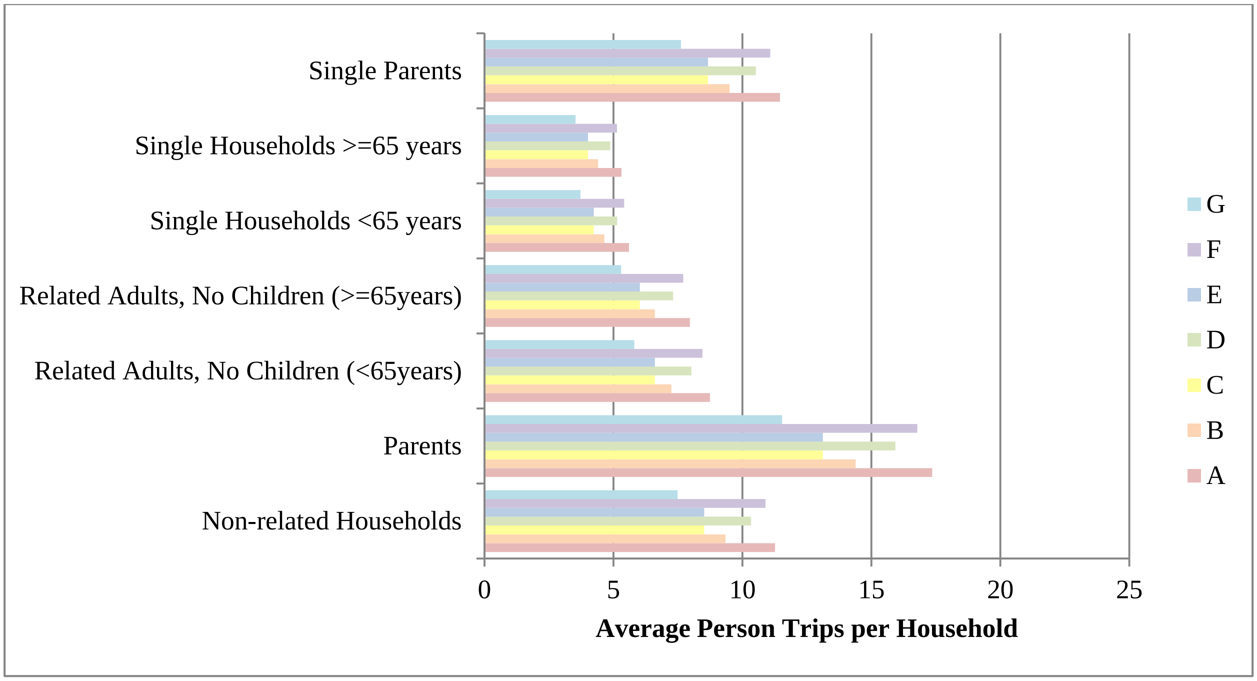

Figure 6.1: Total Household Person Trips, with Access to Light-Rail (MAX)

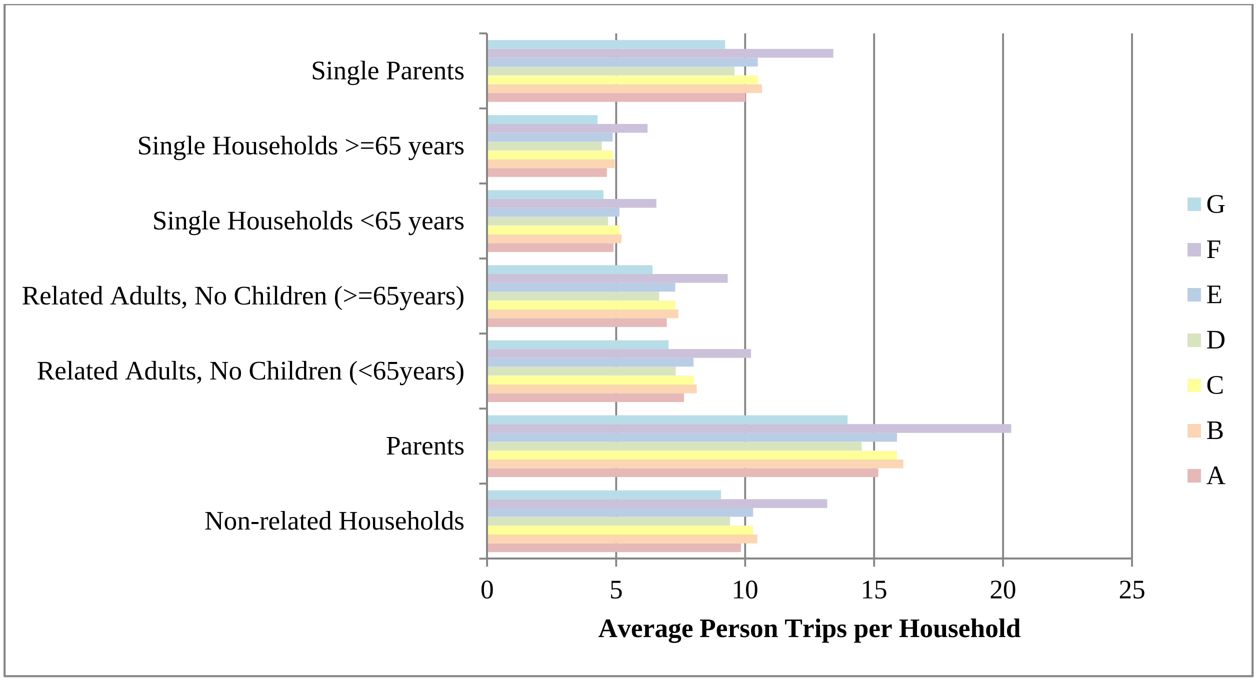

Figure 6.2: Total Household Person Trips, without Access to Light-Rail (MAX)

6.1.2 Household Person Trips, by Vehicle

Similarly to the analysis in the previous section, the second model presented in Table C.2 investigated the relationship between the household person trips taken by vehicle for each household with the household characteristics. Using the lifecycle stages developed in Section 3.2 (Lifecycle Stage Classifications) and the process described in the previous section, the data supporting Figure 6.3 and Figure 6.4 were estimated.

Average person trips by vehicle for households in the most urban of neighborhoods (A) varied only slightly for locations with and without access to MAX transit. This may be due to the fact that very few observations in this most urban of areas (downtown Portland) do *not* have access to MAX transit. Access to MAX transit had a negative effect on person trips by vehicle for all neighborhood types, after accounting for changes in interactions between neighborhoods and access to MAX transit. Interactions between neighborhood type and access to MAX transit was not found to be significant in explaining changes in the relationship between neighborhood type, access to MAX transit and the household's person trips by vehicle.

Head of household age did not significantly contribute to explaining the variation in person trips by vehicle taken in households. The accessibility of vehicles (as a ratio with household licenses), transit passes or bicycles (as a ratio with household size) were all significant predictors in explaining household person trips taken by vehicles. Transit passes and bicycles, intuitively, had a negative effect on person trips taken by vehicle, while vehicle ownership per licensed individuals had a positive effect. The presence of children per household size also had a significant and large positive effect on vehicle trips taken, as did the number of workers per household size.

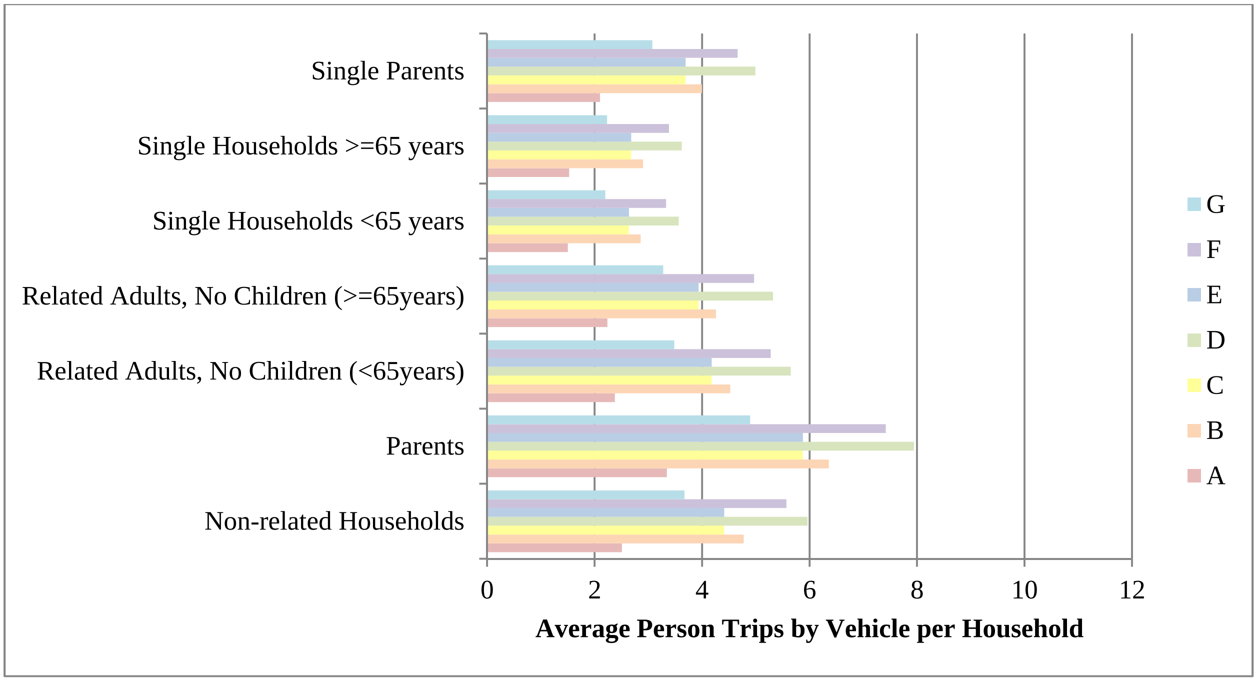

Figure 6.3: Household Person Trips by Vehicle, with Access to Light-Rail (MAX)

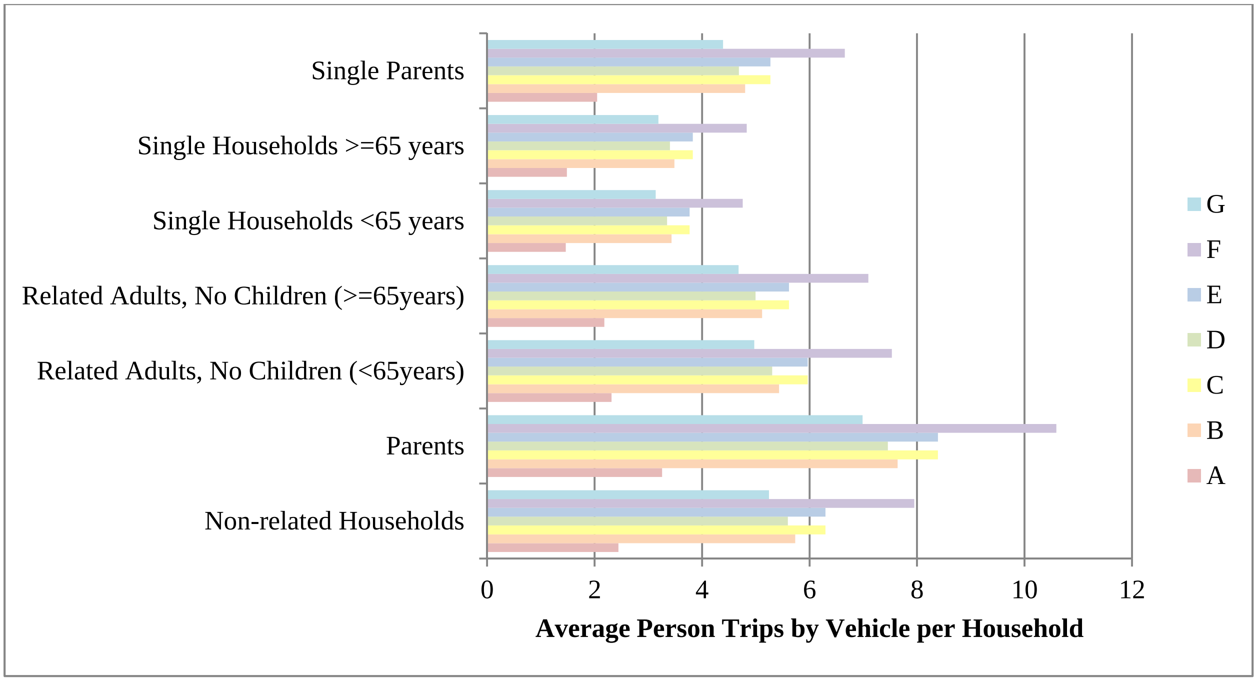

Figure 6.4: Household Person Trips by Vehicle, without Access to Light-Rail (MAX)

6.1.3 Household Person Trips, by Bicycle

Similarly to the analysis in the previous sections, the first model presented in Table C.3 investigated the relationship between the household person trips taken by bicycles for each household with the household characteristics. Using the lifecycle stages developed in Section 3.2 (Lifecycle Stage Classifications) and the process described in the previous section, the data supporting Figure 6.5 and Figure 6.6 were estimated.

