LATENT CLASS ANALYSIS OF RESIDENTIAL AND WORK LOCATION CHOICES

DRAFT FINAL REPORT

Prepared by:

Principal Investigator
Sabya Mishra, Ph.D., P.E.
Assistant Professor, Dept. of Civil Engineering, University of Memphis,
112D Engr. Sc. Bldg., 3815 Central Avenue, Memphis, TN 38152
Tel: 901-678-5043, Fax: 901-678-3026, Email: smishra3@memphis.edu

Co-Principal Investigators
Mihalis M. Golias, Ph.D. A.M. ASCE
Associate Professor, Dept. of Civil Engineering,
Associate Director for Research Intermodal Freight Transportation Institute,
University of Memphis, 104C Engr. Sc. Bldg., 3815 Central Avenue, Memphis, TN 38152,
Tel: 901-678-3048, Fax: 901-678-3026, Email: mgkolias@memphis.edu

Rajesh Paleti, Ph.D.
Assistant Professor, Dept. of Civil & Environmental Engineering,
Old Dominion University, 135 Kaufman Hall, Norfolk, VA 23529
Tel: 757-683-5670, Email: rpaleti@odu.edu

Research Assistants
Afrid A. Sarker
Research Assistant, Dept. of Civil Engineering, University of Memphis,
302A Engineering Admin. Bldg., 3815 Central Avenue, Memphis, TN 38152
Phone: 260-797-1886, Email: aasarker@memphis.edu

Khademul Haque
Research Assistant, Dept. of Civil Engineering, University of Memphis,
302A Engineering Admin. Bldg., 3815 Central Avenue, Memphis, TN 38152
Phone: (860) 617-1489, Email: khaque@memphis.edu

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EXECUTIVE SUMMARY

Residential and work location choices are medium-to-long term decisions that have a significant impact on day-to-day activity-travel decisions of people. Typically, these choices are modeled using discrete choice models, but, several important aspects including attitudes and preferences (e.g., greener lifestyle and tech-savvy attitude), the consideration choice set, and the decision making mechanism are typically not observed in the revealed preference dataset. These unobserved factors can lead to heterogeneity in travel sensitivities across different population segments or lead to variation in the consideration choice set across decision makers. Thus, standard choice models (e.g., MNL) cannot control for these factors. In such scenarios, latent class models that can probabilistically classify households into latent classes (e.g., neo and conventional) are particularly useful.

Since, location choices are usually undertaken at the zonal level (e.g., TAZ), the size of choice set is typically large, comprising thousands of alternatives. While sampling techniques can be used to resolve the computational problem associated with large choice sets, the sampling mechanism itself might introduce some bias and make it more difficult to identify latent segments. To avert this problem, this study proposes a two-stage decision framework for location choices. In the first stage, a household (or a worker) is assumed to select a neighborhood type (such as central business district, urban, suburban) to live (or work). In the second stage, the household (or worker) is assumed to choose a specific zone based on the selected neighborhood type. The latent class analysis is undertaken at the first stage which has a much smaller choice set than the conditional zonal choice model in the second stage. However, these two components are not completely independent. Both the model components are estimated sequentially but the *expected utility* or *logsum* from the zonal destination choice is used as an explanatory variable in the neighborhood type choice alternatives to link the two model components.

For case study purposes, data from a 2012 household travel survey, conducted in Nashville, Tennessee, is used. The model results indicate significant heterogeneity in the consideration probability of different neighborhood type alternatives both in the residential and work location choices. Also, the model applicability is tested by calculating elasticity effects and identifying demographic groups with different residential and work location preferences. Compared with standard MNL models, that assume all decision makers consider the complete universal choice set, the latent class neighborhood models were found to perform more strongly.

CHAPTER 1: BACKGROUND

Residential and work location choices are medium-to-long term decisions that have a significant impact on day-to-day activity-travel decisions of people. These choices are typically modeled using discrete choice models that assume certain decision making mechanism. For instance, the Random Utility Maximization (RUM) rule is one such mechanism in which the decision maker is assumed to choose the alternative that provides the highest utility. Within the class of discrete choice models, the multinomial logit (MNL) and its generalizations (e.g., nested logit, cross nested logit *etc.*) are commonly used to analyze travel-related choices. In these models, the utilities of different alternatives are specified as a function of different observed variables collected from household survey data that can affect the choice being modeled. However, several important aspects including the attitudes and preferences, the consideration choice set, and the decision making mechanism are typically not observed in the survey data (Walker and Li, 2006). For instance, it is reasonable to assume that there are certain households/people who have greener life styles or tech-savvy attitudes from the rest of the population. People in these '*neo'* households are likely to have different residential and work location preferences compared to those in '*conventional'* households (Bhat and Guo, 2007). But, these attitudinal variables are not available in most revealed preference datasets. The effects of these unobserved factors can manifest in different ways. For instance, these factors can lead to heterogeneity in travel sensitivities across different population segments or lead to variation in the consideration choice set across decision makers. So, standard choice models such as the MNL model cannot control for these factors. In such scenarios, latent class models that can probabilistically classify households into latent classes (e.g., neo and conventional) are particularly useful. It is important to note that these groups or classes are not observed in the real world (and hence the name '*latent*').

Latent class choice models have been applied in various disciplines. Methodological development and model application is spread over multiple domains including marketing research (Dillon et al., 1994; Grover and Srinivasan, 1987; Russell and Kamakura, 1993; Swait, 1994; Swait and Sweeney, 2000), economics (Boxall et al., n.d.; Boxall and Adamowicz, 2002), transportation (Walker and Li, 2006), geography(Baerenklau, 2010; Hynes et al., 2008; Scarpa and Thiene, 2005), agriculture (Mitani et al., 2008) and health science (Bandeen-Roche et al., 2006; Bucholz et al., 1996; Jung and Wickrama, 2008; Lanza and Rhoades, 2011). Application of latent class models in transportation planning can be summarized into four categories. *First*, studies that focused on varying travel sensitivities and preferences where endogenous market segmentations are made based on intrinsic biases and responsiveness to level-of-service attributes (Bhat, 1998, 1997; Greene and Hensher, 2003). Recently, researchers also started to explore *attribute non-attendance* where some respondents only consider a subset of attributes during decision making *(22)*. These studies can also be grouped under the category of those dealing with varying travel sensitivity. *Second*, studies that analyze the variation in consideration choice sets across decision makers (Manski, 1977; Martínez et al., 2009). *Third*, studies that recognize that people might use alternate decision making mechanisms or decision rules such as RUM or Random Regret Minimization (RRM) while evaluating choice alternatives (Hess and Stathopoulos, 2013). *Fourth*, studies that considered all possible dependency pathways while modeling multiple choices simultaneously. For instance, work location decisions can be made conditional on residential location or vice-versa leading to two different dependency pathways (Waddell et al., 2007).

The current research belongs to the second group of studies that aim to uncover population segments with varying choice sets in residential and work location choices. Typically, location choices are undertaken at the zonal level (*i.e.*, traffic analysis zone, block, or parcel). The size of choice set in location choice models is typically large extending into thousands of alternatives. Even with moderately sized choice sets, it is difficult to identify more than 2-3 latent classes in most empirical applications. So, it can be quite challenging to uncover latent classes with large choice sets. While researchers have used sampling techniques to resolve the computational problem associated with large choice sets, the sampling mechanism itself might introduce some bias and make it further difficult to identify latent segments. To address this problem, the current study adopted a two-stage decision framework for location choices. In the first stage, a household (or a worker) will select a neighborhood (such as central business district, urban, suburban *etc.*) to live (or work). In the second stage, the household (or worker) will choose a specific zone conditional on the selected neighborhood in the first stage. The latent class analysis is undertaken at the first stage which has a much smaller choice set compared to the conditional zonal choice model in the second stage. For instance, certain households might only consider high density neighborhoods while deciding where to reside leading to varying consideration choice sets in the neighborhood choice model. The two-stage modeling framework is also reasonable from a behavioral standpoint because households are very unlikely to consider all zones within the study area while making decisions regarding where to live and work. They are more likely to choose a neighborhood and then explore residential choices within the neighborhood. However, these two components are not completely independent. Better zonal alternatives within a neighborhood should increase the likelihood of choosing that neighborhood over others. This dependence between the neighborhood and zonal choice components is captured by using log-sum from conditional zonal choice model as an explanatory variable in the utility of the neighborhood choice model component.

The remainder of the report is organized as follows. A review of the relevant literature is presented in the next section followed by the methodology. The case study section (fourth section) describes the study area and data used for model development. The results and discussion section (fifth section) provides insights on the case study findings and possible application of the model and its results in transportation planning and travel demand modeling. The sixth section explores potential applications of proposed latent class models in modeling more efficient and accurate (residential/work) location choices. The final section concludes the report and outlines the scope of future research.

CHAPTER 2: LITERATURE REVIEW

As briefly discussed in the introduction section, the literature review is presented along four themes to draw insights from past transportation research: (1) Endogenous market segmentation; (2) choice set variation; (3) heterogeneous decision rules, and (4) alternative dependency pathways. Before proceeding to specific segments, a broad literature review is presented below.

Modern research on housing choice began with the study by Alonso, 1964, which considers a city where employment opportunities are located in a single center (a monocentric city). In Alonso's study, the residential choice of households is based on maximizing a utility function that depends upon the expenditure in goods, size of the land lots, and distance from the city center. Several studies (Harris, 1963; Mills, 1972; Wheaton, 1974) extended the work of Alonso by relaxing the assumption of a monocentric city of employment opportunities. One of the most criticized aspects of these early research works is that location is represented as a one-dimensional variable - distance from the CBD. These models are therefore incapable of handling dispersed employment centers and asymmetric development patterns (Waddell, 1996).

Even before Alonso's, 1964 work, geographers and transportation planners had developed the "gravity model" that provides a reasonable basis for the prediction of zone-to-zone trips. Lowry applied the gravity model to residential location modeling in the well-known Lowry Model. Specifically, Lowry assumed that retail trade and services are located in relation to residential demand, and that residences are located in relation to combined retail and basic employment. Workers are hypothesized to start their trips to home from work, and distribute themselves at available residential sites according to a gravity model, which attenuates their trips over increasing distance. This vital feature of the Lowry model continues to dominate models of residential location in many practical applications (Harris, 1996).

Another stream of research on modeling residential location is based on discrete choice theory. In the context of residential location, the consumption decision is a discrete choice between alternative houses or neighborhoods. The work by McFadden represents the earliest attempt to apply discrete choice modeling to housing location. More recent works using this approach include Gabriel and Rosenthal (1989), Waddell (1993, 1996), and Ben-Akiva and Bowman (1998). As discussed next, these studies differ essentially in their model structures, the choice dimensions modeled, the study region examined, and the explanatory variables considered in the analysis.

The study by Gabriel and Rosenthal (1989) develops and estimates a multinomial logit model of household location among mutually exclusive counties in the Washington, D.C. metropolitan area. The findings indicate that race is a major choice determinant for that area, and that further application of MNL models to the analysis of urban housing racial segregation is warranted. Furthermore, the effects of household socio-demographic characteristics on residential location are found to differ significantly by race. Waddell (1993) examines the assumption implicit in most models of residential location that the choice of workplace is exogenously determined. A nested logit model is developed for worker's choice of workplace, residence, and housing tenure for the Dallas-Fort Worth metropolitan region. The results confirm that a joint choice specification better represents household spatial choice behavior. The study also reaffirms many of the influences posited in standard urban economic theory, as well as the ecological hypothesis of residence clustering by socio-demographic status, stage of life cycle, and ethnicity.

In a later study, Waddell (1996) focuses on the implications of the rise of dual-worker households. The choices of work place location, residential mobility, housing tenure and residential location are examined jointly. The hypothesis is that home ownership and the presence of a second worker both add constraints on household choices that should lead to a combination of lower mobility rates and longer commutes. The results indicate gender differences in travel behavior; specifically, the female work commute distance has less influence on the residential location choice than the male commute. Ben-Akiva and Bowman (1998) presented a nested logit model for Boston, integrating a household's residential location choice and its members' activity schedules. Given a residential location, the activity schedule model assigns a measure of accessibility for each household member, which then enters the utility function in the model of residential location choice. The results statistically invalidate the expected decision hierarchy in which the daily activity pattern is conditioned on residential choice.

2.1 Endogenous Market Segmentation

Bhat (1997) recognized the need to accommodate differences in intrinsic mode biases (preference heterogeneity) and differences in responsiveness to level-of-service attributes (response heterogeneity) across individuals. He incorporated preference and response heterogeneity into the MNL when studying mode choice behavior from cross-sectional data in an intercity travel. The study found that endogenous segmentation model described causal relationship best and provided intuitively more reasonable results compared to traditional approaches (Bhat, 1997). Walker and Li (2006) conducted an empirical study of residential location choices and uncovered three lifestyle segments – suburban dwellers, urban dwellers, and transit riders with varying location preferences (Walker and Li, 2006). Similarly, Wen and Lai (2010) demonstrated using air carrier choice data that the latent class model outperforms the standard MNL model considerably (Wen and Lai, 2010). Arunotayanun and Polak (2011) identified three latent segments in the context of freight mode choice of shippers with three alternatives – small truck, large truck, and rail as a function of several attributes including transport time, cost, service quality and service flexibility (Arunotayanun and Polak, 2011). While the first segment was found to be highly sensitive to all attributes considered, the second segment preferred better service quality and the third segment preferred better service flexibility.