Access to MAX (alone or by neighborhood type) had no significant effect on how many person trips by biking were taken. Only two neighborhood types were found to have significant differences in the amount of person trips by biking compared with the reference neighborhood (C, inner suburban): The second most urban neighborhood type (B, representing mostly central city area) which had significantly greater average person trips by bike per household; and, the most rural neighborhood type (G) which had significantly lower average person trips by bike per household. All other neighborhood types estimated to vary, but were not significantly different from the reference neighborhood (C).

Single households and related adult households with no children rarely take bike trips in rural neighborhood types (G). From the sample of households observed and their respective travel diaries, the results indicated households with children and multiple parents had, on average, more trips by bicycle than any other lifecycle class indicated here. These households tended to have fewer vehicles per licensed driver than other lifecycle stages (approximately 1.0 vehicles per licensed person, compared with 1.2 for single parents, and 1.1 for single households (with individuals over 65 years old) and related-adult households without children (with individuals less than 65 years old). Additionally, these households also tended to have a larger number of bikes per household individual (0.6 bikes per individual, compared with 0.4 for non-related households and 0.6 for single households with individuals less than 65 years of age) possibly supporting a higher rate of bicycle trips.

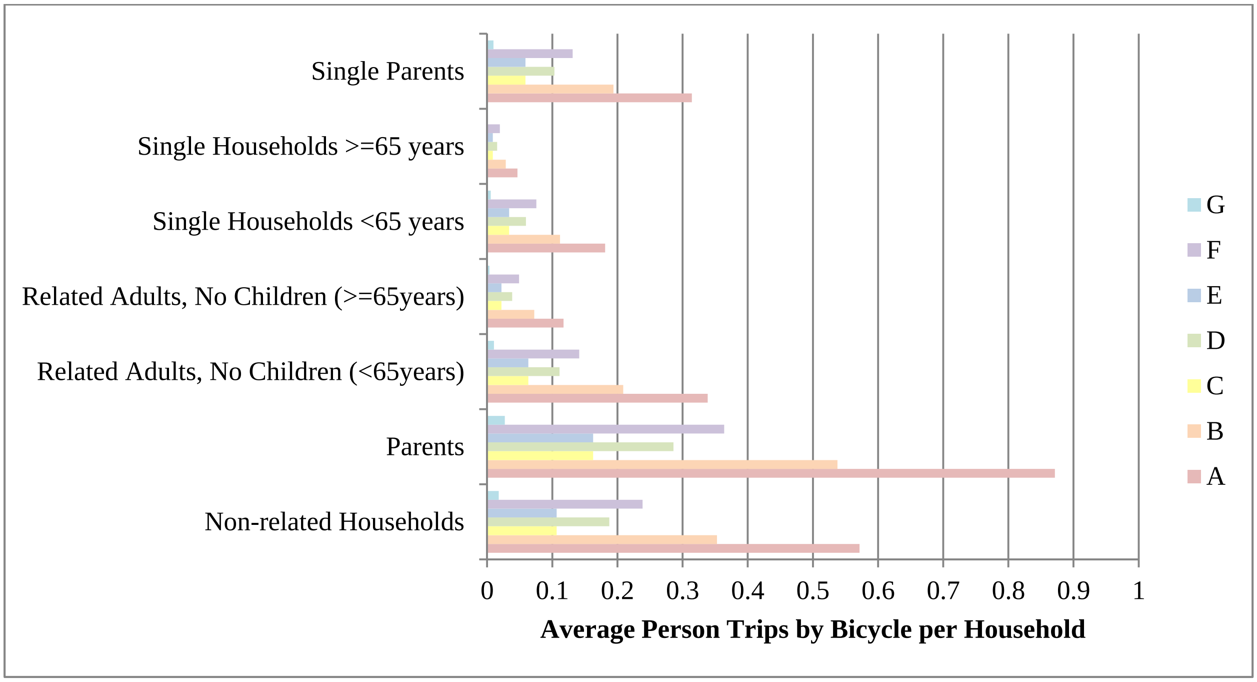

Figure 6.5: Household Person Trips by Bicycle, with Access to Light-Rail (MAX)

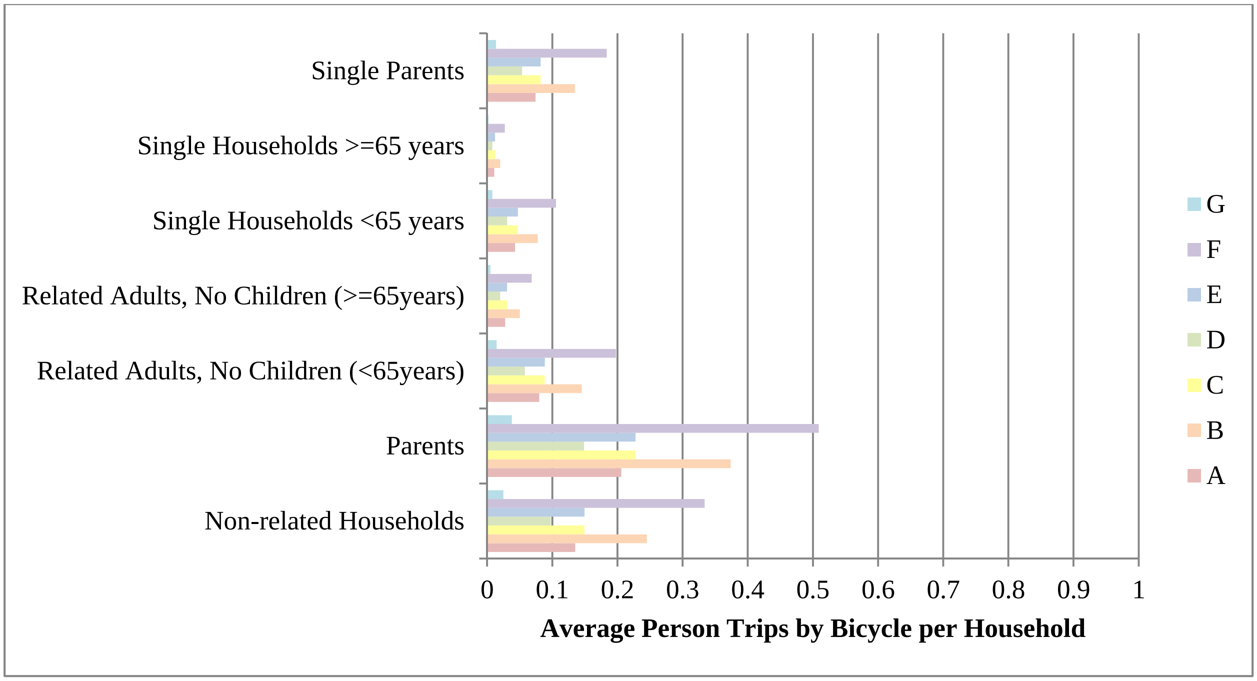

Figure 6.6: Household Person Trips by Bicycle, without Access to Light-Rail (MAX)

6.1.4 Household Person Trips, by Walking

Finally, the relationship between the household person trips taken by walking for each household with the household characteristics was estimated as shown in the second model of Table C.3. Once again, using the lifecycle stages developed in Section 3.2 (Lifecycle Stage Classifications), the data supporting Figure 6.7 and Figure 6.8 were estimated.

Access to MAX (alone or by neighborhood type) had no significant effect on how many walk trips were taken. More urban areas had a greater amount of walk trips per household than more suburban or rural households. Additionally, the most urban area types (A and B) had significantly greater walk trips per household, on average, compared with the base case (neighborhood C, inner suburban neighborhoods). The most rural of neighborhood types (G) had significantly fewer walk trips per household than the base case. All other neighborhoods (D, E and F) which are more rural than the base case (C) were not significantly different from the base case in explaining the amount of walk trips taken by a household, which indicated similarities in walk behavior around these neighborhoods. Households in the most urban of neighborhood types (A) which represents, for the most part, the central business district of Portland, had the greatest amount of walking trips.

Families with children had similar walk rates on average, with one or more parents. The ratio of children in the household to household size, as well as household size variable itself, were both significant in explaining the amount of walking a household did, but the number of workers did not significantly relate to the amount of walking a household did (in trips), which suggested that households with kids do roughly the same amount of walking in similar neighborhoods. Households with a head of household older than 65 years of age walked the least (in the number of trips) when compared to other households. Related adult households, compared with single households, were observed to have roughly the same amount of walk trips per household, on average, despite having one additional person per household, on average.

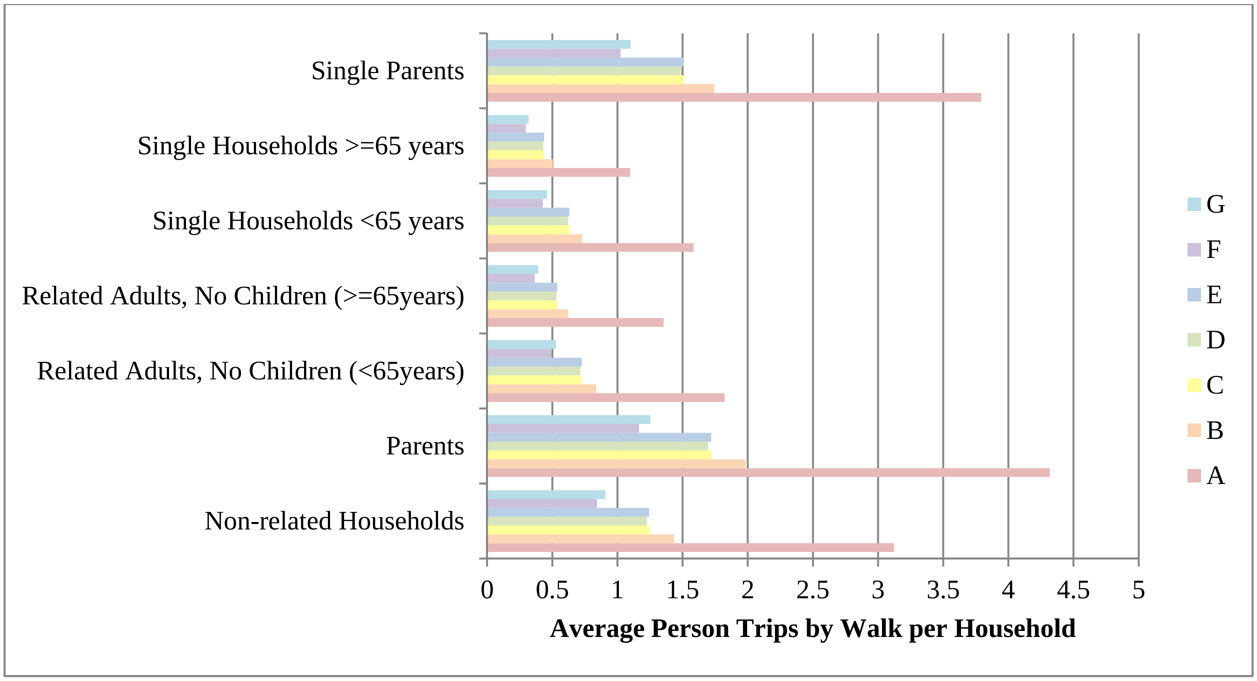

Figure 6.7: Household Person Trips by Walk, with Access to Light-Rail (MAX)

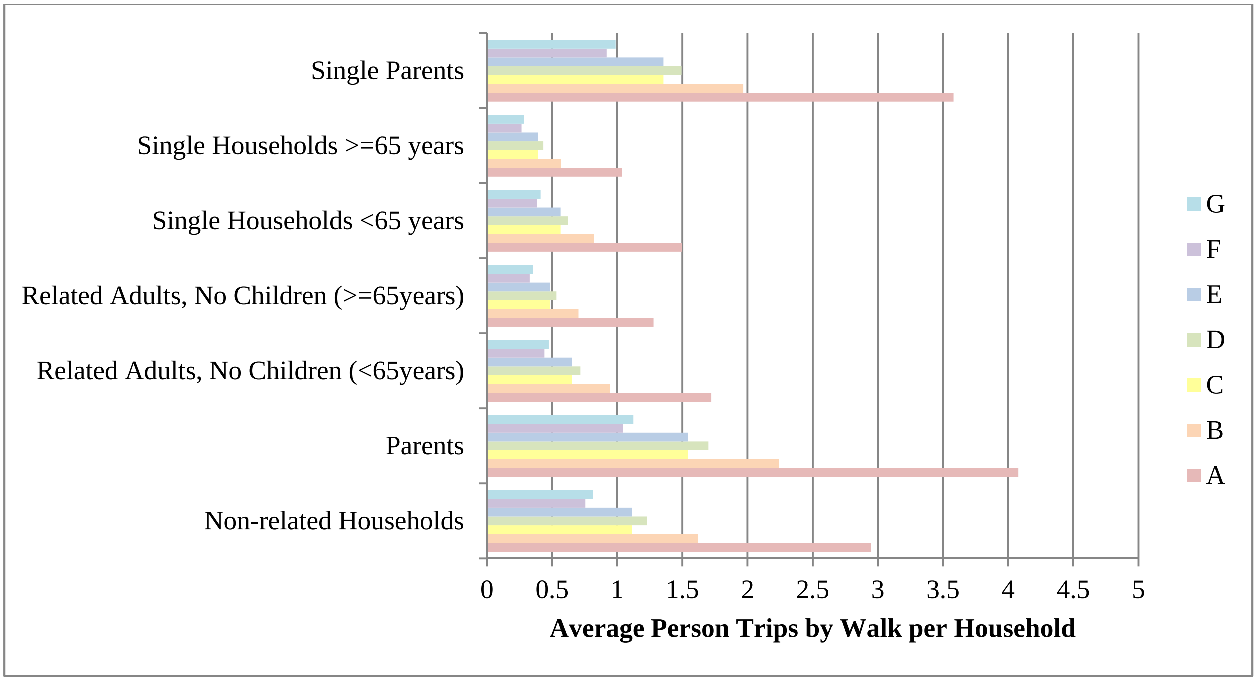

Figure 6.8: Household Person Trips by Walk, without Access to Light-Rail (MAX)

6.2 HOUSEHOLD PERSON MILES TRAVELED, BY MODE

The second travel outcome metric investigated was person miles traveled measured at the household-level. In this analysis, four linear regressions were estimated for the following types of modes: total person miles traveled by any mode, vehicle miles traveled[6], person miles traveled by bicycle and person miles traveled by walking[7]. The distribution of unobserved factors in each of these four model segmentations of person miles traveled violates a foundational assumption of linear regression, assuming the variance of the error is constant across observations. Box-Cos tests were used to determine a range of potential transformations on the person miles traveled for each mode to optimize the explanatory power of the regression estimation[8]. To simplify the interpretation across models, an exponential transformation using a value of 0.2 was selected. A similar transformation was used in the vehicle miles traveled analysis developed within GreenSTEP *(Clifton and Gregor 2012)*. These regressions predict the fifth root[9] of the person miles traveled for each mode (vehicle, bike or walk) and total person miles traveled. Each coefficient represents the change in the fifth root of miles traveled for each unit change in the independent variable. Additionally, for each of these estimations, only households that took a person trip of each type of mode were included in regression. This means that only households with observed bicycle trips were included in the household person miles traveled by bicycle analysis, further limiting the sample size. More sophisticated modeling techniques, such as hurdle models which account for an excess of zero-values, may improve each of these analysis with further research.

6.2.1 Household Person Miles Traveled, Total

For the first person miles travel metric analysis, the relationship between the total household person miles traveled by any mode for each household and the household characteristics was estimated as shown in the first model of Table C.4. Once again, using the lifecycle stages developed in Section 3.2 (Lifecycle Stage Classifications), the data supporting Figure 6.9 and Figure 6.10 were estimated.

The access to the MAX light-rail had a significant effect on the amount of total person miles traveled for households living in only the most urban of neighborhood types (A). Households located in block groups with access to MAX stations in the central business district (A) had significantly more total person miles traveled than households not living within a block group with access to MAX stations. Moreover, households in the most rural locations (G) had the

[6] Vehicle miles traveled includes only those miles accumulated by drivers of the automobile. While this metric is not consistent with the person miles traveled by the alternative modes, measuring vehicle miles traveled instead of person miles traveled by vehicles allows for more consistent comparisons to investigate the environmental impact of automobile use at the household-level for the region.

[7] Once again, the sample size for transit-specific trips, and corresponding calculations of miles traveled on bus (versus access/egress modes), limited the ability for transit-specific analysis to be performed.

[8] For each person miles traveled travel metric, a 95% range of exponential transformation values was examined to determine the optimal transformation necessary to minimize the overall log-likelihood of the estimation. For person miles traveled by vehicle, bike, walk and the overall person miles traveled, the recommended exponential transformation value ranges were 0.21 to 0.24, 0.18 to 0.37, 0.05 to 0.10, and 0.17 to 0.20 (respectively).

[9] The transformation used ($x^{0.2}$) was equivalent to the fifth root ($\sqrt[5]{x}$) of the independent variable.

largest total person miles traveled per household, on average, than any other households. The total person miles traveled in households in more rural areas (D, E and F) was not significantly different from households in the base case (C).

Households with more than one adult and kids had the highest average person miles traveled for each neighborhood type. Comparing the total household person miles traveled to the trends of household size across lifecycle stages (shown in Table 6.1), the trends across lifecycle stages were similar. Household size was a highly significant predictor, and the standardized coefficient indicated the impact of a unit change in household size was larger than any other predictor. Single parent households, however, had similar average total person miles traveled with related adults (no children) despite having larger household sizes. These households also tended to rent more often which the results indicated would have a significant, negative effect on overall person miles traveled. The presence of children (as a ratio to household size) was not a significant predictor of the total person miles traveled, although it was significant in predicting some mode-specific miles traveled. Whether a household has a transit pass available to them was a highly significant predictor of total miles traveled, and the results indicated it had the second greatest impact when comparing standardized coefficients.

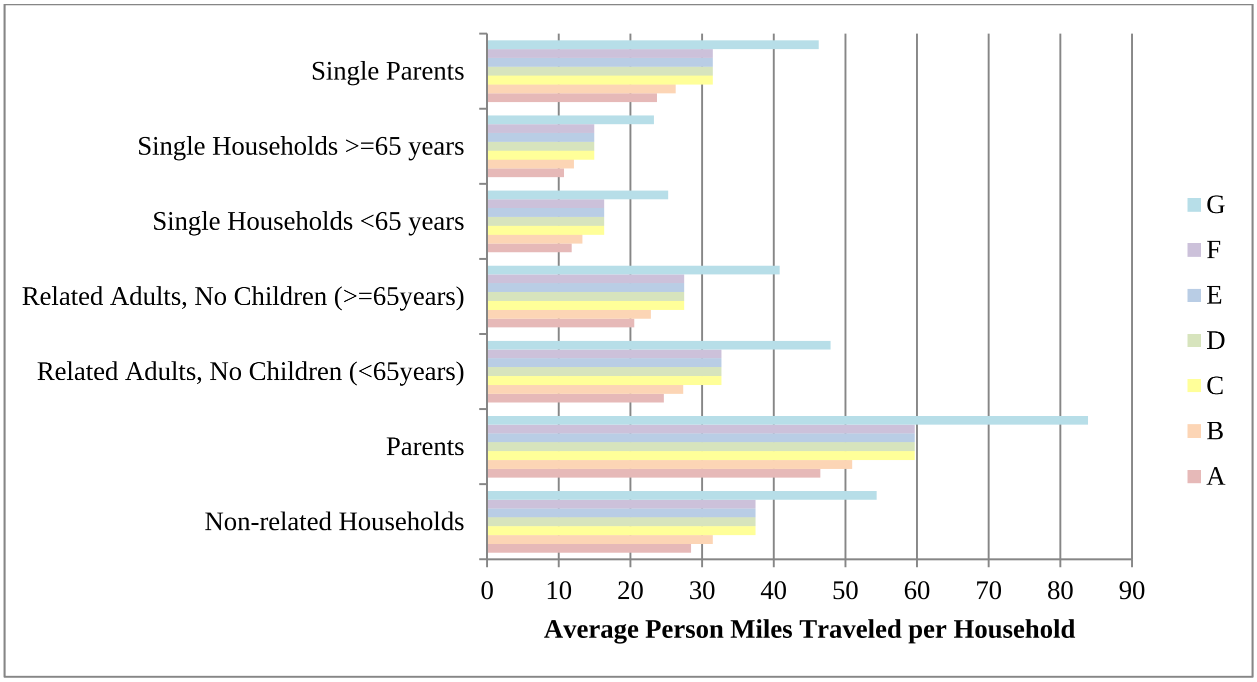

Figure 6.9: Household Person Miles Traveled, Total, with Access to Light-Rail (MAX)

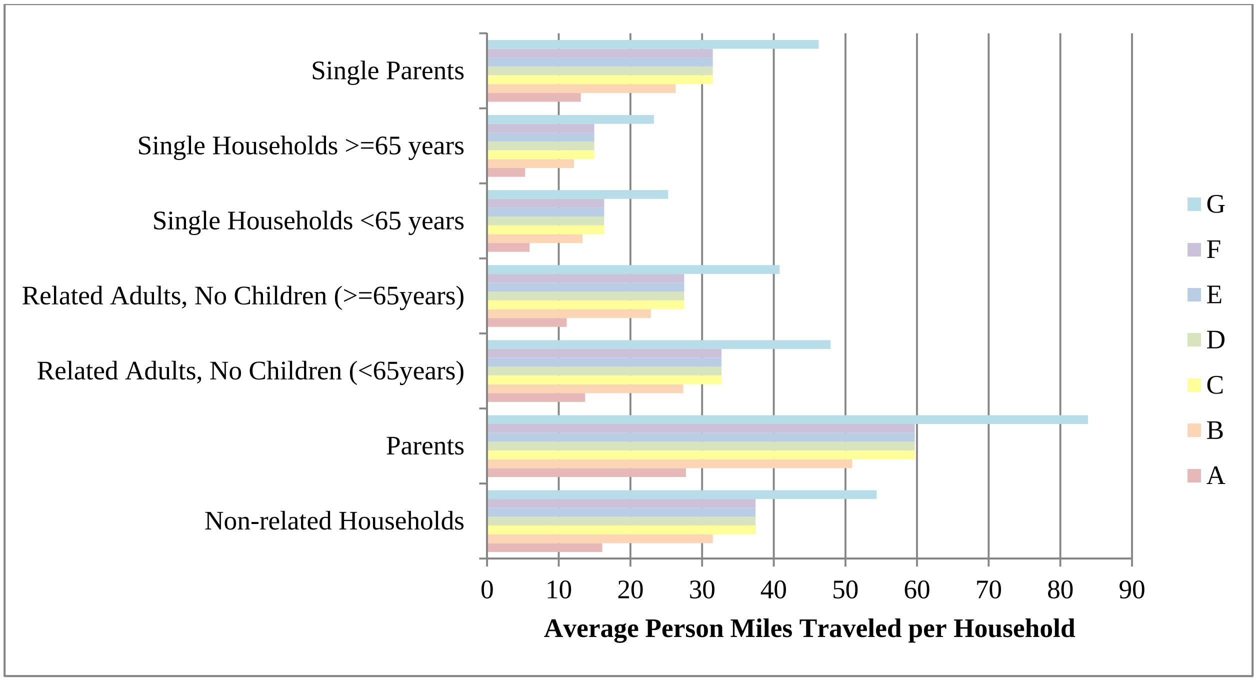

Figure 6.10: Household Person Miles Traveled, Total, without Access to Light-Rail (MAX)

6.2.2 Household Vehicle Miles Traveled

The metric of vehicle miles traveled was measured by the total miles for each household that an individual took as a driver of an automobile. The relationship between vehicle miles traveled and the household-level characteristics was estimates as shown in the second model of Table C.4. Figure 6.11 and Figure 6.12 depict the average vehicle miles traveled estimated for the lifecycle stages developed in Section 3.2 (Lifecycle Stage Classifications) across each neighborhood type.

Results for vehicle miles traveled were similar to total household person miles traveled due to the dominance of vehicle miles traveled within the person miles traveled metric. The interaction between access to MAX and neighborhood type was only significant for central city (B), indicating that households in these areas with access to the MAX had statistically significant and lower average person miles traveled by vehicles than households in these areas without access.

Housing type and tenure were not significant predictors of vehicle miles traveled, but all other socio-economic and demographic characteristics considered were significant. Household size, the ratio of household workers to household size, income, and whether the household owned a transit pass had the largest effect on vehicle miles traveled when comparing the standardized coefficients (in that order). Households located in rural towns (neighborhood F) also had a large effect size when comparing standardized coefficients, similar to income. Of these coefficients, only the coefficient descripting the relationship between VMT was negative.