Wen *et al.* (2012) used a nested logit latent class model for high speed rail access in Taiwan and showed that flexible substitution patterns among alternatives and preference heterogeneity in the latent class nested logit model outperformed traditional models (Wen et al., 2012). More recently, several studies analyzed attribute non-attendance which may be considered as a variant of taste heterogeneity in which some respondents make their choices based on only a subset of attributes that described the alternatives at hand (Hensher, 2010). For example, it is possible that a portion of respondents do not care about time savings while making travel decisions. Scarpa (2009) showed that 90% of the respondents do not consider cost while choosing rock-climbing destination spots. Similarly, Campbell *et al.* (2011) revealed that 61% of respondents are not attending to cost while making environmental choices (Campbell et al., 2010). Hess and Rose (2007) proposed a latent class approach to accommodate attribute non-attendance (Hess and Rose, 2007), and a number of studies adopted similar approach thereafter (Hensher et al., 2011; Hensher and Greene, 2009; Hess and Rose, 2007). Hess *et al.* (2012) suggest that with this approach, different latent classes relate to different combinations of attendance and non-attendance across attributes (Hess et al., 2012). Model estimation is conducted to compute a non-zero coefficient, which is used in the attendance classes, while the attribute is not employed in the non-attendance classes, *i.e.* the coefficient is set to zero. In a complete specification, covering all possible combinations, this would thus lead to 2^K classes, with *K* being the number of attributes (Hess et al., 2012).

2.2 Choice Set Variation

Manski (1977) developed the theoretical framework for the two stage decision process that accounts for choice set heterogeneity (Manski, 1977). Decision makers were assumed to first construct their choice set in a non-compensatory manner and then make choice conditional on the generated choice set using a compensatory mechanism (e.g., RUM). The choice probability of an alternative is obtained as a weighted probability of choosing that alternative over all possible choice sets. Swait and Ben-Akiva (1987) and Ben-Akiva and Boccara (1995) build on Manski's framework and used explicit random constraints to determine the choice set generation probability (Ben-Akiva and Boccara, 1995; Swait and Ben-Akiva, 1987). Bierlaire *et al.* (2009) stated that earlier latent class choice set generation methods are hardly applicable to medium and large scale choice problems because of the computational complexity that arises from the combinatorial number of possible choice sets. If the number of alternatives in the universal choice set is *C*, the number of possible choice sets is ($2^C - 1$) (Bierlaire et al., 2009). Several heuristics that derive tractable models by approximating the choice set generation process were developed. The most promising heuristics are based on the use of penalties of the utility functions, and were proposed by Cascetta and Papola (2001) and further expanded by Martinez *et al.* (2009) (Cascetta and Papola, 2001; Martínez et al., 2009). These heuristics were recently further modified to closely replicate the Manski's original formulation (Paleti, 2015).

2.3 Heterogeneous Decision Rules

An increasing number of studies investigated the use of alternatives to random utility maximization (RUM) rule to explore which paradigm of decision rules best fits a given dataset as well as the variation in decision rules across respondents. Srinivasan *et al.*

(2009) developed a latent class model that assigns respondents to either the utility maximizing or disutility minimizing segments probabilistically for analyzing mode choice decisions. This study found that only 32.5% respondents belong to the utility maximizing segment whereas a majority (67.5%) belonged to the disutility minimizing segment (Srinivasan et al., 2009). Along similar lines, Hess *et al*. (2013) developed latent class models that linked latent character traits to choice of decision rule between RUM and RRM. This found an almost even split between the shares of respondents that adopted the two decision rules in the context of commute mode choice (Hess and Stathopoulos, 2013). Zhang *et al.* (2009) examined different types of group decision-making mechanisms in household auto ownership choices using latent classes models (Zhang et al., 2009).

2.4 Alternate Dependency Pathways

Joint choice modeling can result in several pathways of dependency among the choice dimensions considered. However, one of the challenges is that as the number of choice dimensions in the integrated modeling framework increases, the number of possible dependency pathways among choice dimensions can explode very quickly. Specifically, there are $K!$ possible dependency structures in an integrated model with K choice dimensions. So, it is not always possible to estimate latent models with all possible dependency pathways. However, latent class models can be useful in empirical contexts where there are very limited dependency pathways. For instance, Waddel *et al.* (2007) used latent class models to estimate the proportion of households in which residential location choice is made conditional on workplace location choice and *vice versa* (Waddell et al., 2007). However, this study only considered single-worker households because of several possible permutations of work and home location choices in multi-worker households. Additionally, the authors also mention the complexity involved in modeling the interdependencies when dynamics among choice dimensions can change over time.

In summary, latent class models have proven useful with better policy insights and improved statistical fit in a wide array of empirical contexts within transportation. Moreover, these models have the same data requirements as standard un-segmented models. However, it might not be analytically tractable to estimate latent class models in certain choice contexts without making some simplifying assumptions.

CHAPTER 3: METHODOLOGICAL FRAMEWORK

In this chapter, the methodology for identifying residential and work location choices at neighborhood and zonal level is presented. Before proceeding with the methodology, we present the nomenclature used throughout the report.

Nomenclature

Notation	Description
q	The decision-maker
i	Neighborhood alternatives
C	Universal choice set at neighborhood level
ϕ_q^i	Probability of decision maker *q* considers alternative *i*
V_q^i	Observed utility experienced by *q* for alternative *i*
$\boldsymbol{X}_q^i$	Vector of explanatory variables
ε_q^i	Hidden utility experienced by *q* for alternative *i*
U_q^i	Total utility experienced by *q* for alternative *i*
V_q^s	Observed utility by *q* for each alternative for the zone *s*
$\boldsymbol{LOS}_{q,h,s}$	Level-of-service variables between home zone *h*, and work zone *s*
$D_{h,s}$	Distance between home zone h, and work zone *s*
$Size_q^s$	Size variable for destination zone *s* for decision maker *q*
$\boldsymbol{f}\left(D_{h,s}\right)$	Vector of non-linear functions of $D_{h,s}$
$\boldsymbol{\pi}, \boldsymbol{\alpha}, \boldsymbol{\delta}$	Coefficients

In this study, a two-stage decision making process is assumed in which the decision maker (*household* for residential location choice and *individual employee* for work location choice) first chooses the neighborhood in the first stage and then looks for a specific zone within the chosen neighborhood in the second stage. Both these two model components were estimated sequentially but the expected utility or logsum from the zonal destination choice was used as an explanatory variable in the neighborhood choice alternatives to link the two model components. Moreover, it is unlikely that all decision makers consider the full set of neighborhoods while making the first stage neighborhood choice. This variation in the consideration choice set of neighborhood choice is accounted using the latent choice set Manski model. Lastly, the universal choice set of zonal choice conditional on the neighborhood in the second stage comprises of all zones within the chosen neighborhood of the decision maker. The size of this choice set can still be quite large. So, importance sampling methods were used to construct the sampled choice set for zonal choice in the second stage. A brief overview of different modeling components is presented below. Let *q* be the index for the decision maker.

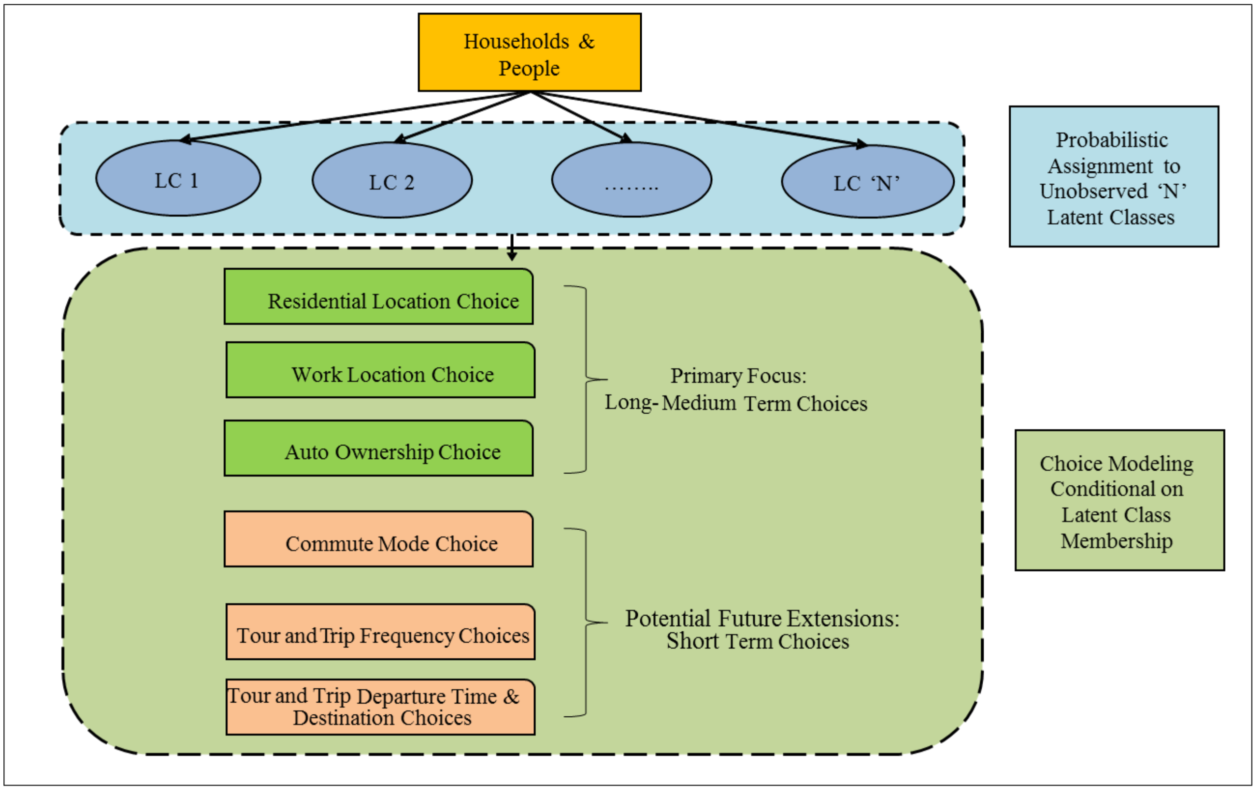


Figure 3-1. Conceptual framework of the proposed latent class model

3.1 Neighborhood Choice Component

Let *i* be the index for neighborhood alternative and C denote the universal choice set of the neighborhood choice $C = \{1 = \text{CBD}, 2 = \text{URBAN}, 3 = \text{SUBURBAN}, 4 = \text{RURAL}\}$. It is very likely that decision maker *q* only considers a subset C_q (of *C*), known as the consideration choice set, while making the actual choice. In the multinomial logit (MNL) framework, the utility associated with alternative *i* can be written as:

$$U_q^i = V_q^i + \varepsilon_q^i = \boldsymbol{\beta}_i' \boldsymbol{X}_q^i + \varepsilon_q^i \quad (1)$$

Where $V_q^i = \boldsymbol{\beta}_i' \boldsymbol{X}_q^i$ is the observed part of the utility, $\boldsymbol{X}_q^i$ is the vector of explanatory variables, and $\boldsymbol{\beta}_i$ is the corresponding column vector of coefficients, and ε_q^i is standard gumbel random variable that captures all unobserved factors that is independent and identically distributed across alternatives and decision makers. The vector $\boldsymbol{X}_q^i$ also includes logsum from the conditional zonal destination choice model.

So, the probability of a decision maker *q* choosing an alternative '*i*' from a set of mutually exclusive and exhaustive alternatives C_q is given by:

$$P_q(i|C_q) = \frac{e^{V_q^i}}{\sum_{j \in C_q} e^{V_q^j}} \tag{2}$$

However, the consideration set C_q is not observed by the analyst. To resolve this problem, past researchers have assumed that observed choice is an outcome of two latent (unobserved) steps – (1) formation of consideration set C_q from the universal choice set and (2) choice conditional on the consideration set C_q. So, the unconditional probability that decision maker *q* chooses neighborhood *i* is obtained as a weighted average across all possible consideration sets using Bayes' theorem as follows (Manski, 1977):

$$P_q(i) = \sum_{C_q \in C} P_q(i|C_q) \times P_q(C_q) \tag{3}$$

The consideration set formation step of the Manski model is viewed as a non-compensatory process whereas the second step is viewed as an outcome of compensatory mechanism (in our case, this is the Random Utility Maximization (RUM) principle in the MNL model). Consistent with this notion, the probability ϕ_q^i that decision maker *q* considers alternative *i* is specified as a binary logit model as follows:

$$\phi_q^i = \frac{e^{\gamma_i' Z_q^i}}{1 + e^{\gamma_i' Z_q^i}} \tag{4}$$

where $\boldsymbol{Z}_q^i$ is the vector of variables that impact whether alternative *i* is considered by decision maker *q* or not and $\boldsymbol{\gamma}_i$ is the corresponding column vector of coefficients. The probability of different consideration sets can be computed using these individual consideration probabilities. For instance, the probability of decision maker *q* considers the choice set {CBD, URBAN} is given as follows:

$$P_q\left[(CBD, URBAN)_q\right] = \phi_q^{CBD} \times \phi_q^{URBAN} \times \left(1 - \phi_q^{SUBURBAN}\right) \times \left(1 - \phi_q^{RURAL}\right) \qquad (5)$$

There are 15 possible consideration sets in the universal choice set comprising of four alternatives – CBD, URBAN, SUBURBAN, and RURAL, excluding the null choice set without any alternatives. However, all these subsets of alternatives are not intuitive from a behavioral standpoint. For instance, {CBD, RURAL} is one such possible subset of alternatives. However, it is difficult to justify why someone might consider both the extreme neighborhoods (CBD and RURAL) that have very different residential and employment composition but not intermediate options (URBAN and SUBURBAN). To avoid such instances of behavioral inconsistency, we only considered the following 10 feasible consideration choice sets that avoid discontinuity: {CBD, URBAN, SUBURBAN, RURAL}, {URBAN, SUBURBAN, RURAL}, {CBD, URBAN, SUBURBAN}, {CBD, URBAN}, {URBAN, SUBURBAN}, {SUBURBAN, RURAL}, {CBD}, {URBAN}, {SUBURBAN}, {RURAL}.

Lastly, to ensure that the sum of probabilities across all alternatives in the universal choice set add up to one, all the choice probabilities are re-scaled by the factor (1-probability of all infeasible choice sets).