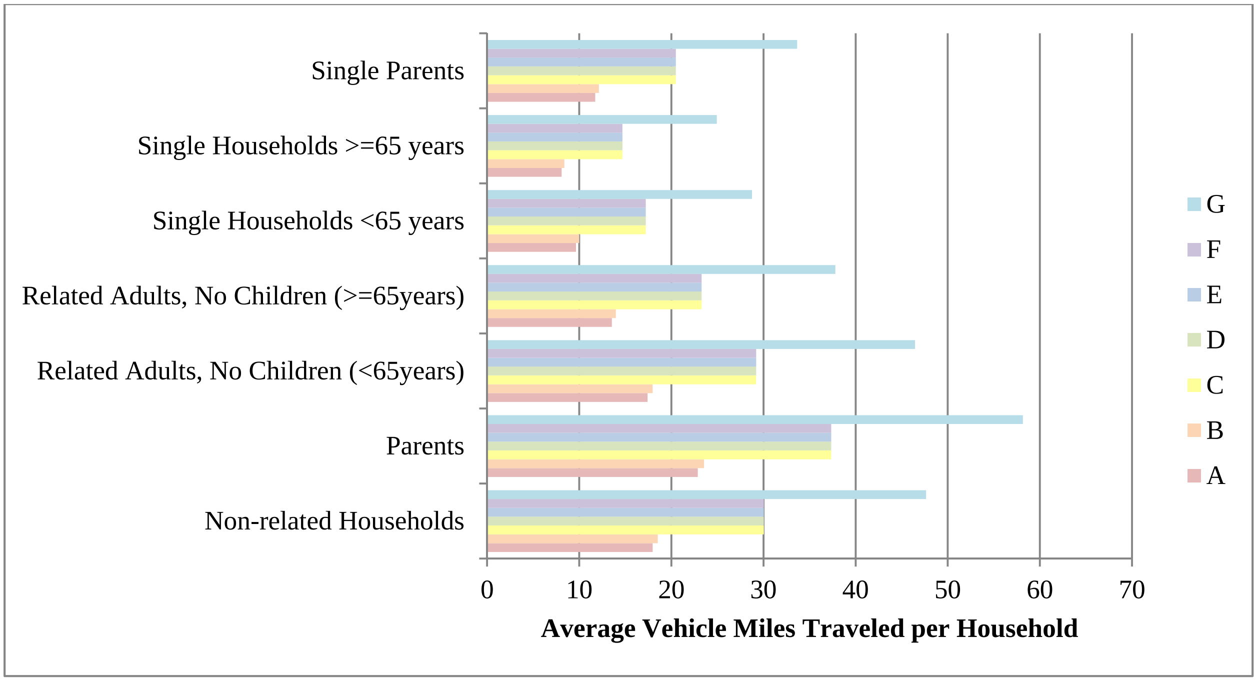

Figure 6.11: Household Vehicle Miles Traveled, with Access to Light-Rail (MAX)

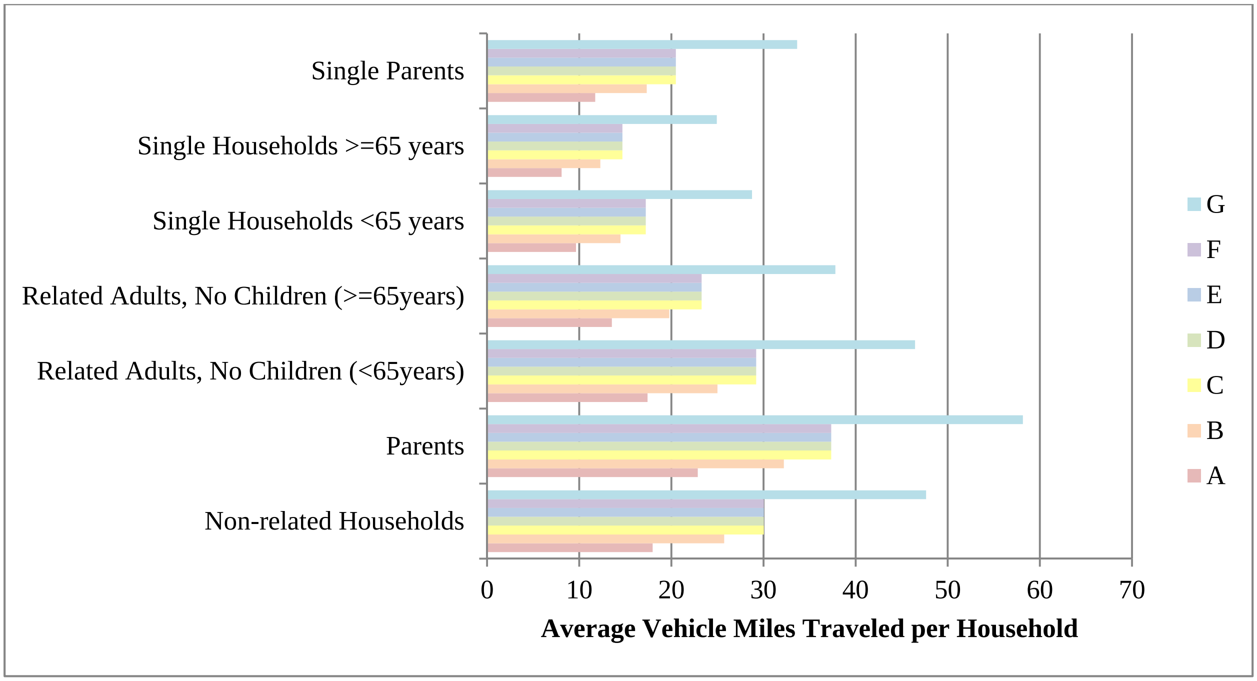

Figure 6.12: Household Vehicle Miles Traveled, without Access to Light-Rail (MAX)

6.2.3 Household Person Miles Traveled, by Bicycle

The relationship between household person miles traveled by bicycle and the household-level characteristics was estimates as shown in the first model of Table C.5. Figure 6.13 and Figure 6-14 depict the average person miles traveled by bicycle estimated for the lifecycle stages developed in Section 3.2 (Lifecycle Stage Classifications) across each neighborhood type. This analysis had the smallest sample size with 316 households with person trips taken by bicycle, accumulating person miles traveled by bicycle. This analysis may benefit the most from more sophisticated model structures, such as hurdle models, to account for the prominence of zero-values, instead of discarding them for use in the person trips taken by bicycle models.

Access to MAX was both significant and negative in explaining variation in household person miles traveled by bike, suggesting a synergy between cycling and transit availability. Whether a household owned a monthly transit pass, however, was not a significant predictor of miles cycled per household. Households located within the most urban neighborhoods (A) had significantly less person miles traveled by bike (compared to the base case, neighborhood C) when MAX transit was not available, but significantly more miles traveled by bike when the MAX was available, suggesting the availability of MAX transit and cycling use complements each other in the most urban neighborhoods (A). Households in more rural areas (such as E and G) observed significantly less person miles traveled by bike compared with the base case (neighborhood C), with or without MAX accessibility.

The only significant socio-demographic predictors of person miles traveled by bike were household workers (as a ratio to household size), income, household vehicles per licensed driver and household bikes owned. Tenure, housing type, household size, presence of children, head of household age and transit pass ownership were not significant predictors. Households without children (single adult or related) had the highest average person miles traveled by bike than any other lifecycle class.

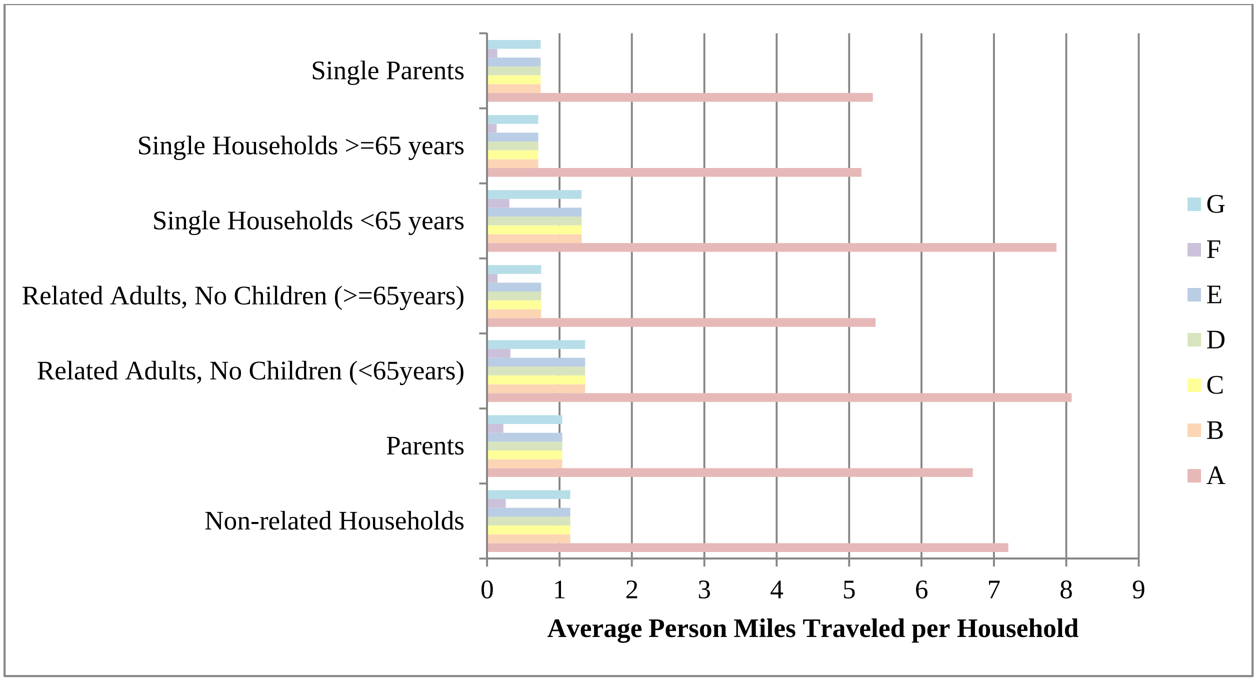

Figure 6.13: Household Person Miles Traveled, by Bicycle, with Access to Light-Rail (MAX)

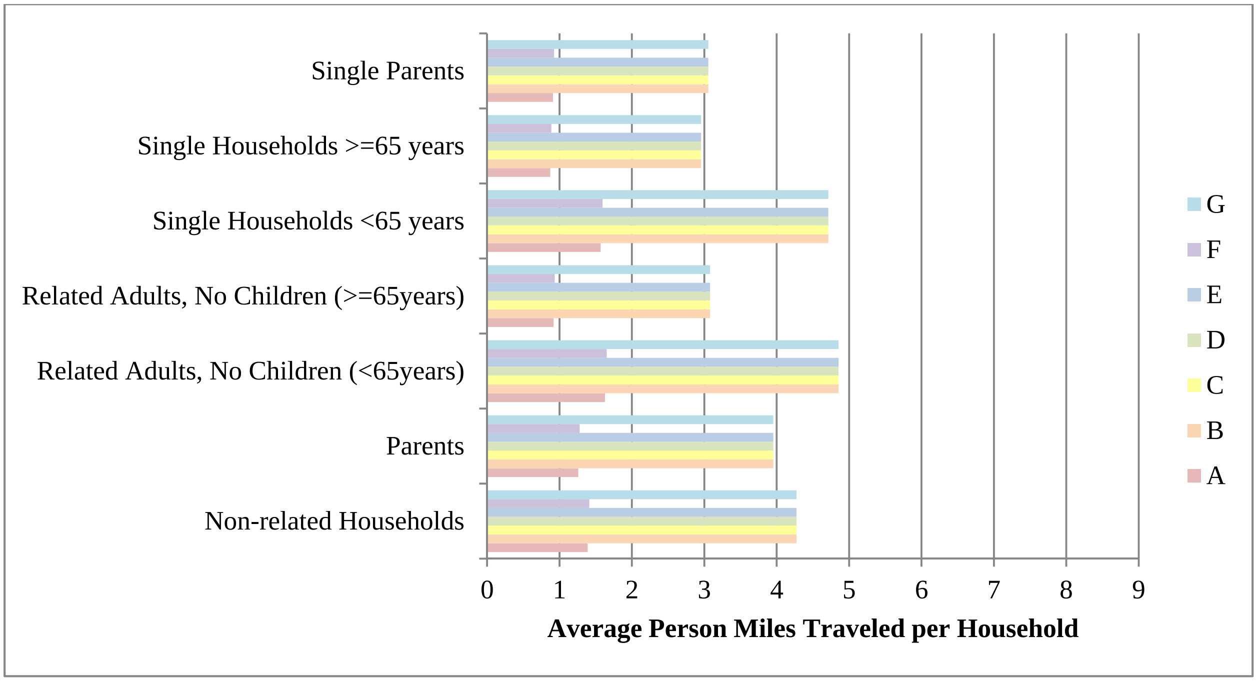

Figure 6.14: Household Person Miles Traveled, by Bicycle, without Access to Light-Rail (MAX)

6.2.4 Household Person Miles Traveled, by Walking

The relationship between household person miles traveled by walking and the household-level characteristics was estimates as shown in the second model of Table C.5. Figure 6.15 and Figure

6.16 depict the average person miles traveled by bicycle estimated for the lifecycle stages developed in Section 3.2 (Lifecycle Stage Classifications) across each neighborhood type.