3.2 Conditional Zonal Destination Choice Component

Let *s* denote the index for location *i.e.* Traffic Analysis Zone (TAZ). The observed part of the utility function for each alternative in the zonal choice set V_q^s can be written as follows:

$$V_q^s = LN\left(Size_q^s\right) + \boldsymbol{\pi}'\boldsymbol{W}_s + \boldsymbol{\alpha}' \times \boldsymbol{LOS}_{q,h,s} + \boldsymbol{\delta}' f\left(D_{h,s}\right) \qquad (6)$$

where is $Size_q^s$ the size variable for destination zone *s* for decision maker *q* (zonal household population for residential location and industry-specific zonal employment for work location), $\boldsymbol{W}_s$ is vector of zonal variables describing zonal alternative *s* and $\boldsymbol{\pi}$ is the corresponding vector of coefficients, $\boldsymbol{LOS}_{q,h,s}$ is the set of level-of-service variables between zone pair (*h,s*) where *h* is the home zone and their interaction with decision maker characteristics and $\boldsymbol{\alpha}$ is the corresponding vector of coefficients, $D_{h,s}$ is the network distance between home zone *h* and work zone alternative *s*, and $\boldsymbol{f}(D_{h,s})$ is a vector of non-linear functions of $D_{h,s}$ (for example, linear, squared, cubic, and logarithmic) and $\boldsymbol{\delta}$ is the corresponding vector of coefficients. Please note that the last two components (LOS and distance-based impedance measures) are relevant only to the work location component where we assume that the home location is already known. Assuming *i.i.d.* standard Gumbel term assumption for the unobserved part of utilities will lead to the MNL model.

3.3 Sampling Destination Zones

As mentioned earlier, it is computationally difficult to consider all location alternatives within a neighborhood during model estimation. While a completely random sampling approach will produce consistent parameter estimates, it is not an efficient option. So, a sampling-by-importance model with TAZ activity-specific size terms (for both residential and work location models) and a coefficient of -0.1 for “Distance between home and work TAZ” variable (only for work location choice) was applied. During model estimation, a correction term equal to $\ln\left(\frac{n_i}{N \times q(i)}\right)$ was added to the utility function of the sampled alternative to account for the difference in the sampling probability and the frequency of the alternative in the sample. The sampling correction term represents natural logarithm of the ratio of the sampling frequency to selection probability for each alternative as was substantiated in the theory (Ben-Akiva and Lerman, 1985; McFadden, 1978). In this correction term, $q(i)$ is the selection probability (probability to be drawn) which is a function of size variable and simplified distance-based impedances, n_i is the selection frequency in the sample or the number of times an alternative is chosen, and *N* is the sample size (= 50 because we sample fifty TAZs).

CHAPTER 4: CASE STUDY

In this chapter, we present the data sets used and the steps performed to produce the effective dataset needed for modeling and estimation purposes.

4.1 Data Sources

The data for this study is derived from the 2012 household travel survey data conducted in Nashville metropolitan area. In addition to geo-coded location information, the data include detailed socio-economic and demographic data and activity travel diary data of all respondents. The travel skims and network related variables were gathered form the Nashville Travel Demand Model (TDM). The following describes data collected for the study:

- National Household Travel Survey (NHTS) data: The preliminary dataset contained 5,164 households with 11,114 people and 5,682 of them were employed. The NHTS serves as the nation's inventory of daily travel. Data is collected on daily trips taken in a 24-hour period. It also includes:
  - Household data on the relationship of household members, education level, income, housing characteristics, and other demographic information
  - Information on each household vehicle, estimates of annual miles traveled
  - Data about drivers, including information on travel as part of work;

- Network Characteristics: Travel demand model was provided by the Nashville MPO which included travel skims and network related variables.
- Socio-economic characteristics: NHTS data provided all the necessary socio-economic characteristics used in this study.
- School ratings: Tennessee Department of Education maintains a rating scale using Tennessee Value-Added Assessment System (TVAAS). It is a statistical method used to measure the influence of a district or school on the academic progress (growth) rates of individual students or groups of students from year-to-year. It should be noted that, rating is available only for the public schools in the state of TN.

4.2 Data Assembly

The first step in this stage was to geocode the work location coordinates in order to obtain the work locations TAZs. Since the data was missing several key attributes, the following approach is implemented (in order) to create a complete and effective dataset:

- Exclude records with missing work location coordinates or work location outside the TAZ system
- Exclude records with missing information on any of the explanatory variables
- Exclude records where a person is employed in a zone where there is zero employment in the corresponding industry

To construct the choice set for work location with 50 alternatives, 49 alternatives, different from the observed work location, were randomly sampled. Once the 50 alternatives were produced, for each individual, following tasks were performed:

- For each zonal pair (residential TAZ and potential work location TAZ), append distance and *logsum* information.
- Append zonal employment information of the industry in which the person is employed for all the sampled alternatives. For example, for a person employed in the manufacturing industry, only manufacturing zonal employment must be used
- Append household and person explanatory variables to the estimation data set.

Some of the primary explanatory variables used in the model estimation are shown below:

Explanatory variables for household	Explanatory variables for individual
Household Income	Work Industry
Housing Tenure (Own/Rent)	Work hours (part-time/full-time)
Presence of children	Work Flexibility
Household Auto ownership	Educational Attainment
Highest education attainment	Gender
Number of students per household	Age
Number of children per household	Valid License
Number of workers per household	Student status (Part-time/Full-time)
Number of disabled people per household	

Instead of using the standard definition of spatial unit of location choices (census tract or TAZ), this paper employs neighborhood categories based on household and employment density to characterize location choices. This helps make the definition of choice alternatives clear and manageable and more effectively captures the notion that people are looking for a built environment (land use density) that suits their mobility and lifestyle preferences. In other words, people are not choosing between TAZ A or B directly, but rather between a unit that offers a built environment of certain attributes versus another unit that offers a different built environment. Residence and workplace locations are categorized into four possible alternatives or neighborhoods based on a combination of population and employment density (population and employment in the half mile radius).

Only workers with work location outside home were considered in our analysis. One of the key variables in the work location choice model is industry in which the worker is employed. The Nashville travel demand model (TDM) uses work industry definition with five categories – agriculture and mining, retail, manufacturing, transportation, and office. The disaggregate work industry variable in the survey data was grouped together into these five categories to be consistent with the regional TDM. Several explanatory variables were considered in this study including age and gender composition, worker characteristics, household income, educational attainment, housing type, housing tenure, auto and bike ownership, typical commute mode choice and average daily trip frequency. In addition, distance, auto travel time, transit availability, and transit generalized cost were obtained from the network skims. Also, Hansen-type accessibility measures that indicate a zone’s accessibility to different types of activity opportunities and mode choice log-sums were calculated using zonal data and network skim files.

After extensive data cleaning, the final estimation sample includes 4,344 households and 3,992 employed individuals without any missing information on all explanatory variables used in this study. The distribution of individuals in the four residential neighborhood alternatives was - 8.90% rural, 29.74% suburban, 60.36% urban, and 1.00% CBD as shown in Fig 4-1. The distribution of individuals with respect to work neighborhood was 2.96% rural, 17.41% suburban, 65.88% urban, and 13.75% CBD. In the final sample, the share of respondents who live in CBD was quite low. So, the estimation of latent choice set model where people considered CBD alternative probabilistically is difficult with such small sample size. So, respondents are assumed to either consider or do not consider both the CBD and URBAN alternatives as a bundle but not separately. So, the set of feasible choice sets is reduced to the six possibilities: {CBD, URBAN, SUBURBAN, RURAL}, {CBD, URBAN, SUBURBAN}, {CBD, URBAN}, {SUBURBAN, RURAL}, {SUBURBAN}, {RURAL}. For the same reasons, the SUBURBAN and RURAL alternatives are considered as bundle in the latent choice set component of the work neighborhood choice model.

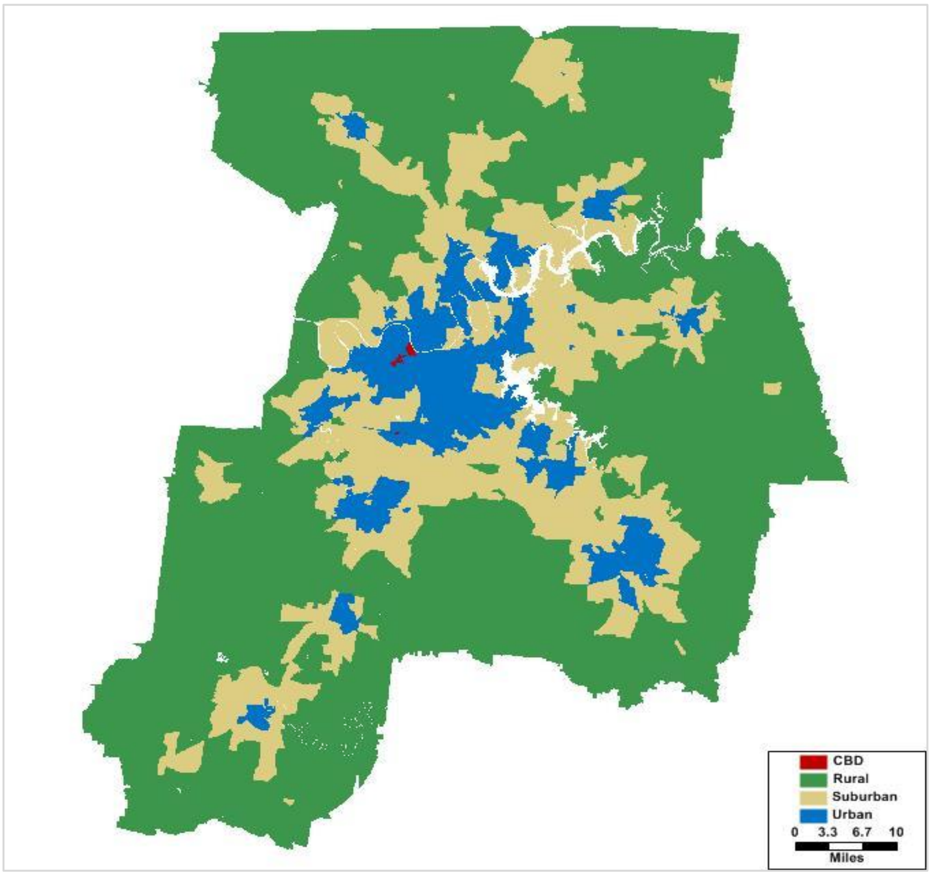


Figure 4-1. Neighborhood Definition Based on Residential & Employment Density

4.3 Statistical Analysis

This section gives an overview of how different socio-economic attributes affect the commute distance, one of the crucial factor in work location choice.

Figure 4-2 suggests that young age group commute longer distances compared to overall. A large fraction of them, about 9%, tend to travel 8-10 miles to work compared to total aggregate of 6%. For larger distances, such as 34-36 miles, the difference is 4%

to 2.8%. This phenomenon can be explained by the fact that young age group are more flexible when comes to work place location choice. At that age, commute distance is a trivial factor when deciding where to work.

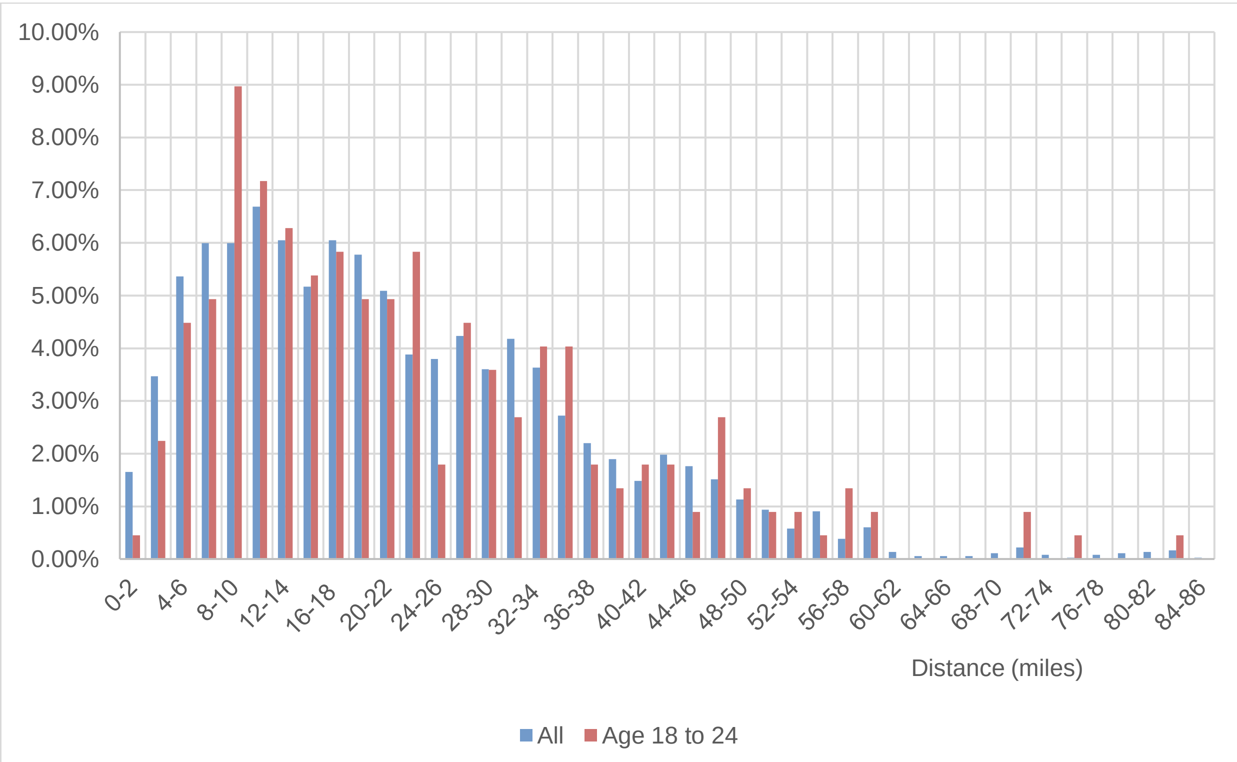


Figure 4-2. Commute distance- Age 18 to 24 years

Figure 4-3 shows how work flexibility affects the commute distance. Though, the work flexibility has no significant effect for short commute distance, individuals with a job with a provision of work flexibility tend to commute larger distance as the graph suggests. It can be due to the reason that work flexibility is more appealing for the individuals and hence s/he is willing to commute a few more miles to get the benefit.

Figure 4-4 shows the trend in commute distance for female individuals. It can be observed that for shorter commute distance, less than 10 miles, there are less females compared to others. But, for relatively larger distance such as 22-38 miles, there are more females. This trend can be explained by the fact that women have less flexibility when deciding on work locations which force them to commute larger distances in general.

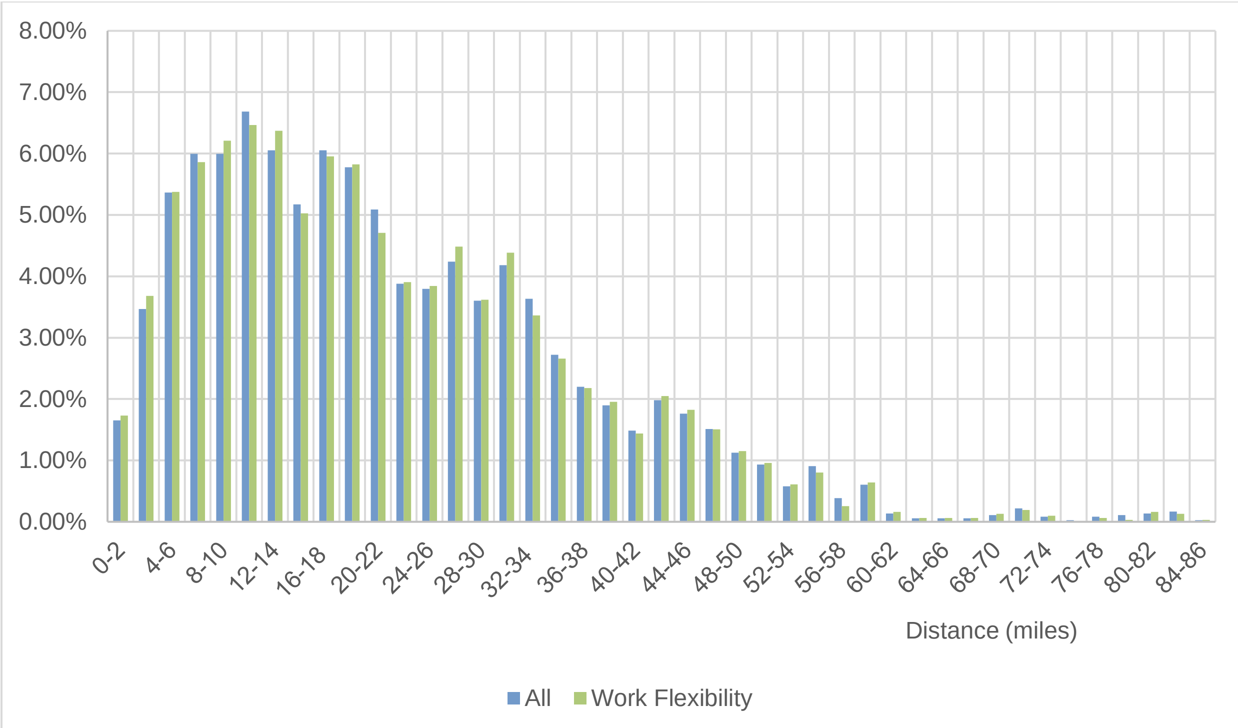


Figure 4-3. Commute Distance: Work Flexibility

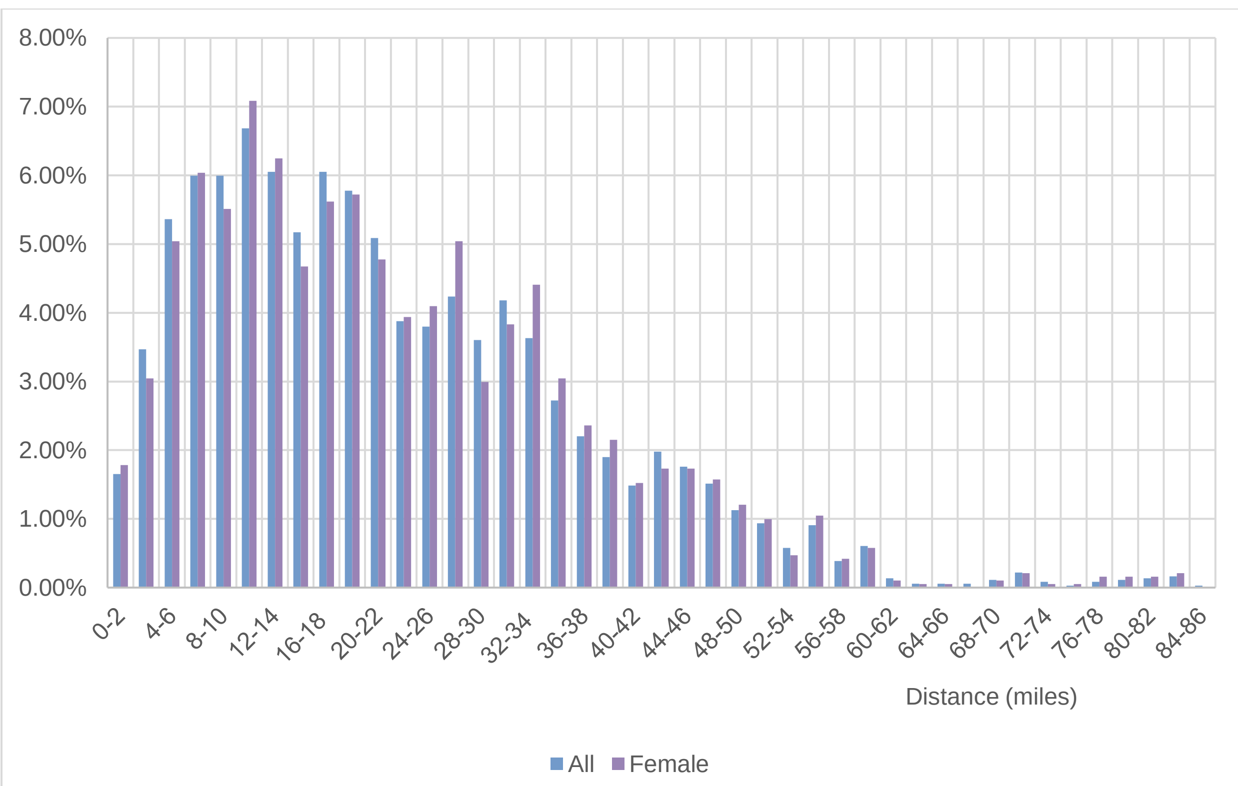


Figure 4-4. Commute distance: Gender

Figure 4-5 shows the relation between households with young children and commute distance. It can be observed that a significant proportion of these households prefer to live within 32 miles of work. There is also a fraction, about 10%, of these households who commute more than 40 miles. This can be explained from the perspective school's location. Individuals with children tend to choose their residential location based on school district which in some cases may be far away from their work location. Hence, some people are forced to commute long way to work. But, nonetheless, commute distance plays a significant role in workplace location choice.

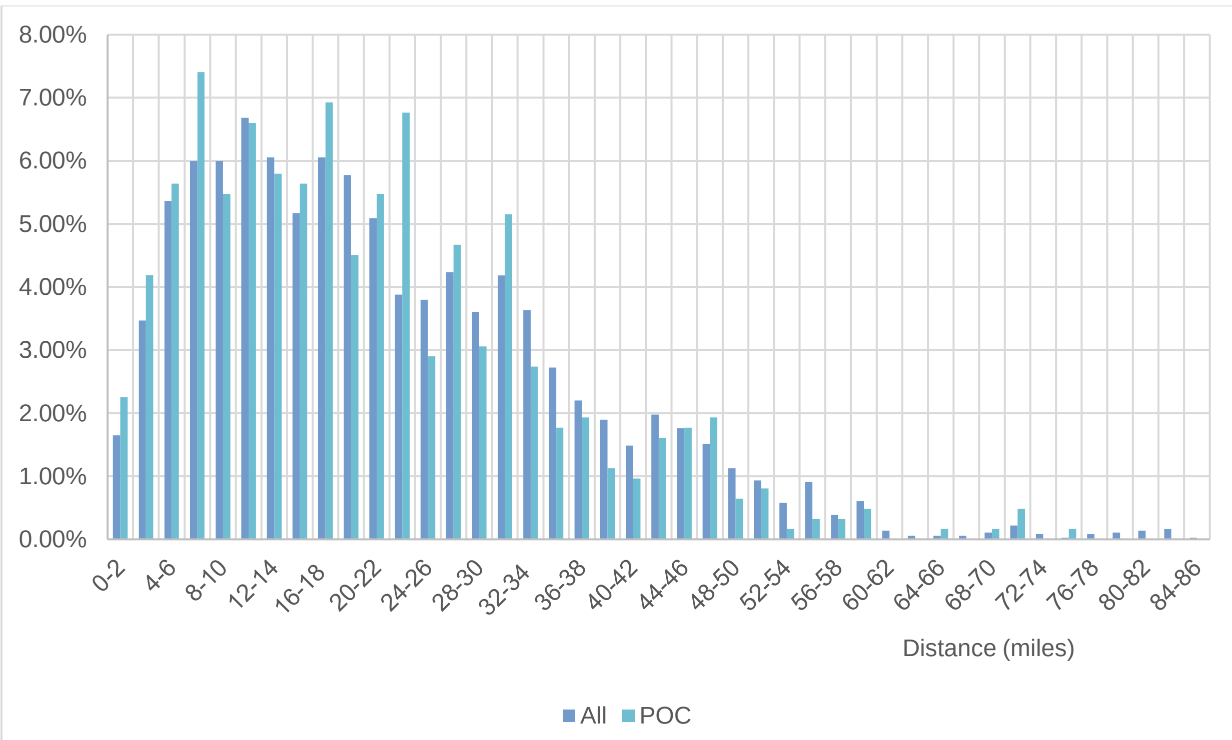


Figure 4-5. Commute distance: Presence of child (0-5 years)

Figure 4-6 shows that female with young children prefer to live closer to home. A very large fraction, about 8.3%, prefer to live within 6-8 miles of work and about 60% live within 26 miles from work. When comparing with Fig 4-4 and 4-5, we can see that the effect of "presence of children" is similar to the combined effect of "female with children". This trend is expected as mothers are the primary care giver for the young children and because of the children's school's location, work locations closer to home are more attractive.

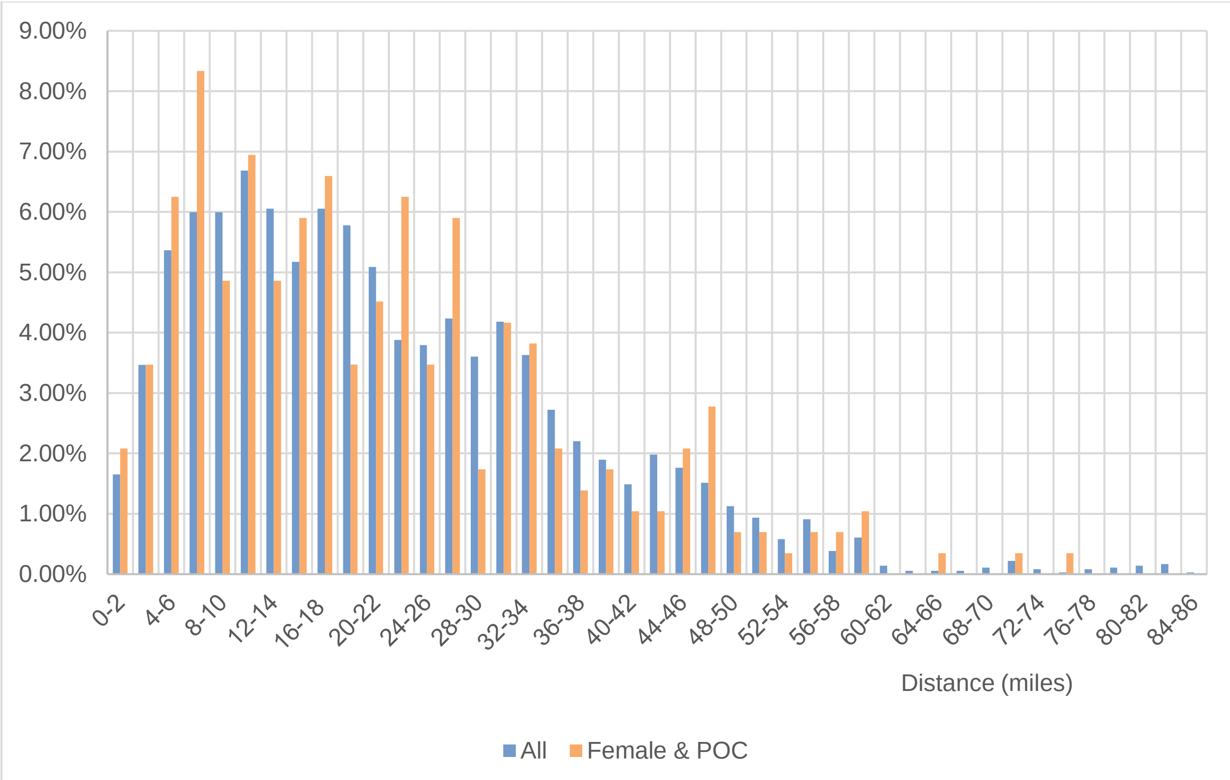


Figure 4-6. Commute distance: Female and Presence of child (0-5 years)

Figure 4-7 shows the relation between possession of valid driver's license and commute distance. It can be noticed that having a valid license doesn't affect the commute distance significantly. For almost any commute distance, these individuals are comparable with others suggesting that individuals without a license commute as much as the ones with license but underlines the fact that they are using other modes of transportation.