Access to MAX was not significant predictor of household person miles traveled walking, overall nor within each neighborhood. Only the most urban neighborhood types (A and B) contributed to explaining the variation in person miles traveled by walking significantly different than the base case (C). Both effects were positive, and of a larger effect size in more urban areas (A).

The variables indicating multifamily housing types was significant and positive, suggesting households that live in multifamily housing walk more than those that live in single-family detached housing. Household size had the greatest significant effect on explaining the amount of walking observed in households when comparing the standardized coefficients, suggesting that the larger the household size, the more miles the household walked on average. The ratio of vehicles owned to household size and whether the household owned a monthly transit pass were both significant and negative predictors of person miles traveled by walking.

Additionally, the ratio of household workers to overall household size was a significant and negative predictor of person miles traveled by walking for each household. These results might suggest that households with more workers walk less due to greater amounts of time spent doing other activities (such as working or commuting by a different mode)[10].

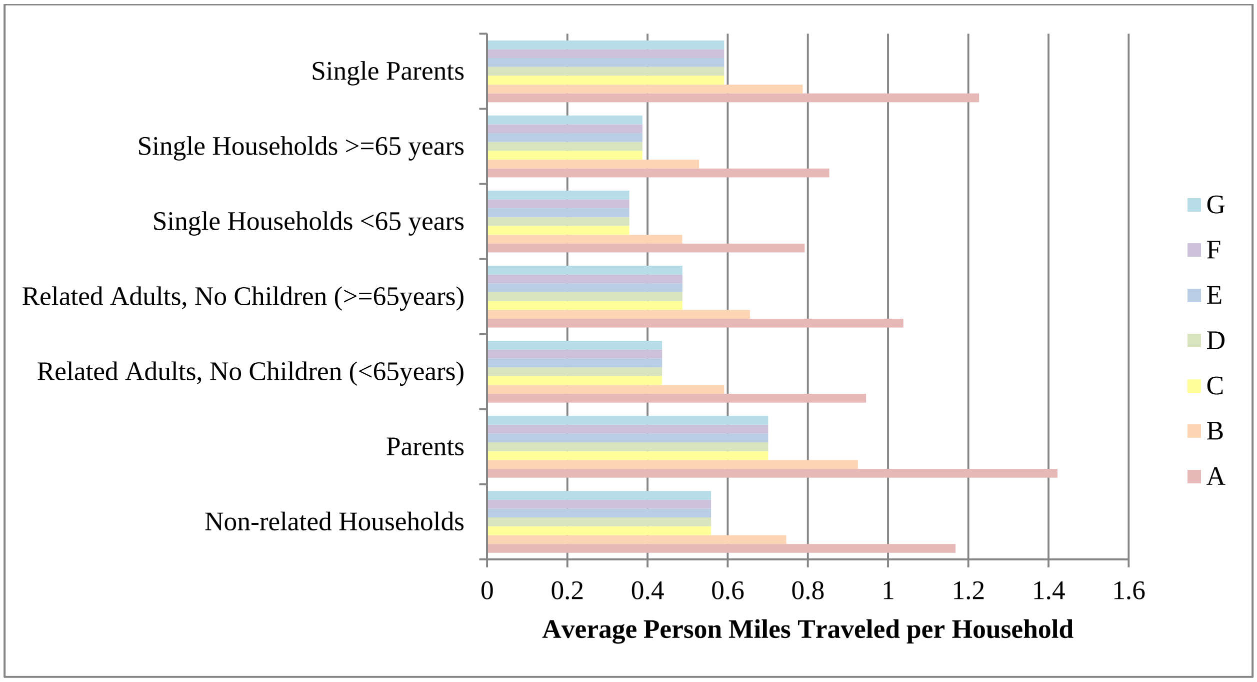

Figure 6.15: Household Person Miles Traveled, by Walk, with Access to Light-Rail (MAX)

[10] Investigating the interaction of the ratio of workers to household size with neighborhood type, or including the activity profiles controlling for how households spend their time as discussed in Section 3.1 (Household Activity Profile Classifications), may provide insight on this relationship.

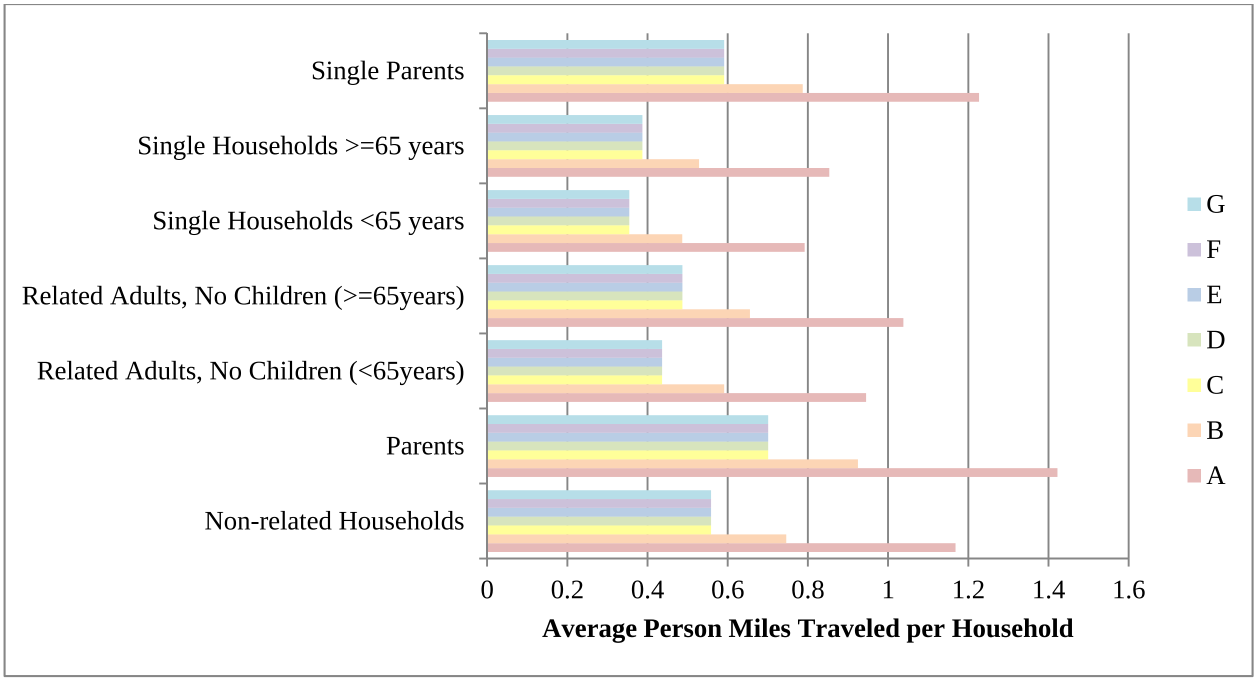

Figure 6.16: Household Person Miles Traveled, by Walk, without Access to Light-Rail (MAX)

6.3 HOUSEHOLD VEHICLE OWNERSHIP

To investigate the relationship between household vehicle ownership and the characteristics of the households socio-economic, demographic and neighborhood characteristics, another negative binomial regression was estimated at the household level.

The negative binomial regressions[11] predicted the natural log of the count of vehicle owned by each household. The unobserved factors were assumed to have mean value that was statistically different from the variance of the distribution, which accounted for the over-dispersion of the unobserved factors due to the count-based, negative binomial distributed nature of the unobserved factors[12]. This regression is presented in Table C.5 in Appendix C: Travel Outcomes - Regressions. Each coefficient in these regressions represents the change in the natural log of the vehicles owned for each unit change in the independent variable considered.

[11] The authors acknowledge the endogeneity present in modeling the ownership of vehicles (i.e., the decision to buy a third vehicle is related to the decision to own the first and second). Potential improvements to the model structure would be to incorporate ordinal relationships within the unobserved factors to account for the correlation between decisions to own additional vehicles. Ideally, discrete choice models accounting for the alternative purchases would allow for the most accurate measurements of relationships between neighborhood and household characteristics and decisions of fleet ownership.

[12] Chi-square tests showed large statistical improvement when controlling for over-dispersion in Poisson regression using negative binomial, rejecting Poisson assumption that the mean and variance of unobserved components were statistically equal for each of the four regressions presented in this section.

In these findings, households with access to MAX light-rail tended to own fewer automobiles, on average, compared with those without access to the MAX. This effect, however, was not significant due to large standard errors. Overall, households located in more rural areas had significantly greater vehicle ownership, on average, than households located in more urban locations. Households residing in the most urban neighborhood (A) around the central business district had far fewer average vehicles owned compared with households in more inner suburban neighborhoods (C, the base case). The results indicated that households living in a multifamily housing (versus single-family detached dwelling) owned fewer vehicles than those households living in single-family detached dwellings. Additionally, those households renting tended to own fewer vehicles than those households that own or mortgaged their housing. Single parent households and single adult households (with any head of household age) have approximately the same rates of household vehicle ownership across each neighborhood type.

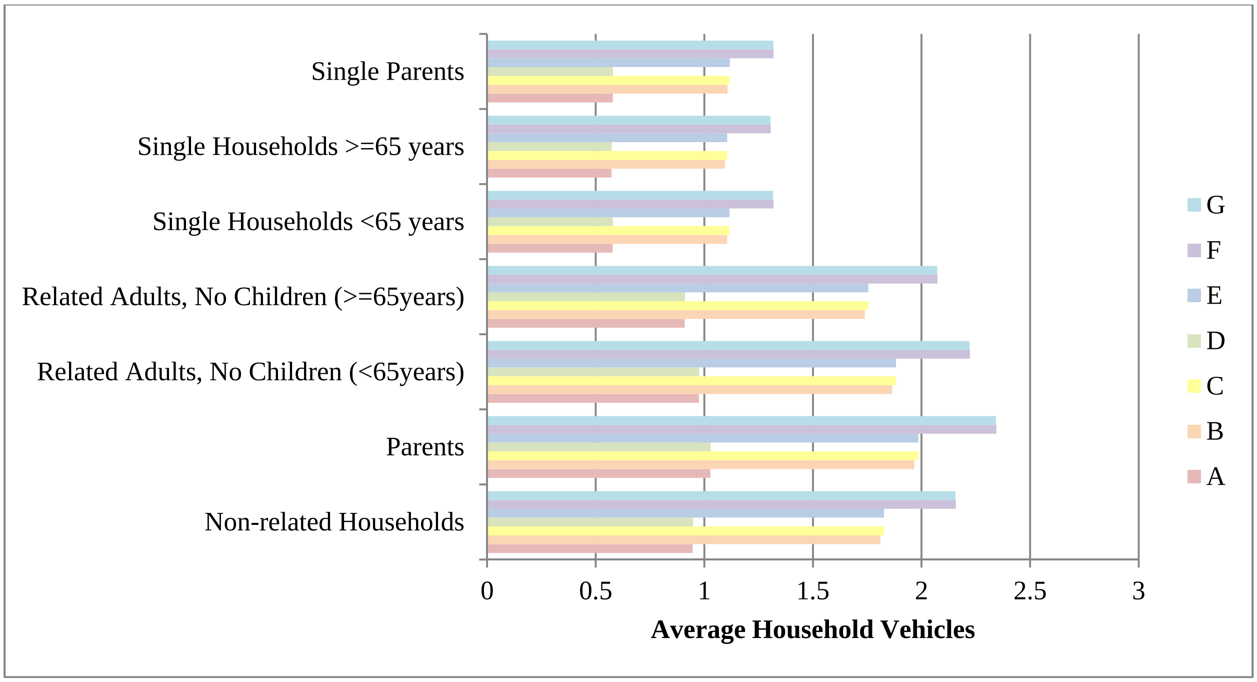

Figure 6.17: Household Vehicle Ownership, with Access to Light-Rail (MAX)