Figure 4-8 shows the effect of home-ownership on commute distance. It can be noticed that households who live in their owned-home are commuting more than the other households by small extent. The figure shows that about 50% of these households commute in the range of 4-22 miles. For larger commute distance they are comparable with other households suggesting that they don't prefer to commute more than 22 miles in general. Also, home-ownership affects commute distance significantly because the residential location tends to dictate the work location choice and hence factors such as commute distance comes into play.

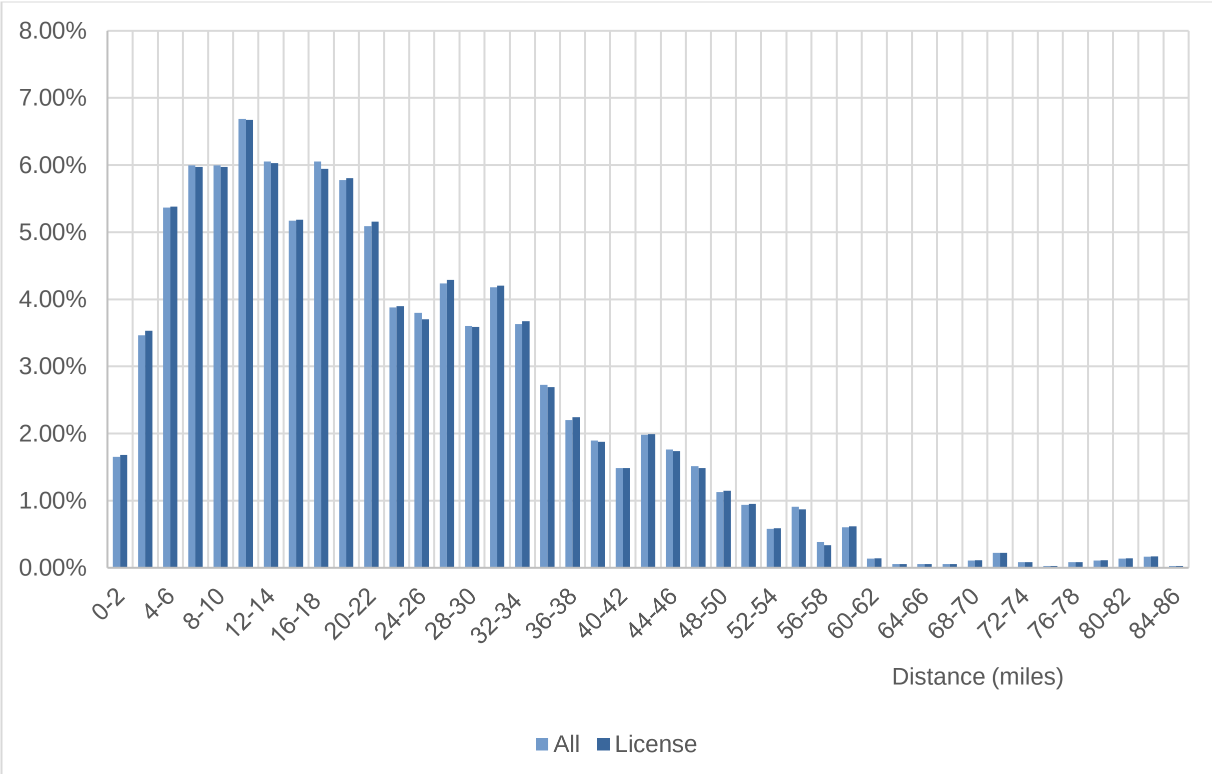


Figure 4-7. Commute distance: Valid driver's license

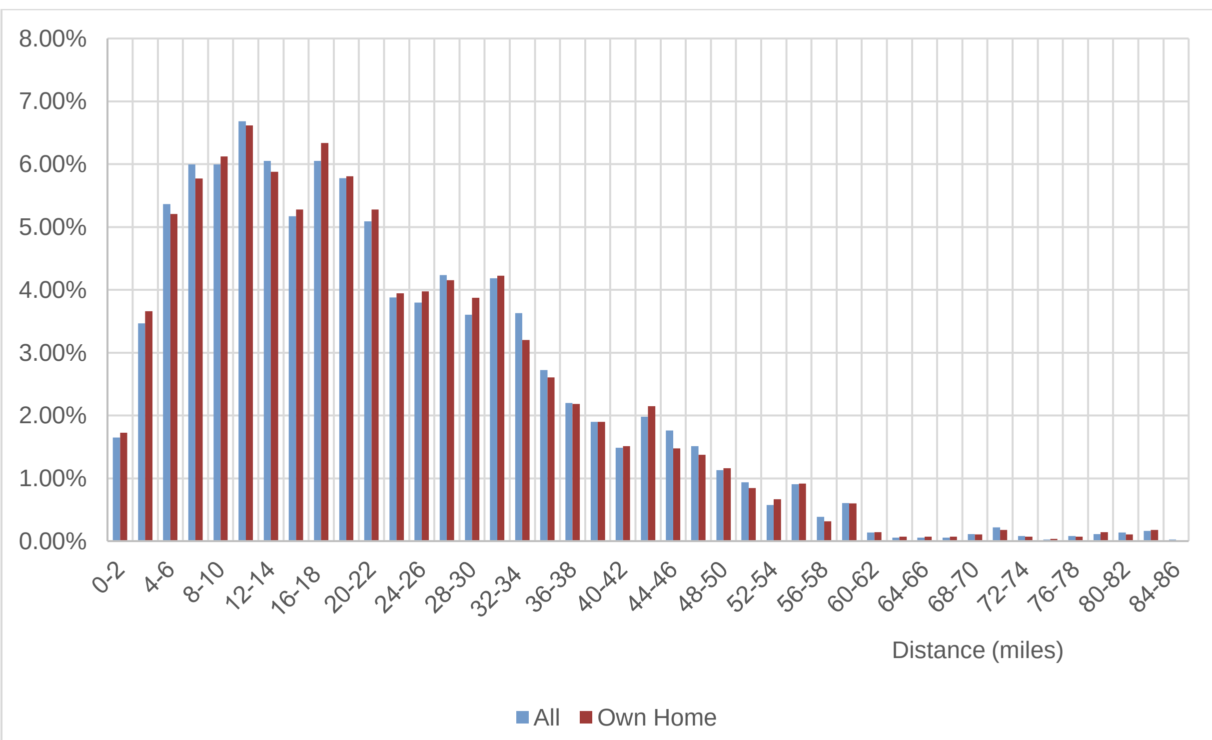


Figure 4-8. Commute distance: Home owners

Figure 4-9 shows the relation between income and commute distance. It can be noticed that high income households are commuting significantly more than the other households. The figure shows that a large portion, about 22%, of these households commute in the range of 16-24 miles. These households have less presence in the categories between 10-16 miles suggesting that they usually commute more than 16 miles or less than 10 miles in general. Intuitively, we would expect the individuals in high-income households to be trivially affected by the commuting distance.

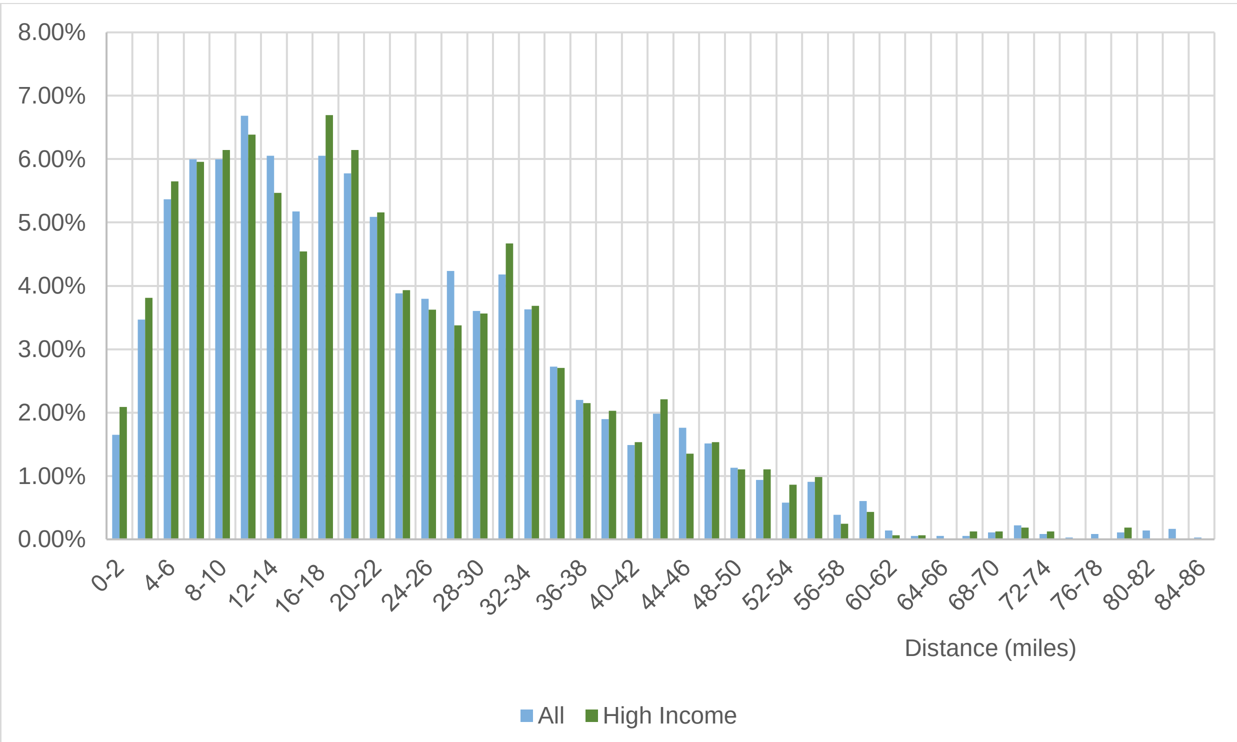


Figure 4-9. Commute distance: High Income

Figure 4-10 shows the effect of auto-ownership on commute distance. It can be noticed that households with 4 or more vehicles are commuting significantly more than the other households. The figure shows that about 10% of these households commute 12-14 miles, 8% travel 30-32 miles and 6% commute more than 50 miles. These households have less presence in the categories between 14-22 miles suggesting that they usually commute more than 22 miles or less than 14 miles in general. Also, commuting distance tends to have less effect on the individuals belonging to these type of households when deciding on workplace locations.

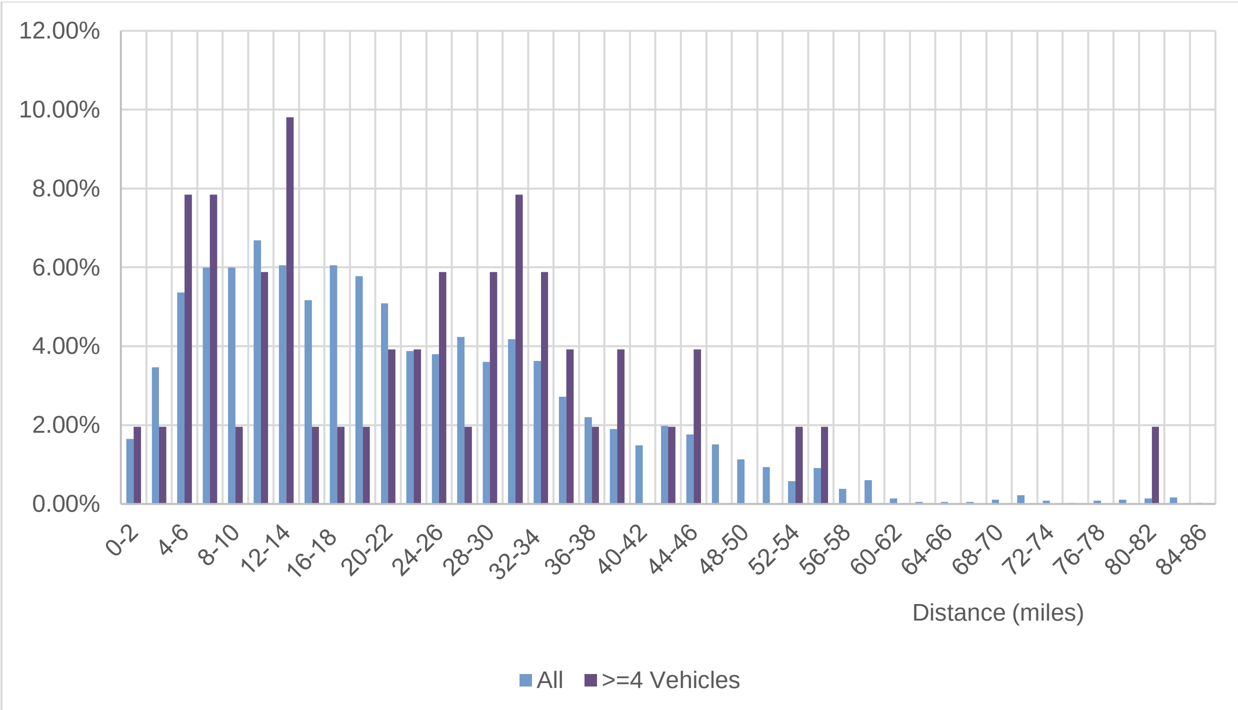


Figure 4-10. Commute distance: Auto ownership

CHAPTER 5: RESULTS AND DISCUSSION

The location choice models comprise of two components – neighborhood choice and zonal choice conditional on neighborhood. For brevity, only results of the final models are presented in this study. For the Manski models with probabilistic choice sets, each explanatory variable was tested both in the utility specification as well as the alternative consideration probability specification for each alternative and the specification that provided better data fit as chosen.

5.1 Neighborhood Choice Component

The CBD alternative was chosen as the reference alternative. Given that there are several other variables in the model, the constants in the model do not have substantive behavioral interpretation. Nonetheless, the relative magnitude of constants suggests that people, on average, prefer URBAN, SUBURBAN, and RURAL neighborhoods (and in that order) compared to CBD areas. Households with higher trip frequency are more likely to reside in the URBAN and SUBURBAN regions of the study area. As expected, households with children are more likely to reside in SUBURBAN and RURAL areas. Interestingly, households with more jobs (*i.e.,* workers) are less likely to live in URBAN areas. Households with more female members are more inclined to reside in less dense neighborhoods. Households with higher number of licensed drivers tend to live in the suburban and rural neighborhoods. The high positive parameter estimates on single family detached households show that these households almost certainly do not live in CBD neighborhood. Households with zero vehicles are most likely group to live in the CBD whereas households with more cars than driving age adults are more inclined to live in less dense neighborhoods. Households with more than $75K income and higher educational attainment (bachelor degree and higher) are less likely to reside in low density neighborhoods.

Among the four alternatives, the two low density options – SUBURBAN and RURAL were found to be considered probabilistically. Specifically, owner-occupied households are more likely to consider SUBURBAN and RURAL households. Also, while higher bicycle ownership levels are associated with higher likelihood of choosing SUBURBAN neighborhood, it reduces the likelihood for RURAL neighborhood. This result is probably indicative of inadequate bicycle and pedestrian infrastructure in RURAL areas. As expected, households with higher average age are more likely to consider RURAL neighborhood compared to relatively younger households.

Tables 5-1 to 5-4 present the results of the neighborhood choice components of residential location and work location models respectively. For comparison purposes, a multinomial logit model (MNL) model, that assumes that all households consider all the four neighborhood options, was also estimated as shown in Table 5-1.

Table 5-1. Residential Neighborhood Choice: Multinomial Logit (MNL) Model

Variables Description	**Urban**		**Sub-Urban**		**Rural**	
(Base Alternative: CBD)	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff*	*t-stat*
Constant	3.696	7.605	1.383	2.758	-1.471	-2.502
Children per household aged 6 to 10 years			0.342	3.621	0.573	3.637
Children per household aged 11 to 15 years					0.409	2.715
Jobs per household			-0.146	-3.451		
Number of females per household	0.887	3.284	0.887	3.284	0.887	3.284
Number of licensed drivers per household			0.401	5.589	0.645	6.853
Average age per household					0.015	3.955
Residence type: single-family detached house	6.659	1.965	7.461	2.200	7.461	2.200
Household Residence Ownership: Owned/bought			0.549	4.582	1.011	4.437
Auto sufficiency: Zero vehicle	-1.387	-3.126	-2.169	-4.254	-1.927	-2.966
Auto sufficiency: Category 1			-0.264	-1.838		
Auto sufficiency: Category 3			0.356	3.892	1.166	9.397
Household income: More than $75K	-0.989	-2.553	-0.771	-1.949	-1.056	-2.571
Number of bikes owned per household	0.634	1.541	0.634	1.541	0.634	1.541
Highest Education Attainment in household: Graduate Degree	-1.854	-3.776	-2.205	-4.422	-2.768	-5.360
Highest Education Attainment in household: Bachelor Degree	-1.273	-2.652	-1.570	-3.224	-1.727	-3.461
Number of Observations	4344					
Number of Parameters Estimated	16					
Mean log-likelihood at convergence	-0.808					
Log-likelihood	-3509.719					

5.1.1 Residential Neighborhood Choice

The positive magnitudes of the constants suggest that there is a baseline preference for “Rural”-to-“Urban” neighborhoods for residential location choice. The model estimates significantly suggest that households with increasing number of trips are more likely to prefer “Urban” and “Sub-urban” neighborhood locations. The model also suggests that households with children are more likely to choose “Sub-Urban” or “Rural” neighborhood locations due to the presence of good schools in these neighborhood levels. Households with higher number of jobs are less likely to choose “Sub-Urban” alternative than “CBD”. This is intuitive since people with more jobs tend to remain extremely busy and they prefer closest possible household locations from their work place which is more available in “CBD” areas. Households with more number of female members are more likely to choose between “Urban”, “Sub-Urban” and “Rural” neighborhood locations than “CBD”. Households with higher number of licensed drivers have higher propensity to choose between “Sub-Urban” or “Rural” locations. Households with zero auto sufficiency are less likely to choose between the three alternatives than the base alternative, “CBD”. This is because people without vehicles prefer transit for commuting and travelling and hence they prefer “CBD” area for household locations where transit is more accessible. On the other hand, people with higher auto sufficiency are more likely to select “Sub-Urban” or “Rural” area since presence of a number of vehicles makes trip distance an insignificant factor while travelling. Households with higher income and higher degrees are less likely to choose from any of the 3 alternative than the “CBD” alternative since they prefer urban and luxurious lifestyles and friendlier environment.

The log-likelihood of the MNL and Manski models are -3,509.7 and -3,502.1, respectively. The Likelihood Ratio (LR) test statistic of comparison between the two models is 19.30 that is significantly greater than 14.07 which is the critical chi-squared value corresponding to 3 degrees of freedom at 95 percent confidence level. This underscores the importance of accounting for latent choice sets in residential neighborhood choices.

Table 5-2. Residential Neighborhood Choice: Manski Model

Variables Description	Urban		Sub-Urban		Rural	
(Base Alternative: CBD)	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Constant	3.914	7.275	2.375	4.146	1.191	1.843
Children per household aged 6 to 10			0.804	2.261	1.138	2.721
Children per household aged 11 to 15					0.472	1.785
Jobs per household			-0.167	-2.568		
Number of females per household	0.821	2.918	0.821	2.918	0.821	2.918
Number of licensed drivers per			0.562	4.497	1.158	4.122
Residence type: single-family detached	6.791	29.560	7.888	27.126	7.888	27.126
Auto sufficiency: Zero vehicle	-1.444	-3.065	-2.334	-4.193	-1.883	-2.339
Auto sufficiency: High			0.707	3.707	2.206	4.502
Household income: More than 75k	-0.886	-2.226	-0.672	-1.624	-1.212	-2.554
Highest Education Attainment in household: Bachelor Degree	-1.182	-2.239	-1.644	-3.005	-1.990	-3.341
Highest Education Attainment in household: Graduate Degree	-1.743	-3.300	-2.352	-4.267	-3.348	-5.225
Latent Choice Set Component						
Constant			-0.615	-2.007	-	-3.757
Housing Tenure: Own			0.799	3.654	0.5891	1.877
Number of bikes owned per household			0.311	1.819	-0.297	-1.589
Average age per household					0.018	3.164
Number of Observations	4344					
Number of Parameters Estimated	16					
Mean log-likelihood at convergence	-0.806					
Log-likelihood	-3502.072					
Chi-Square	19.296					
Critical Chi-Square $(df = 3, \alpha = 0.05)$	7.815					

5.1.2 Work Neighborhood Choice

Table 5-3 presents the estimation results for the MNL model of work location neighborhood choice and Table 5-4 presents the estimation results for the Manski model. From Table 5-4, it can be observed that a worker with disability is more likely to choose “Urban” or “Sub-Urban” alternative for work location than “Rural” alternative because the disabled workers prefer neither long trips to limit their mobility that is common in “Rural” alternative nor crowded environment which is common in “CBD” alternative. The negative coefficients suggest that workers who use auto for commuting to work are less likely to choose “CBD” and “Urban” alternative than “Rural” since they do not have to worry about using any other form of transport and they have voluntary control over the distance and time for travel. On the other hand, workers with flexible work schedule and working 5 days a week are more likely to choose “CBD” and “Urban” alternative than “Rural”. The negative coefficients suggest that workers working in agricultural sector are less likely to choose between the 3 alternatives than “Rural” alternative which is very much intuitive since most of the agricultural lands and working conditions are situated in rural areas. This is similar with workers working in manufacturing and transportation sector since most of the factories, highway and freeway construction and other road maintenance works are mostly located in rural areas. On the other hand, workers working in office or performing mostly desk jobs more likely prefer the “Urban” or “CBD” alternative which is intuitive. Individuals with high school degrees tend to find jobs in “Sub-urban” alternative than “Rural” whereas individuals with higher degrees less likely prefer “CBD” than “Rural”. It is also interesting to observe that individuals with household neighborhood location choice as “CBD” are more likely to prefer “CBD” alternative for work location choice whereas individuals with “Urban” or “Sub-Urban” household neighborhood location alternative are more likely to choose from the three alternatives than the base alternative, that is, “Rural”. This is because individuals with “Urban” or “Sub-Urban” alternative usually have owned residence which means they are looking for permanent settlements or have children. Hence they prefer these alternative for work location due to friendlier environment, good schools and country life.

The RURAL alternative was chosen as the reference alternative. Workers with disability are more likely to be employed in the URBAN and SUBURBAN neighborhoods compared to CBD and RURAL areas. This is intuitive because disabled workers do not prefer longer trips typically associated with RURAL neighborhood as well as crowded environment of CBD neighborhood. Workers who use auto mode for commute are less likely to be employed in CBD and URBAN areas. On the other hand, workers who have flexible work schedule and work five days a week are more likely to be employed in CBD and URBAN neighborhoods. Industry type was found to have a strong impact on work neighborhood choice. For instance, workers in agriculture, manufacturing, and transportation industries are more likely to be working in RURAL neighborhood which is consistent with the land use in these areas (e.g., agricultural land, factories, construction sites *etc.*). On the other hand, workers employed in the office sector with desk jobs tend to work in CBD and URBAN neighborhoods. There was strong dependence between residential and work neighborhood choices with workers who reside in denser neighborhoods being more inclined to work in denser neighborhoods. Workers with lower education levels are more likely to work in low density neighborhood and less inclined to work high density CBD neighborhood.

Table 5-3. Work Neighborhood Choice: MNL Model

Variables Description	**CBD**		**Urban**		**Sub-Urban**	
(Base Alternative: Rural)	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	0.788	2.353	1.967	7.703	0.660	3.497
Worker has disability (Yes = 1, No = 0)			0.818	2.690	0.833	2.372
Worker uses auto to travel to work (Yes = 1, No = 0)	-1.938	-9.370	-0.730	-3.939		
Worker has ability to change work schedule (Yes = 1, No = 0)	0.779	6.444	0.207	2.386		
Number of working days of the worker: Equal to 5 days per week (Yes = 1, No = 0)	0.842	6.292	0.251	2.893		
Industry type of the worker: Agriculture	-2.259	-4.267	-1.314	-3.793	-1.053	-2.869
Industry type of the worker: Manufacturing	-2.751	-4.149	-0.728		-2.103	
Industry type of the worker: Transportation	-1.610	-4.104	-0.328	-1.844		
Industry type of the worker: Retail	-0.936	-4.421				
Industry type of the worker: Office	0.155		1.663			
Household neighborhood choice of worker: CBD	1.601	4.024				
Household neighborhood choice of worker: Urban	2.489	8.296	2.307	9.901	1.521	6.067
Household neighborhood choice of worker: Sub-Urban	1.852	5.934	1.606	6.650	1.519	5.901
Education Attainment of the Worker: Grade 12 or High school graduate					0.356	3.212
Education Attainment of the Worker: College credit or associate or technical school degree	-0.421	-3.387				
Number of Observations	3992					
Number of Parameters Estimated	15					
Log-composite likelihood at convergence	-0.885					
Log-likelihood	-3531.774					

Table 5-4. Work Neighborhood Choice: Manski Model

Variables Description	**CBD**		**Urban**		**Sub-Urban**	
(Base Alternative: Rural)	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Constant	-0.969	-2.155	0.141	0.349	0.668	3.471
Worker has disability (Yes = 1, No = 0)			0.815	2.616	0.868	2.241
Worker uses auto to travel to work (Yes = 1, No = 0)	-2.348	-8.960	-1.148	-4.653		
Worker has ability to change work schedule	2.493	7.333	1.948	5.860		
Number of working days:5 days per week (Yes = 1, No = 0)	0.985	6.187	0.403	3.257		
Industry type of the worker: Agriculture	-2.708	-4.574	-1.758	-4.293	-1.225	-3.368
Industry type of the worker: Manufacturing	-2.639	-3.736	-0.599	-1.603	-0.599	-1.603
Industry type of the worker: Transportation	-1.915	-4.046	-0.658	-1.973		
Industry type of the worker: Retail	-0.966	-4.529				
Education Attainment of the Worker: Grade 12 or High school graduate					0.423	2.758
Education Attainment of the Worker: College credit or associate or technical school degree	-0.421	-3.433				
Residential neighborhood choice: CBD	1.447	3.720				
Residential neighborhood choice: Urban	2.903	8.995	2.781	10.332	1.504	5.918
Residential neighborhood choice: Sub-	1.925	5.813	1.727	6.326	1.504	5.778
Latent Choice Set Component						
Constant			-0.320	-1.597	-0.320	-1.597
Worker has ability to change work			5.518	9.267	5.518	9.267
Industry type of the worker: Retail			-0.530	-2.905	-0.530	-2.905
Number of Observations	3992					
Number of Parameters Estimated	17					
Log-composite likelihood at convergence	-0.880					
Log-likelihood	-3511.227					
Chi-Square	41.094					
Critical Chi-Square $(df = 3, \alpha = 0.05)$	7.815					

Among the four alternatives, the two low density options – SUBURBAN and RURAL were found to be considered probabilistically. But, as discussed earlier, these alternatives were assumed to be considered as a bundle in the latent choice component of the Manski model. Workers with flexible work schedule are more likely to consider these low density neighborhoods compared to workers with fixed work schedule. Also, workers employed in retail industrial sector are less likely to consider low density neighborhoods in their work neighborhood choices. Again, the log-likelihood of the MNL and Manski work neighborhood models are -3,531.8 and -3,511.2, respectively. The LR test statistic of comparison between the two models is 41.09. This value is considerably larger than 7.82 which is the critical chi-squared value corresponding to 3 degrees of freedom at 95 percent confidence level. This indicates superior data fit in the Manski model.

Table 5-5: Summary comparison of Log-likelihood and BIC

Neighborhood choice components	Log-likelihood		BIC	
	MNL	*Manski*	*MNL*	*Manski*
Residential Location Choice	-3509.719	-3502.072	7153.463	7138.169
Workplace Location Choice	-3531.774	-3511.227	7189.196	7164.855

5.2 Zonal Destination Choice Component

The results of conditional zonal destination choice model components of residential and work location choice model are presented and explained in this sub-section.