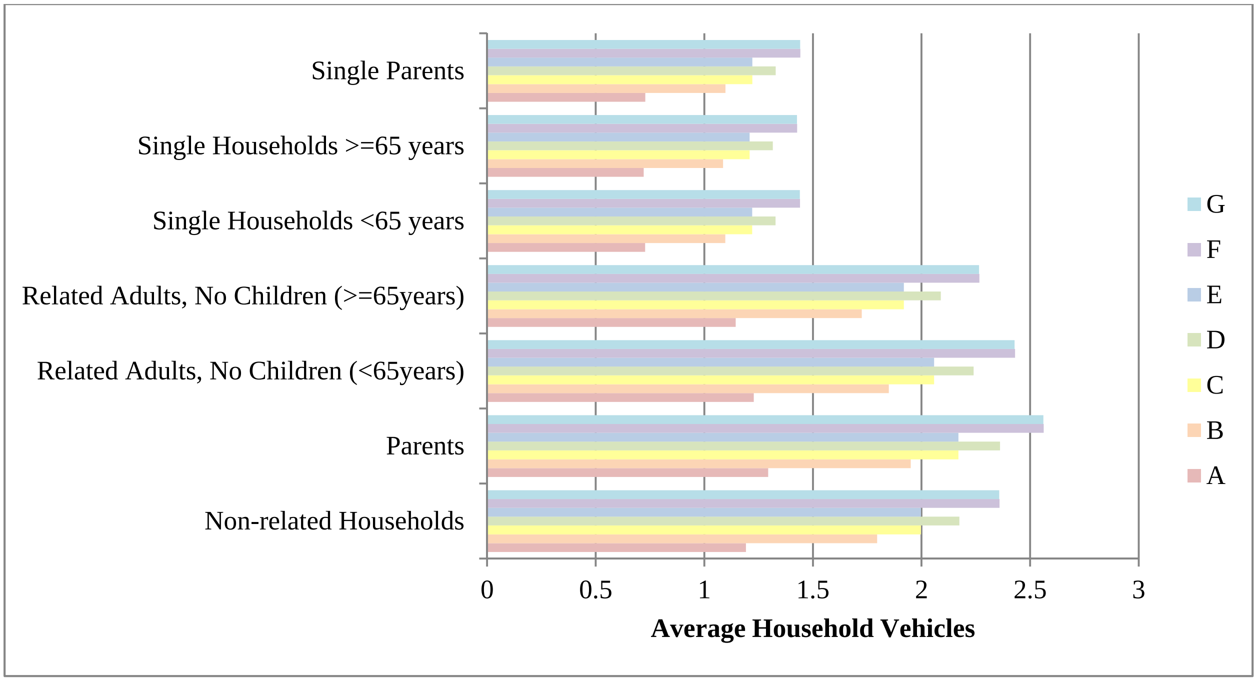

Figure 6.18: Household Vehicle Ownership, with Access to Light-Rail (MAX)

7.0 DISCUSSION AND FUTURE DIRECTIONS

The first phase of this study has made several contributions based upon the analysis of these empirical data to the knowledge base and methodological approaches.

In the Housing Market Segmentation analysis, the first approach attempted to define market segments based upon household time allocation to activities based upon one day's observation. The data reduction approach using a "bottom up" analysis of time allocation of activities resulted in interesting groupings of household. This analysis revealed spatial differences in activity allocation defined coarsely as Portland Metro, outside of Portland and statewide. Future spatial analysis of these household market segments defined by activities may reveal important variations worth closer investigation. While these activity profiles are not useful in linking to medium- or long-term residential location decisions, they are clearly a key component in the future analysis of travel, which are observed for the same day.

The additional lifecycle segmentation, similar to the constructs used by others, which imposes a "top down" structure on the designation of markets segments, was not used in the modeling directly as it did not allow for a straightforward interpretation of the impact of individual socio-demographic characteristics on residential or travel choices. Rather the individual attributes were used in the model estimation directly and the lifestyle segments and their residential and travel choices were reconstructed in the model sensitivity analysis to test for differential impacts across these lifecycles.

The range of housing types and attributes examined were limited by the observations in the OHAS data set and the lack of detailed archived information about housing characteristics – housing and lot size, number of rooms, year built, price, etc. – available for the entire state. Similarly, the definition of neighborhood had limitations in the commonly accessible built and socio-economic environmental attributes available from archived sources and the restrictions on the number of choices that could be easily be accommodated in the choice model structure. This information is more readily available and more detailed for the Portland metropolitan area and a future analysis that is focused on this area may yield more robust and policy-relevant findings.

The residential choice model estimation efforts explored several model structures, neighborhood segmentations, nesting order and specifications. While the modeling results did not prove to reveal relevant policy or socio-economic findings, the exercise was valuable in providing lessons learned that can inform next steps and future work.

First, we suggest limiting the revealed preference residential choice modeling to the Portland Metropolitan region to better exploit the rich sources of archived spatial information about housing, neighborhood and transportation characteristics. Expanding the analysis statewide and to other regions is useful from a policy and implementation perspective; however, absent specific information about the residential alternatives in the model (primarily neighborhood type and housing type), a generic model for the state does not have much application. Using the data available for the Portland region, future analysis could have a more sophisticated representation and differentiation of neighborhood types. We have already developed more detailed neighborhood types for this area, although they were not utilized in model structure and these neighborhoods could be attributed with better information about price, housing supply, accessibility, access to transportation alternatives, and other characteristics of place and population that would allow a much more robust policy analysis. The results from such a limited spatial scope could still be extended to other areas, particularly the elasticities, key relationships and other aspects of estimation results.

Second, the model structure and specification should be reconsidered. Our estimation results suggest that a nested model may not be appropriate, pointing to a joint model structure for future work. This has advantages in that not all housing type and tenure options are available in all neighborhood types and a joint model structure would provide a more simple estimation process. As noted in the previous paragraph, the model specification could be expanded to include additional attributes of the choices for a more telling policy analysis. Since residential and travel choices are complex decisions, they are best explored in a data rich environment.

Finally, the analysis connecting the residential choices to travel outcomes was the most telling aspect of this first phase of the project and yielded more policy relevant results. While some of the results from this analysis were intuitive (e.g. households with more members lead to more vehicle trips and vehicle miles traveled), some findings were also unexpected, and perhaps worth more detailed investigation. Some of the more notable findings are listed in the bulleted points below:

- Access to light-rail transit had no significant effect on the number of person trips by bicycle per household, but it had a significant and negative effect on the amount of person miles traveled by bicycle for those households that did take a bike trip for all neighborhood types except the most urban (type A, including the Central Business District). The results indicated a significant and positive relationship between the person miles traveled by bicycle and access to transit in neighborhood type A.

- For single adult households or related adult households without children, the age of the head of household did not have a significant effect on person trips, overall or by vehicle, but it had a significant and negative effect on person trips, by bicycle or walk. For person miles traveled however, the age of the head of household has a significant and negative effect on person miles traveled overall and vehicle miles traveled, but no significant effect on the person miles traveled by bicycle or walking.

- The results also indicated a significant and positive effect of more rural neighborhood (type F) which identifies more rural small towns (e.g., Canby, Newberg or Sandy) with the number of person trips by bicycle.

- Household vehicle ownership in neighborhood D, located in the outer suburbs (e.g., near parts of Forest Grove, Hillsboro, Wilsonville, or Gresham) was significantly lower than the base case (neighborhood C) for areas that had accessibility to light-rail access. These household ownership rates were similar to ownership rates observed in the most urban neighborhood type (A).

- Access to light-rail had a significant and negative effect on person trips, total and by vehicle, and a significant and negative effect on person miles traveled, overall and by bicycle. Access to light-rail was also significant for certain neighborhood types, indicating differences in travel behavior responding to greater transit access across certain neighborhood types.

Although there were many interesting findings that resulted from this analysis, this research raises more questions and further exploration. The current analysis of travel outcomes presented in this section was completed to provide as much parody as possible with the analysis and results provided in Section 5.0 (Residential Location Choice Model), including using the same spatial segmentation of the OHAS data (ODOT Region 1 and Clark County households, rural and urban areas), neighborhood types (seven-levels of neighborhoods statewide), household type aggregation (multifamily/attached single-family and detached single family), and a simplified transit layer (access to MAX light-rail transit within the block group of the household). By further restricting the sample of households to urban areas of Portland metro area and Vancouver, increased data availability would allow for more detailed analysis may be completed. Some options for future work might include consideration of:

- Additional segmentation of neighborhood types for inner and outer suburban neighborhoods which represent a large and varied residential landscape,

- Segmenting the size of single-family detached household to explain variation between large and small single-family dwellings,

- Access to high-quality bus transit as well as distance to transit centers or light-rail stations.

- Additional model structures may be investigated to account for an excess of zeros (or zeros with dual means), such as zero-inflated or hurdle models. These structures can be tested for improvements to the overall model fit, and may reduce standard errors for coefficients, and possibly improving the identification of significant characteristics.

- By running the models estimated using average characteristics of lifecycle stages, the aggregate effects of the variables may be summarized to market segments that ease interpretation of travel impacts. Additional market segmentations (such as those found in GreenSTEP or Metroscope) may improve the usability or application of these results.

- Since household size was often a significant predictor with a large effect size, further analysis of person trips or miles traveled normalized by household size may provide additional insight into the effects of neighborhoods, housing characteristics or household demographics.

The next phase of this work will continue to explore residential choices and travel using state choice experiment survey methodologies. In this effort, we will move away from examining revealed preferences to poise hypothetical situations to a sample of participants to gage their responses to conditions that may not currently exist. The survey design and infrastructure developed in this phase will provide a valuable tool for examining the tradeoffs that households may make in their neighborhood, housing and transportation choices now and their desires for the future.

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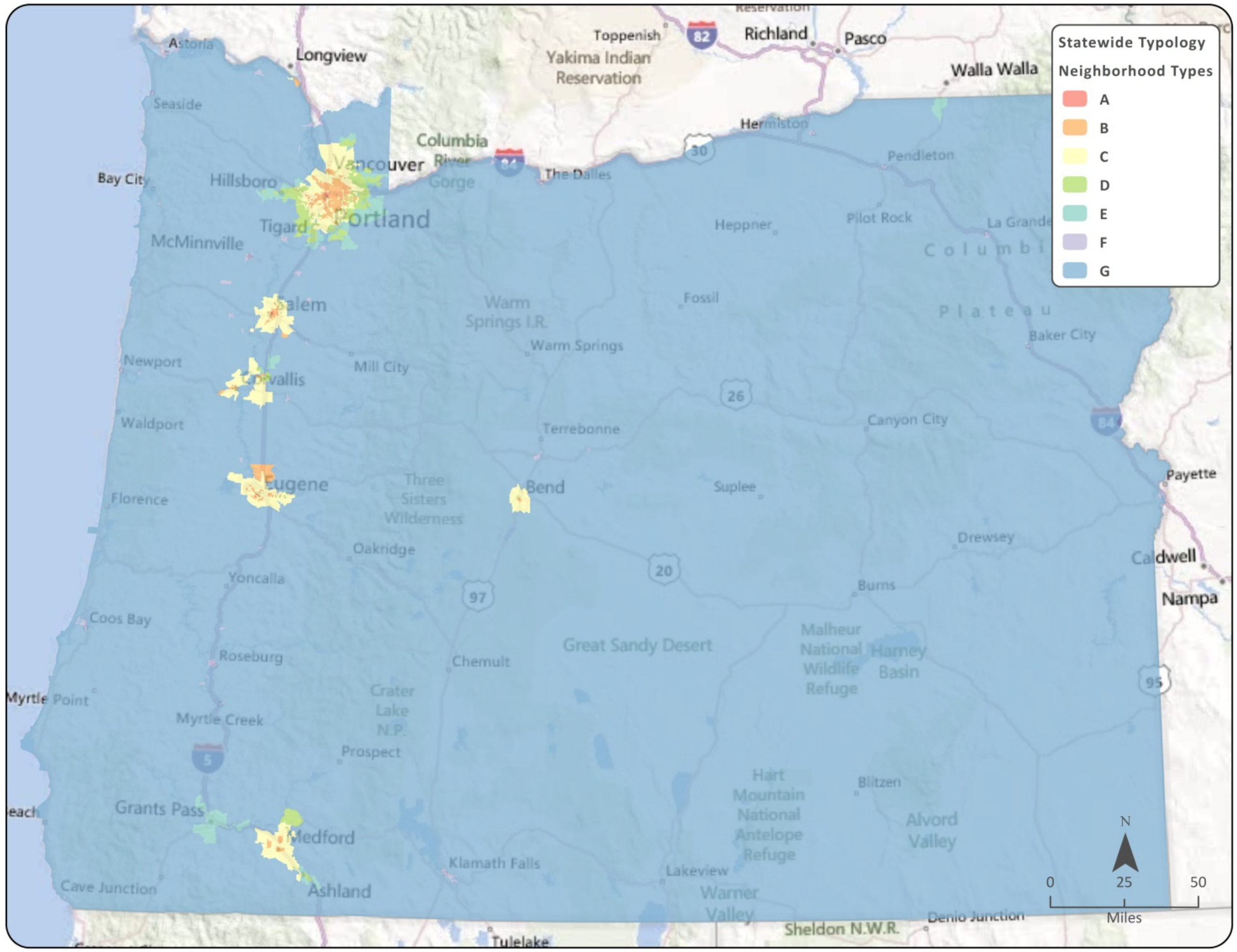
APPENDIX A:

MAP OF STATEWIDE NEIGHBORHOOD TYPOLOGY FOR OREGON

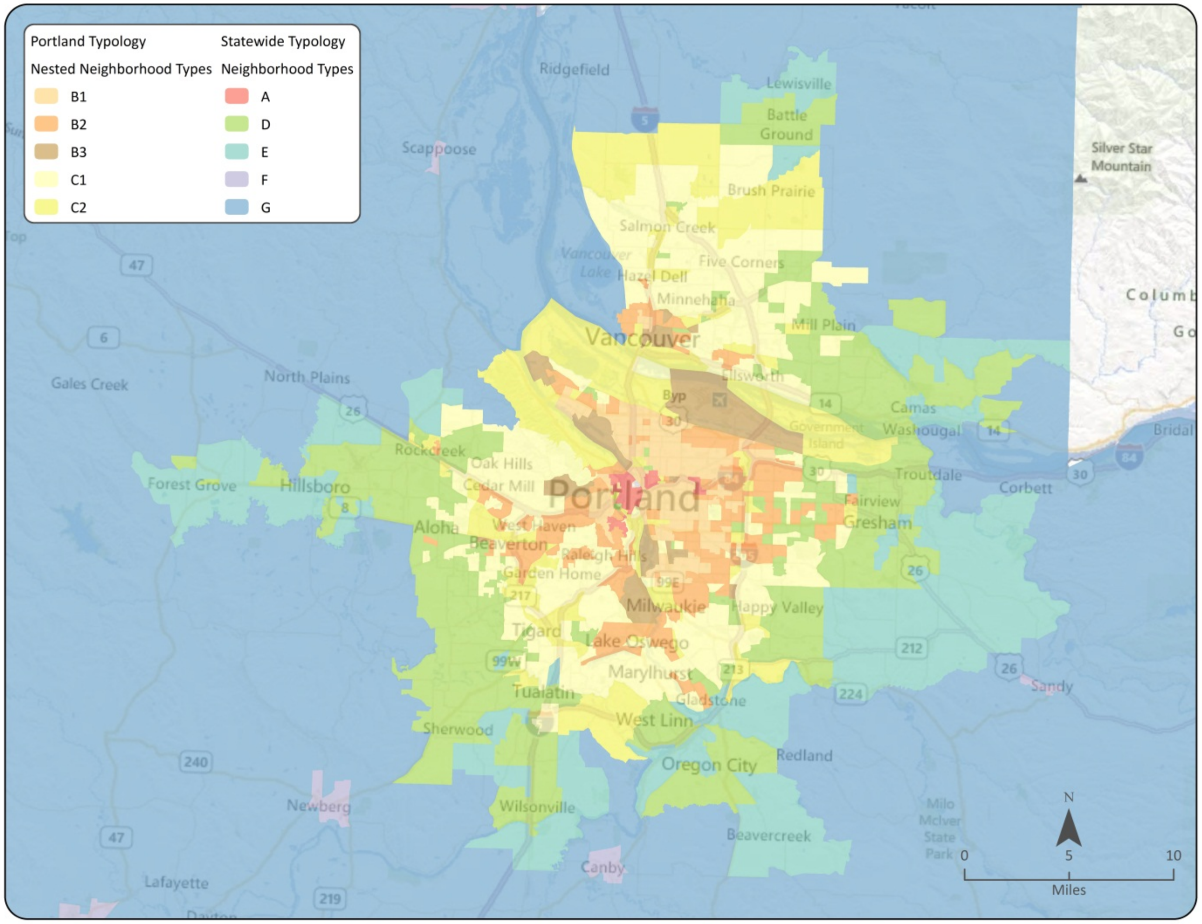
Appendix A: (1) Map of Statewide Neighborhood Typology for Oregon

Appendix A: (2) Map of Neighborhood Typology for Portland Metropolitan

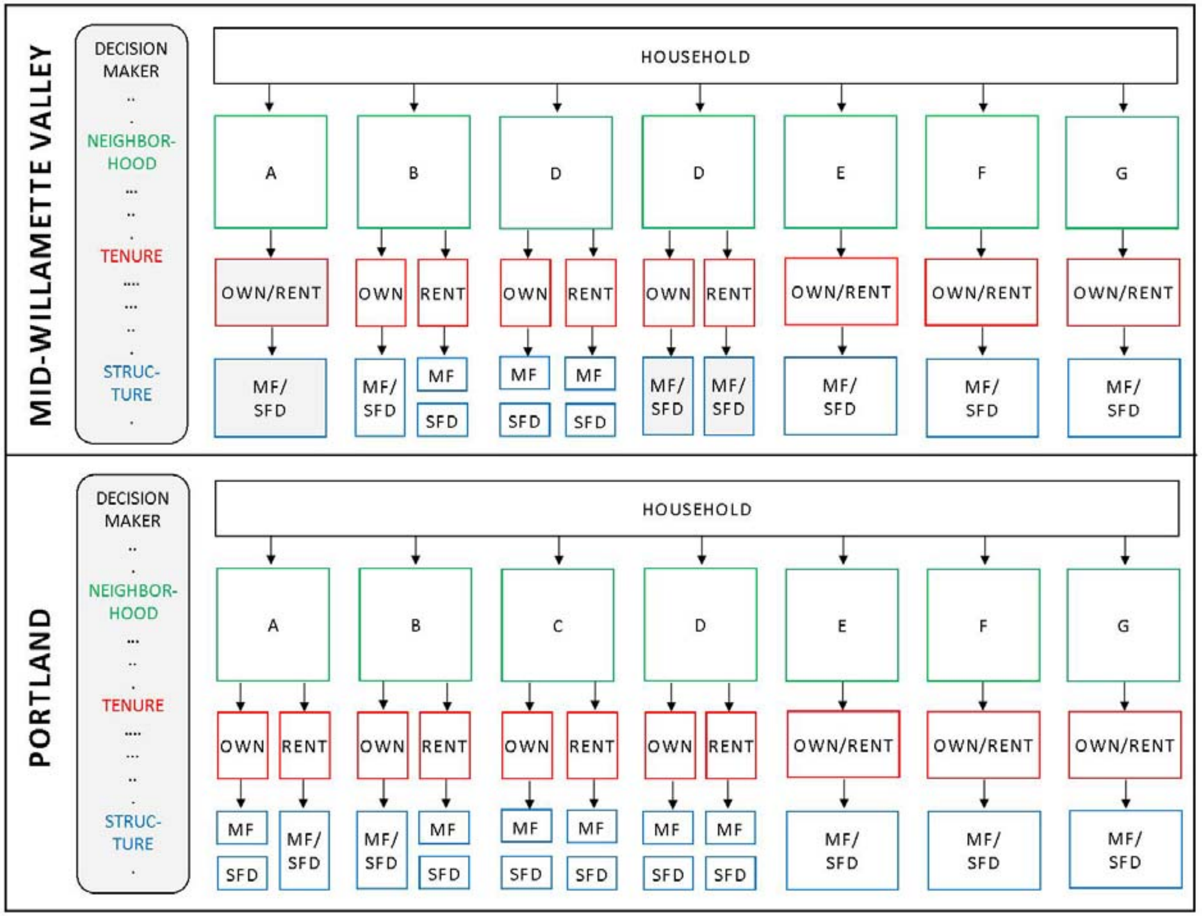


APPENDIX B:

STRUCTURE OF RESIDENTIAL LOCATION CHOICE MODEL



Appendix B: (1) Structure of Residentail Location Choice Model


MID-WILLAMETTE VALLEY
DECISION MAKER
NEIGHBOR-HOOD
TENURE
STRUC-TURE
HOUSEHOLD
A
B
D
D
E
F
G
OWN/RENT
OWN
RENT
MF/SFD
MF
SFD
PORTLAND
DECISION MAKER
NEIGHBOR-HOOD
TENURE
STRUC-TURE
HOUSEHOLD
A
B
C
D
E
F
G
OWN
RENT
OWN/RENT
MF
SFD
MF/SFD

Appendix B: (2) Residential Location Choice Model Estimation for Portland and Mid-Willamette Valley Region

	Portland Region						Mid-Willamette Valley Region				
	Observations		5,938				Observations		3,452		
	Deviance		-12,824				Deviance		-5,735		
	Deviance (Constants)		-12,120				Deviance (Constants)		-6260		
	Log-sum (Neighborhood Type)		1.00				Log-sum (Neighborhood Type)		1.00		
	Log-sum (Tenure)		1.05				Log-sum (Tenure)		1.19		
	Log-sum (Housing Structure)		1.02				Log-sum (Housing Structure)		0.73		
	Variable	Alternative	Coefficient	t-Statistic			Variable	Alternative	Coefficient	t-Statistic	
¤	Constants	A_O_SF	(base)	---		¤	Constants	A	-3.24	-17.65	
¤		A_O_MF	0.6526	1.035		¤		B_O	-0.75	-12.37	
¤		A_R	2.7467	14.081		¤		B_R_SFD	-0.11	-0.19	
¤		B_O	1.6505	23.053		¤		B_R_MF	-12.37	-3.03	
¤		B_R_SF	0.9541	2.862		¤		C_O_SFD	(base)	---	
¤		B_R_MF	2.9551	31.666		¤		C_O_MF	-1.74	-4.12	
¤		C_O_SF	0.9771	10.390		¤		C_R_SFD	-3.81	-21.94	
¤		C_O_MF	1.3606	8.563		¤		C_R_MF	0.88	1.41	
¤		C_R_SF	0.4927	1.288		¤		D_O	-2.61	-17.44	
¤		C_R_MF	2.4669	21.548		¤		D_R	-2.16	-4.91	
¤		D_O_SF	1.0812	10.710		¤		E	-3.04	-13.96	
¤		D_O_MF	0.4874	1.927		¤		F	-0.49	-1.50	
¤		D_R_SF	-0.7748	-1.998		¤		G	-2.69	-20.36	
¤		D_R_MF	2.3131	18.660			Household Size	B_O	-0.22	-3.10	
¤		E	-0.1483	-0.764				B_R_SFD	-0.99	-54.27	

¤		F	0.0004	0.002				C_O_MF	-1.23	-5.04	
¤		G	-0.9415	-1.372				C_R_SF D	0.46	5.73	
	Price Sensitivity		-1.9697	-13.667				C_R_MF	-1.25	-30.00	
	Household Size	A_R						D_R	-0.43	-1.72	
		B_R_SF					Students/Member	B_R_SF D	3.27	2.18	
		B_R_MF						C_R_MF	3.72	2.07	
		C_O_SF				¤	Head HH Age (18-25)	B_R_SF D	1.43	1.78	
		C_R_MF				¤		C_R_MF	1.81	2.66	
		D_O_SF				¤	Head HH Age (26-39)	B_R_SF D	1.29	1.86	
		D_O_MF				¤		C_R_MF	1.36	2.45	
		D_R_SF				¤		D_R	1.96	1.90	
		D_R_MF				¤		G	1.16	2.52	
		E				¤	Head HH Age (65+)	G	0.75	2.51	
		F									
	Workers/Member	A_R	0.3934	1.692							
		B_O	1.2749	24.413							
		B_R_SF	1.2590	7.819							
		B_R_MF	0.6630	6.333							
		C_O_SF	1.2008	24.488							
		C_O_MF	1.1470	6.203							
		C_R_SF	0.5680	1.881							
		C_R_MF	1.0730	18.453							
		D_O_SF	1.1786	36.389							
		D_O_MF	0.9972	4.367							
		D_R_SF	0.9289	3.405							
		D_R_MF	0.7358	6.557							
		E	1.1921	9.914							

		F	1.0358	12.007							
	Students/Member	B_R_SF	0.7270	5.067							
		B_R_MF	0.5045	4.445							
		C_O_SF	0.1824	2.006							
		C_O_MF	0.9366	19.270							
		C_R_MF	0.5277	3.602							
		D_O_SF	0.1802	1.871							
		D_O_MF	0.3762	6.419							
		D_R_SF	0.4216	4.470							
		D_R_MF	0.8337	9.646							
		F	0.1287	1.747							
	Head HH Age	B_O	0.0267	17.047							
		B_R_MF	-0.0093	-4.594							
		C_O_SF	0.0360	27.277							
		C_O_MF	0.0269	12.389							
		C_R_SF	-0.0180	-2.186							
		D_O_SF	0.0274	14.545							
		D_O_MF	0.0292	9.714							
		E	0.0246	10.342							
		F	0.0269	12.969							

NOTES: Statistical significance of coefficients: "***" p < 0.001, "**" p < 0.01, "*" p < 0.05, "." p < 0.1; ¤ Indicates binary variable.