5.2.1 Zonal Residential Location Choice

For residential location choice, the primary contributing factor is the "accessibility" in a given TAZ. Accessibility for a given employment category is the metric to reflect the employment opportunities in a particular TAZ. Therefore, it is expected that a household would have a tendency to locate in a TAZ with higher accessibility. While that is true for total accessibility, when broken down by categories, accessibility in manufacturing sector shows a conflicting result, as shown by the negative coefficient in table 5-6. Though this is counter-intuitive, the rationale behind is that a household may not prefer to locate in an area containing lot of factories and manufacturing plants. To assess the effects of socio-economic attributes, they are combined with total accessibility and the results show that when the residence is owned leads to lower utility compared to when rented. Also, households with children, senior adults are more sensitive to the accessibility because of school locations and mobility restrictions. Areas with higher accessibility is more likely to attract households with lesser number of vehicles which is evident by the decreasing coefficients with respect to increasing number of vehicles. On the other hand, household with high income enjoys higher utility compared to lower income households. Similarly, household individuals with higher education levels tends to locate in areas with higher accessibility.

The coefficient on the size variable – natural logarithm of the “total number of households in the TAZ’ is fixed to one to ensure that individual destination zone preferences sum up to zonal control totals. Accessibility to different types of employment opportunities was found to a significant determinant of zonal residential location decisions. To be specific, households are less likely to reside in zones with high manufacturing accessibility which is expected given that these zones tend to have higher pollution levels and limited infrastructure for recreational activities. Interestingly, owner-occupied households tend to reside in areas with lower total employment accessibility compared to rental households. On the other hand, households with more children and senior adults prefer zones with better accessibility. Also, zones with higher total employment accessibility attract households with lower auto ownership levels, higher income, and higher educational attainment.

5.2.2 Zonal Work Location Choice

The workplace location choice components of the model suggest that an individual’s decision or choice rely very significantly on the commuting distance and the morning peak hour travel time. It is very intuitive that a particular TAZ is more likely to be chosen if it is closer to one’s residential location. Among the commuting factors, presence of at least one type of transit between residence and work was found to be crucial. This indicator variable shows when there is at least a feasible mode of public transport, among bus rapid transit, commuter rail, urban rail, express bus, local bus, the utility of a given work location increases to a large extent since the individual is not forced to drive to work every day. Since commute distance and time are so highly significant, their interaction with socio-economic attributes are also examined during model estimation. When socio-economic attributes are combined with the commute distance, females are found to be more sensitive to the commute distance when compared to males. When a worker’s household has 3 vehicles, the choice is relatively less affected by the distance since longer commutes and auto- ownership go hand-in-hand. When there are children present in the household, worker experiences sharper decline in utility with increase in distance (also for travel time) compared to one with no children, possibly because the residential location tends to remain unchanged due to the location of desired children's schools. Individuals with higher education level are also more sensitive to commuting distance. Similar effects can also be observed when interacting with commute time by auto. When a worker works for more than 40 hours per week and has multiple work location, commute time plays a significant role in choosing workplace location. Moreover, if the worker's residential location is in a suburban area increase in commute time leads to decreased utility.

The coefficient on size variable – natural logarithm of "zonal employment in the industry of the worker' was fixed to one for the reasons alluded to above. Zones that are closer to home TAZ and with shorted auto travel times from home TAZ are more likely to be chosen compared to farther alternatives. Also, presence of transit service between home TAZ and destination TAZ was found to significantly enhance the likelihood of the person working in that zonal alternative. Women, workers in households with young children, and workers with higher educational attainment tend to prefer zonal alternatives that are in closer proximity to home TAZ. Also, workers with young children, varying work location, and those who work more than 40 hours per week are more sensitive to inter-zonal travel time between home and destination TAZ indicative of relatively higher time pressure on these individuals. Lastly, workers who reside in sub-urban neighborhood are more sensitive to travel time compared to those who reside in CBD, URBAN, and RURAL neighborhoods.

Table 5-6. Zonal Residential and Work Location Choice Components

Variables Description	Coefficient	t-stat
Residential Location		
Size Variable: LN(Total number of households in TAZ)	1.0000	-
Correction Factor (Fixed)	1.0000	-
TAZ Attributes		
Accessibility in TAZ: Manufacturing sector	-0.4325	-4.25
Socio-economic Attributes (interacting with Total Accessibility)		
Household residence ownership: Owned (Yes=1 or No = 0)	-0.6498	-5.52
Presence of children in household (Yes=1 or No = 0)	-0.1869	-1.54
Presence of senior adults in household (Yes=1 or No = 0)	-0.4830	-4.21
Presence of disabled person in household (Yes=1 or No = 0)	0.3204	1.83
Household vehicle-ownership: Zero Vehicles (Yes=1 or No = 0)	0.8543	3.41
Household vehicle -ownership: One Vehicles (Yes=1 or No = 0)	0.5021	4.33
Household vehicle -ownership: Two Vehicles (Yes=1 or No = 0)	0.1488	1.32
Household income: $50K- $75K (Yes=1 or No = 0)	0.3508	2.63
Household income: More than $75K (Yes=1 or No = 0)	0.4644	3.35
Highest education attainment in household: Bachelor degree (Yes=1 or No = 0)	0.4642	4.02
Highest education attainment in household: Graduate degree (Yes=1 or No = 0)	0.7185	5.48
Mean Log-likelihood at convergence	-16,963.32	
Work Location	**Coefficient**	**t-stat**
Size Variable: Total number of employment in the industry of individual's employment	1.0000	-
Correction Factor	1.0000	-
Commuting Factors		
Commute distance	-3.4292	-3.21
Commute time by Auto during AM peak	-6.4880	-14.57
Presence of at least one type of transit (Yes=1 or No = 0)	8.2346	20.23
Socio-economic Attributes (interacting with Distance)		
Gender (Female=1, Male=0)	-4.6012	-4.50
Household vehicle -ownership: Three Vehicles (Yes=1 or No = 0)	2.6157	2.34
Presence of children in household (Yes=1 or No = 0)	-3.7878	-2.10
Education attainment of worker: Bachelor degree or higher (Yes=1 or No = 0)	-3.6382	-3.40
Socio-economic Attributes (interacting with Travel Time by Auto)		
Presence of children in household (Yes=1 or No = 0)	-1.0959	-2.47
Varying work location (Yes=1 or No = 0)	-1.3374	-3.94
Works more than 40 hours per week (Yes=1 or No = 0)	-1.2144	-3.87
Residential Location (interacting with Travel Time by Auto)		
Neighborhood type: Suburban (Yes=1 or No = 0)	-0.7219	-2.32
Log-likelihood at convergence	-7,110.875	

5.3 Estimation of Logsum

The “log sum of exponentials” is a functional form very commonly encountered in discrete choice model framework. In this study, the logsum was estimated separately at the zonal level for *residential* and *work location* models. Logsum is essentially the natural logarithm of sum of utility. Based on the zonal *residential* and *work location* models obtained (as shown in table 5-6) the utility for each *household* and *individual* can be estimated respectively. It should be noted that the logsum is estimated for each neighborhood type. For example, let’s assume an individual chose CBD neighborhood in the first stage (at the neighborhood level) for work location. Based on the estimates of the model, utility experienced by that specific individual for all the zones in CBD is computed and aggregated. Then we take the natural log of that value. Similarly, we repeat the process and compute logsum for that individual assuming he chose Urban, Suburban and Rural. As a result, for that particular individual we’ll have four different logsums since s/he has four neighborhood choices.

$$\text{Logsum}_c = \ln\left(\sum_{j\in C} e^{\beta X_q^j}\right)$$

Where,

C is the set of neighborhood types: {CBD, URBAN, SUBURBAN, RURAL}

β is the vector of estimates obtained in previous section

X_q^j is the vector of explanatory variables for individual/household q and zone j belonging to a particular neighborhood type

5.4 Elasticity Effects

The elasticity effects were computed as a percentage change in the aggregate shares of four different neighborhood alternatives due to a unit change in the explanatory variable. The unit change in the case of indicator variables is from 0 to 1 whereas in case of ordinal variables, the variable value was increased by one unit. The results of elasticity analysis for the residential and work neighborhood choice models are presented in Tables 5-7 and 5-8, respectively. For residential location (table 5-7), for instance, households with more cars than adults at legally driving age (defined as “high auto-sufficiency”) are 142.3%

more likely to live in RURAL neighborhood compared to households with fewer or same number of cars as driving age adults. Based on the relative magnitude of elasticity effects, it can be seen that the demographic groups most likely to reside in CBD, URBAN, SUBURBAN, and RURAL neighborhoods are households with high educational attainment (graduate degree), households with zero vehicles, single family detached households, and owner-occupied households, respectively. Similarly, from Table 5, the worker segments most likely to be employed in CBD, URBAN, SUBURBAN, and RURAL neighborhoods are workers who live in CBD neighborhood, workers who live in URBAN neighborhood, workers who use auto mode for commute, and workers employed in agriculture industry, respectively.

Similarly, households having children aged between 6 to 10 years are 28.05% more likely to choose "Sub-Urban" as the household neighborhood location choice, 36.97% more likely to choose "Rural", 9.39% less likely to choose "CBD" and 16.18% less likely to choose "Urban" as the household neighborhood location choice. This result is intuitive since people with children prefers to live in sub-urban or rural area so that the children can grow up in an environment with ample open space. Also, suburban areas tend to have large number of schools which attract individuals with children to move to a suburban neighborhood. Other numbers in the table can be interpreted similarly.

Based on the elasticity effect values, it can be observed that the key factors and conditions that increase the choice of "CBD" as the household neighborhood location choice are: increase in number of jobs per household, zero vehicle auto sufficiency, household income more than 75 thousand and if the highest education attainment by the household includes either a Bachelor or graduate degree. Similarly, the factors that increase the choice of "Urban" as the household neighborhood location choice are: increase in household trips, increase in jobs per household, increase in number of females per household, zero vehicle auto sufficiency and households having Bachelor or graduate degree as the highest education attainment. For the choice of "Sub-Urban", the factors that affect the choice most are households having children between 6 to 10 years, increase in number of licensed drivers, household residence type as single-family detached house, higher auto sufficiency, household income more than 75 thousand, if the household residence is owned or bought and increase in number of bikes per household. Finally, it can be observed that most of the factors increase the propensity to choose "Rural" as the household neighborhood location choice.

Table 5-7. Elasticity Effects of Residential Neighborhood Choice Model

Variables	CBD	Urban	Sub-Urban	Rural
Children per household aged 6 to 10 years	-9.386	-16.177	28.050	36.966
Children per household aged 11 to 15	-0.675	-1.578	-4.437	26.163
Jobs per household (Increased by 1)	1.287	2.814	-8.064	4.648
Number of females per household	-56.540	0.795	0.179	0.084
Number of licensed drivers per household (Increased by 1)	-6.941	-12.509	14.512	46.233
Residence type: single-family detached	-99.902	-17.018	74.245	39.017
Auto sufficiency: Zero vehicle	275.740	13.128	-37.526	-1.705
Auto sufficiency: High	-10.659	-18.349	10.056	142.294
Household income: More than 75k	120.381	-4.104	13.820	-20.975
Highest Education Attainment in household: Bachelor Degree	192.059	8.578	-15.109	-25.359
Highest Education Attainment in household: Graduate Degree	395.559	12.147	-16.129	-51.502
Housing Tenure: Own	-6.063	-18.136	41.664	117.854
Number of bikes owned per household	-0.883	-2.565	9.662	-11.504
Average age per household (Increased by 1)	-0.049	-0.180	0.023	1.240

The elasticity values for the latent class work location neighborhood choice model are presented in Table 5-8. The numbers in the first row indicate that if the worker has disability, he/she is 9.355% more likely to choose "Urban" and 12.719% more likely to choose "Sub-Urban" as the work location neighborhood. Similarly, a disabled worker is 48.804% less likely to choose "CBD" and 50.948% less likely to choose "Rural" as the work location neighborhood. On the other hand, if the worker uses auto to travel to work, he/she is 62.647% less likely to choose "CBD" as the work location neighborhood since the CBD areas are highly operated by transits and 129.132% more likely to choose "Sub-Urban" as the work location neighborhood. Auto usage to work also increase the propensity to choose "Urban" and "Rural" as the workplace location neighborhood but not as much as "Sub-Urban". It can also be observed that other than office, all other industrial sector decreases the likelihood to choose "CBD" as the work location neighborhood. On the other hand, other than agriculture, all other industrial sector increases the propensity to choose “Urban” as the work location neighborhood. It can also be observed from the elasticity values that other than retail and office, agriculture, manufacturing and transportation sector increase the propensity to choose “Sub-Urban” or “Rural” as the work location neighborhood. Moreover, if the worker’s household neighborhood location choice is “CBD”, he/she is 165.156% more likely to choose “CBD” as the work location neighborhood which is intuitive. Also, having the household neighborhood location choice in “Urban” or “Sub-Urban” area increase the propensity to choose “CBD” or “Urban” as the work location neighborhood.