APPENDIX C:

TRAVEL OUTCOMES – REGRESSIONS

Appendix C: Travel Outcomes - Regressions

Table C.1: Negative Binomial Regression Results for Household Person Trips Traveled, by Mode (Table 1 of 2)

			Person Trips (Total)				Person Trips by Vehicle			
			Coefficient	**Standard Error**	**Pr(>|z|)**		**Coefficient**	**Standard Error**	**Pr(>|z|)**	
	Dispersion Parameter		0.132				0.210			
	Deviance		8535				8620			
	Deviance (Null)		3961				3961			
	(constant)		1.321	0.060	0.000	***	0.836	0.075	0.000	***
¤	Neighborhood Type	A	-0.047	0.083	0.573		-0.946	0.145	0.000	***
¤		B	0.015	0.023	0.501		-0.094	0.029	0.001	**
¤		C								
¤		D	-0.070	0.023	0.002	**	-0.081	0.029	0.005	**
¤		E	-0.090	0.036	0.013	*	-0.118	0.045	0.009	**
¤		F	0.246	0.101	0.015	*	0.233	0.127	0.066	.
¤		G	-0.129	0.038	0.001	***	-0.183	0.047	0.000	***
¤	Availability of MAX		-0.191	0.062	0.002	**	-0.356	0.083	0.000	***
	Neighborhood Type * Availability of MAX									
¤		A	0.326	0.143	0.022	*	0.382	0.246	0.120	
¤		B	0.077	0.100	0.438		0.173	0.132	0.192	
¤		C	(base)	---			(base)	---		
¤		D	0.036	0.096	0.712		0.137	0.127	0.278	
¤		E	0.284	0.506	0.574		0.419	0.645	0.516	
¤	Housing Type – Multifamily (versus Single)		-0.015	0.029	0.610		-0.075	0.038	0.047	*
¤	Tenure – Rent (versus Own)		-0.034	0.029	0.236		-0.105	0.037	0.005	**
	Household Size		0.303	0.009	0.000	***	0.266	0.012	0.000	***
	Household workers per size		0.040	0.027	0.137		0.163	0.034	0.000	***
	Household children (age<17) per size		0.409	0.057	0.000	***	-0.187	0.075	0.012	*
	Head of household age		-0.001	0.001	0.089	.	0.000	0.001	0.920	
	Income (10,000 thousands of dollars)		0.014	0.002	0.000	***	0.020	0.003	0.000	***
	Household vehicles per licensed driver		-0.033	0.019	0.070	.	0.186	0.022	0.000	***
¤	Household transit pass		-0.006	0.019	0.763		-0.263	0.024	0.000	***
	Household bikes owned per size		0.045	0.014	0.001	**	-0.057	0.018	0.001	**

NOTES: Statistical significance of coefficients: "***" p < 0.001, "**" p < 0.01, "*" p < 0.05, "." p < 0.1; ¤ Indicates binary variable.

Table C.2: Negative Binomial Regression Results for Household Person Trips Traveled, by Mode (Table 2 of 2)

			Person Trips by Bike				Person Trips by Walk			
			Coefficient	**Standard Error**	**Pr(>|z|)**		**Coefficient**	**Standard Error**	**Pr(>|z|)**	
	Dispersion Parameter		12.416				2.101			
	Deviance		4119				9083			
	Deviance (Null)		3961				3961			
	(constant)		-3.703	0.611	0.000	***	-0.483	0.217	0.026	*
¤	Neighborhood Type	A	-0.101	0.778	0.897		0.972	0.239	0.000	
¤		B	0.495	0.221	0.025	*	0.373	0.082	0.000	***
¤		C								
¤		D	-0.128	0.238	0.592		-0.115	0.087	0.185	
¤		E	-0.426	0.412	0.301		0.097	0.136	0.473	
¤		F	0.804	0.992	0.418		-0.388	0.433	0.369	
¤		G	-1.794	0.581	0.002	**	-0.316	0.158	0.046	*
¤	Availability of MAX		-0.336	0.652	0.606		0.109	0.201	0.589	
	Neighborhood Type * Availability of MAX									
¤		A	1.778	1.280	0.165		-0.051	0.422	0.903	
¤		B	0.700	0.927	0.451		-0.231	0.329	0.483	
¤		C	(base)	---			(base)	---		
¤		D	-1.133	1.295	0.382		-0.500	0.346	0.149	
¤		E	0.990	5.061	0.845		-0.112	1.882	0.953	
¤	Housing Type – Multifamily (versus Single)		0.272	0.295	0.357		0.345	0.102	0.001	***
¤	Tenure – Rent (versus Own)		-0.131	0.291	0.653		-0.005	0.102	0.962	
	Household Size		0.685	0.094	0.000	***	0.199	0.034	0.000	***
	Household workers per size		0.439	0.295	0.136		-0.141	0.098	0.148	
	Household children (age<17) per size		-1.553	0.572	0.007	**	1.035	0.209	0.000	***
	Head of household age		-0.018	0.007	0.006	**	-0.006	0.002	0.010	**
	Income (10,000 thousands of dollars)		0.016	0.023	0.481		0.010	0.008	0.239	
	Household vehicles per licensed driver		-0.826	0.203	0.000	***	-0.517	0.074	0.000	***
¤	Household transit pass		0.123	0.180	0.496		0.935	0.065	0.000	***
	Household bikes owned per size		2.077	0.121	0.000	***	0.262	0.047	0.000	***

NOTES: Statistical significance of coefficients: "***" $p < 0.001$, "**" $p < 0.01$, "*" $p < 0.05$, "." $p < 0.1$; ¤ Indicates binary variable.

Table C.3: Linear Regression Results for Exponentially Transformed Household Person Miles Traveled, by Mode (Table 1 of 2)

			Person Miles Traveled (Total)^0.2				Person Miles Traveled by Vehicle^0.2			
			Coefficient	Standardized Coefficient	Standard Error		Coefficient	Standardized Coefficient	Standard Error	
	Adjusted R^2		32.7%				21.1%			
	Sample Size		3593				3592			
	(constant)		1.515	-0.036	0.045	***	1.549	-0.136	0.042	***
¤	Neighborhood Type	A	-0.322	-0.081	0.058	***	-0.193	-0.060	0.080	*
¤		B	-0.071	-0.064	0.017	***	-0.060	-0.067	0.016	***
¤		C	(base)	---	---		(base)	---	---	
¤		D	-0.004	-0.003	0.018		0.006	0.007	0.016	
¤		E	-0.012	-0.005	0.028		0.007	0.004	0.025	
¤		F	0.011	0.001	0.082		0.089	0.012	0.076	
¤		G	0.159	0.093	0.029	***	0.191	0.138	0.026	***
¤	Availability of MAX		-0.013	-0.005	0.044		0.009	0.005	0.043	
	Neighborhood Type * Availability of MAX									
¤		A	0.211	0.031	0.101	*	0.117	0.022	0.129	
¤		B	-0.114	-0.024	0.071		-0.122	-0.032	0.071	.
¤		C	(base)	---	---		(base)	---	---	
¤		D	-0.107	-0.022	0.070		-0.037	-0.009	0.070	
¤		E	0.257	0.012	0.380		0.210	0.012	0.339	
¤	Housing Type – Multifamily (versus Single)		-0.009	-0.007	0.022		0.027	0.027	0.021	
¤	Tenure – Rent (versus Own)		-0.081	-0.064	0.022	***	-0.060	-0.059	0.021	**
	Household Size		0.163	0.426	0.007	***	0.113	0.364	0.007	***
	Household workers per size		0.121	0.089	0.019	***	0.164	0.150	0.018	***
	Household children (age<17) per size		-0.031	-0.013	0.046		-0.168	-0.084	0.043	***
	Head of household age		-0.001	-0.039	0.000	**	-0.001	-0.046	0.000	**
	Income (10,000 thousands of dollars)		0.010	0.082	0.002	***	0.013	0.127	0.002	***
	Household vehicles per licensed driver		0.083	0.091	0.013	***	0.042	0.056	0.013	**
¤	Household transit pass		-0.157	-0.142	0.014	***	-0.101	-0.114	0.014	***
	Household bikes owned per size		-0.021	-0.029	0.010	*	-0.021	-0.036	0.010	*

NOTES: Statistical significance of coefficients: "***" p < 0.001, "**" p < 0.01, "*" p < 0.05, "." p < 0.1; ¤ Indicates binary variable.

Table C.4: Linear Regression Results for Exponentially Transformed Household Person Miles Traveled, by Mode (Table 2 of 2)

			Person Miles Traveled by Bike^0.2				Person Miles Traveled by Walk^0.2			
			Coefficient	Standardized Coefficient	Standard Error		Coefficient	Standardized Coefficient	Standard Error	
	Adjusted R^2		16.7%				7.5%			
	Sample Size		316				1487			
	(constant)		1.161	-0.412	0.121	***	0.844	0.015	0.045	***
¤	Neighborhood Type	A	-0.269	-0.125	0.109	*	0.142	0.073	0.040	***
¤		B	-0.048	-0.079	0.042		0.053	0.097	0.017	**
¤		C	(base)	---	---		(base)	---	---	
¤		D	-0.083	-0.133	0.050		0.006	0.011	0.018	
¤		E	-0.142	-0.120	0.095		0.011	0.010	0.032	
¤		F	-0.266	-0.054	0.132	*	-0.097	-0.022	0.078	
¤		G	-0.223	-0.238	0.152		-0.006	-0.007	0.037	
¤	Availability of MAX		-0.309	-0.229	0.104	**	-0.002	-0.002	0.038	
	Neighborhood Type * Availability of MAX									
¤		A	0.725	0.197	0.202	***	-0.007	-0.002	0.072	
¤		B	0.198	0.077	0.133		0.032	0.014	0.062	
¤		C	(base)	---	---		(base)	---	---	
¤		D	0.499	0.187	0.357		-0.010	-0.004	0.070	
¤		E	0.516	0.043	0.389		0.003	0.000	0.363	
¤	Housing Type – Multifamily (versus Single)		-0.043	-0.063	0.051		0.049	0.078	0.020	*
¤	Tenure – Rent (versus Own)		0.012	0.017	0.055		-0.016	-0.026	0.021	
	Household Size		0.019	0.093	0.016		0.036	0.192	0.007	***
	Household workers per size		0.269	0.364	0.064	***	-0.060	-0.090	0.021	**
	Household children (age<17) per size		0.027	0.020	0.108		-0.013	-0.011	0.042	
	Head of household age		-0.001	-0.049	0.001		0.001	0.035	0.000	
	Income (10,000 thousands of dollars)		0.007	0.107	0.004	.	0.001	0.011	0.002	
	Household vehicles per licensed driver		-0.094	-0.188	0.031	**	-0.039	-0.086	0.013	**
¤	Household transit pass		0.030	0.050	0.030		-0.039	-0.073	0.013	**
	Household bikes owned per size		0.089	0.228	0.024	***	0.032	0.090	0.011	**

NOTES: Statistical significance of coefficients: "***" $p < 0.001$, "**" $p < 0.01$, "*" $p < 0.05$, "." $p < 0.1$; ¤ Indicates binary variable.

Table C.5: Negative Binomial Regression Results for Household Automobiles Owned

			Household Vehicles Owned			
			Coefficient	Standard Error	Pr(>|z|)	
	Dispersion Parameter		0.00			
	Deviance		1649			
	Deviance (Null)		4321			
	Sample Size (Households)		4322			
	(constant)		0.079	0.078	0.307	
¤	Neighborhood Type	A	-0.517	0.177	0.004	**
¤		B	-0.107	0.033	0.001	**
¤		C				
¤		D	-0.011	0.032	0.733	
¤		E	0.085	0.048	0.075	.
¤		F	0.166	0.141	0.240	
¤		G	0.166	0.046	0.000	***
¤	Availability of MAX		-0.089	0.097	0.358	
	Neighborhood Type * Availability of MAX					
¤		A	-0.141	0.296	0.634	
¤		B	0.097	0.150	0.515	
¤		C				
¤		D	0.036	0.145	0.804	
¤		E	-0.741	0.991	0.455	
¤		+F				
¤		+G				
¤	Housing Type – Multifamily (versus Single)		-0.259	0.046	0.000	***
¤	Tenure – Rent (versus Own)		-0.220	0.045	0.000	***
	Household Size		0.229	0.013	0.000	***
	Household workers per size		0.134	0.037	0.000	***
	Household children (age<17) per size		-0.930	0.086	0.000	***
	Head of household age		-0.001	0.001	0.220	
	Income (10,000 thousands of dollars)		0.024	0.003	0.000	***
¤	Household transit pass		-0.219	0.028	0.000	***
	Household bikes owned per size		0.042	0.019	0.027	*

NOTES: Statistical significance of coefficients: "***" p < 0.001, "**" p < 0.01, "*" p < 0.05, "." p < 0.1; ¤ Indicates binary variable; + Small and Rural Town neighborhood types are outside of Portland Metro and do not have access to MAX.