Table 5-8. Elasticity Effects of Work Neighborhood Choice Model

Variables	**CBD**	**Urban**	**Sub-Urban**	**Rural**
Worker has disability (Yes = 1, No = 0)	-48.804	9.355	12.719	-50.948
Worker uses auto to travel to work (Yes = 1, No = 0)	-62.647	13.062	129.132	110.544
Worker has ability to change work Schedule (Yes = 1, No = 0)	63.909	-3.432	-21.663	-9.171
Number of working days:5 days per week (Yes = 1, No = 0)	67.316	-1.891	-21.593	-19.604
Industry type of the worker: Agriculture	-59.743	-2.344	16.930	260.275
Industry type of the worker: Manufacturing	-83.631	13.855	2.962	78.995
Industry type of the worker: Transportation	-68.743	1.495	44.809	38.987
Industry type of the worker: Retail	-53.779	16.654	-14.135	-13.218
Education Attainment of the Worker: Grade 12 or High school graduate	-4.589	-5.002	26.778	-16.877
Education Attainment of the Worker: College credit or associate or technical school degree	-28.580	5.512	3.119	2.809
Residential neighborhood choice: CBD	165.156	-28.179	-17.894	-15.808
Residential neighborhood choice: Urban	33.856	22.064	-41.107	-85.956
Residential neighborhood choice: Sub-Urban	22.015	2.487	-1.465	-76.092

CHAPTER 6: POTENTIAL APPLICATIONS OF PROPOSED LATENT CLASS MODELS FOR LAND USE PLANNING

In this chapter review state-of-the-art land use models used in practice. Though evolution of land use models occurred to enhance the efficiency of transportation systems and to support increased the need for more research in transportation planning and travel demand modeling. Land use models were developed to determine forecasts of future changes in employment, households and land development. It was evident that changes in transport systems could affect the patterns of land development. On the other hand, household and employment location could substantially affect trip patterns leading to changes on transportation systems. The interdependence of transportation and land use patterns resulted in the development of integrated land use and transportation models.

The first generation of land use models were introduced around 1960s and were aggregate models of spatial interaction and gravity models. Then, utility-based econometric and discrete choice models were developed. These two first classes of models mainly followed the top-down approach (Iacono et al., 2008). More advanced models were gradually developed since the late 1980s. These new models were mainly micro-simulation disaggregate models. Agent and rule based models and Cellular Automata were also designed. Many of these models are considered to follow the bottom up modeling approach. However, the classification of land use models in separate categories can be misleading as many models from different categories can share common concepts and characteristics (White, 2010) . Parallel to the evolution of land use models, travel demand models also evolved. The traditional four step urban transportation planning systems (UTPS) were replaced by the more advanced activity based models. The major concept behind the development of the activity based models was that travel behavior and trip generation is determined upon the individuals need to complete specific activities on a daily basis (Chakraborty et al., 2012; Mishra et al., 2011; Sivakumar, 2007). The development of advanced micro-simulation land use models and activity based travel demand models created the need for a new generation of integrated land use-transport systems. New models such as ILUTE and ILUMASS were developed or existing models such as UrbanSim and PECAS were updated to facilitate the needs for advanced research in the field of integrated land use-transport modeling. The goal of this chapter is not to provide comprehensive overview of land use models but provide the household and workplace location choice models embedded in the adanced land use models. Two more recent models are discussed in this chapter are UrbanSim, and PECAS.

6.1 URBANSIM

UrbanSim is a micro-simulation model for land use, transportation and environmental planning. UrbanSim is one of the most lately developed land use models that keep evolving. It was selected as it promises to provide efficient geographical coverage at the regional level, different spatial detail options (Grid, Parcel and Zone), efficient integration with Travel Demand Models (including both trip based and activity based), and different visualization options for output representation (tables, graphs, animation and lately 3-D representation). However, the huge amount of data required to develop sophisticated land use models at the micro level of analysis, remain the major drawback regarding the implementation of models similar to UrbanSim.

6.1.1 Overview

UrbanSim is a software based land use/transport system, developed by Paul Waddell at the University of Washington (Waddell, 2002, 2000). The rationale for developing UrbanSim was three fold: first to provide MPOs an efficient land use planning tool for growth management and policy evaluation, provide MPOS with a tool that can be integrated with existing travel models and finally develop a system that can be applied in multiple case studies with different characteristics (size, complexity, etc.). UrbanSim can primary be applied for evaluating the impact of alternative transportation, land use, and environmental policies. UrbanSim is open source accessed software that allows data analysis and processing on the grid, parcel or zone level. The software platform, called OPUS (Open Platform for Urban Simulation) was developed by the Center for Urban Simulation and Policy Analysis (CUSPA) at the University of Washington (Waddell et al., 2008). The option of integrating UrbanSim with travel demand models is available to users. Urbansim can be described as a microsimulation model that its modular structure is based on utility theory. Household and employment location choices, real estate development and prices can be modeled. A disaggregate classification of households is carried out, considering the number of individuals, workers, children and the income of each household. Employment is also classified in a disaggregate way, including 10-20 separate sectors. Twenty-four different types of real estate developments can be modeled. The model can also simulate disequilibrium market conditions in cases of unbalanced supply and demand.

6.1.2 Structure/Models

A set of different sub-models are included into the UrbanSim structure to capture the interaction of agent (households, businesses, developers, individuals, governments) choices (Waddell, 2002). The list of these models/modules includes:

- **Local and Regional Accessibility Model**: Determines the accessibility value of each zone of the study area, considering the accessibility of residents and employees to their destinations (shopping, employment, central business districts, etc.)
- **Economic and Demographic Transition Models**: The Economic model determines the number of jobs created or lost and the Demographic Transition model simulates the impact of births and deaths on the number of households created or lost.
- **Household and Employment Mobility Models**: The household and Employment mobility models identify the probability of a household and a job to move to a new location, respectively.
- **Household and Employment Location Models**: The household and Employment location models determine the location among a set of candidates for a new established household and job, respectively, based on land use patterns and prices, accessibility, real estate and market parameters.
- **Real Estate Development Model**: Multinomial land use models are applied to predict the probability of new structures development or redevelopment of existing ones. Different parameters that are considered include land use patterns, policies, accessibility to population and major infrastructure such as arterials, highways, etc.
- **Land Price Model**: Simulates land price for each cell using economic theory. The model is calibrated based on historical data.

Figure 6-1 shows how the previously described sub-models interact as parts of the UrbanSim system.

6.1.3 Data Inputs

A large amount of data is required to develop model databases called the data store. Data inputs include census data, business establishment information and GIS maps with environmental, political and planning boundaries information (Waddell, 2002). Additional inputs for the model include: base-year land use patterns and plans, household, population and employment data, transportation plans and economic forecasts. Information for land-development policies and the related density and environmental constraints should be provided. Information for traffic analysis zones and development costs are also required (Waddell et al., 2008). The user can specify input scenarios that can be imported in UrbanSim and return forecasts of employment, housing and land use change for the target year.

6.1.4 Model Outputs

UrbanSim can provide a set of different outputs for each separate traffic analysis zone (Waddell et al., 2008). These outputs include: number of dwelling units, households classified by income, age, size, and number of children and business/employment information by industry. Different information for land use patterns such as land use acreage or land use value can be provided. The outputs from the travel model mainly include travel utility and travel time by mode. GIS tools are available for data visualization.

6.1.5 Model Applications

UrbanSim is one of the most widely used systems. Some of the major applications in U.S. agencies include: the Southeast Michigan Council of Governments in Detroit, the DCHC Metropolitan Planning Organization in North Carolina, the Lane Council of Governments in Springfield, Oregon, the Maricopa Association of Governments in Phoenix, Arizona, the Wasatch Front Regional Council in Salt Lake City, Utah the San Francisco County Transportation Authority and the County of San Francisco, the Puget Sound Regional Council in Seattle, Washington, the Houston-Galveston Area Council and the Alamo Area Council of Governments in San Antonio, Texas. UrbanSim has also been used for different case studies around the world including Amsterdam, Brussels, Burlington, Rome and Paris, Seoul, Taipei and Tel Aviv (Waddell et al., 2008).

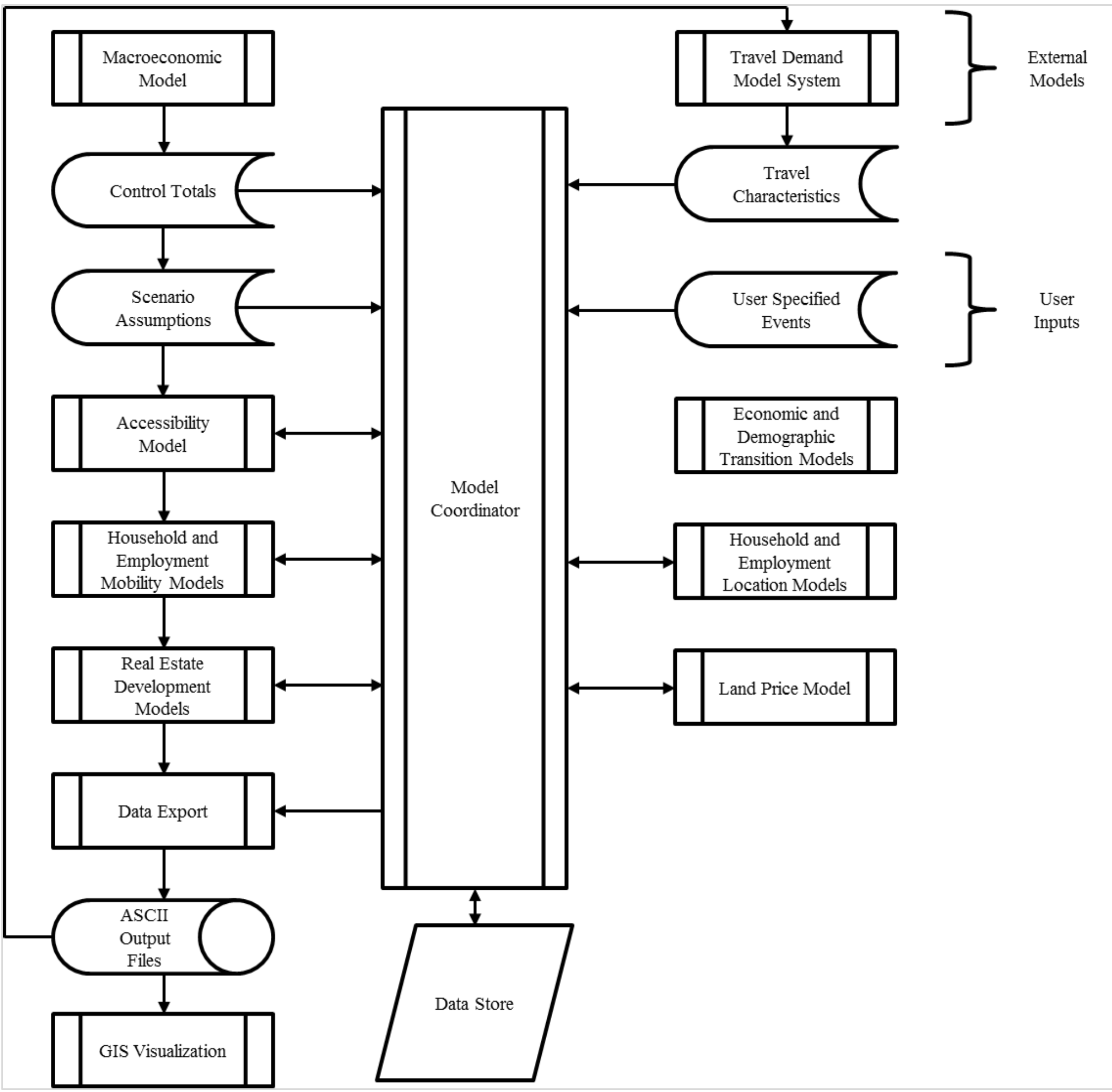


Figure 6-1. URBANSIM Structure (Adapted from: Waddell 2002)

6.2 PECAS

PECAS (Production, Exchange and Consumption Allocation System) is a land use modeling tool designed to operate as part of integrated land use-transport systems (Waddell, 2011)

6.2.1 Overview

The model was developed by Dr. Doug Hunt and Dr. John Abraham, at the University of Calgary to replace TRANUS land use model for the Oregon Department of Transportation. In contrast with similar models such as MEPLAN, PECAS can be considered as a microsimulation model that models the decisions of the agents (Industry, Government, Households). PECAS is a spatial input-output, econometric model for allocating flows of exchanges such as goods, services, labor and space from production to consumption points (Hunt and Abraham, 2009). Land use consumption due to job and household growth can be simulated using Social Accounting Matrix (SAM). Nested Logit Models are applied to allocate flows based on exchange prices and market conditions. The exchange flows are then translated into transport demand for transportation networks. Unlike UrbanSim, PECAS model operates until the equilibrium between supply and demand is reached. PECAS has been applied for developing land use-transport interaction models in different case studies around the U.S.

6.2.1 Structure/Models

PECAS model consists of two PECAS and two non-PECAS modules that operate into an integrated environment (Hunt et al., 2009). The PECAS modules include:

- **Space Development (SD) module**: This module utilizes logit allocation models to identify the land and floor space changes due to developers' actions (new developments, demolitions, etc.).
- **Activity Allocation (AA) module**: Logit models are also applied to allocate activities in space and model the interaction of activities through flows of commodities.

The two non-PECAS modules include:

- **Transport Model (TR) module**: An external transportation planning model is used to represent the transport network and the corresponding demands. The land use model and the transport model are integrated through the translation of commodity flows into travel demand.
- **Economic Demographic Aggregate Forecasting Model (ED) module**: ED module includes a set of different models to forecast household, population and employment future changes.

The integration of the different modules in the PECAS environment is described in Figure 6-2.

6.2.2 Data Inputs

PECAS model has extensive data requirements including parcel boundaries, land prices etc., that may not be available for the study region. In more details, the inputs for the Activity Allocation module include: economic flows, household and employment data, floorspace, transport costs, rents and commodity imports/exports. The Space Development module requires accessibility data (distance to infrastructure, highways, shopping centers, schools, etc.), existing land use types and plans (Waddell, 2011).

6.2.3 Model Outputs

The major outputs of PECAS model include commodity flows that can be translated into transport demands. Additional outputs include predictions of floorspace for a target year, residential/non-residential floorspace, activities allocation, rent change, household and job forecasts (Hunt et al., 2009).

6.2.4 Model Applications

PECAS model has been involved in different projects for case studies mainly in the U.S. and Canada. Many U.S. Transportation agencies have integrated PECAS in their systems for land use planning and allocation. PECAS has been used by transportation agencies in the states of OHIO (Ohio Department of Transportation), Oregon (Oregon Department of Transportation) and California, in the Sacramento (Sacramento Council of Governments) and San Diego regions, the greater Atlanta area and the Baltimore region.

The model has also been applied at the greater areas of Calgary and Edmonton in Canada (Waddell, 2011).

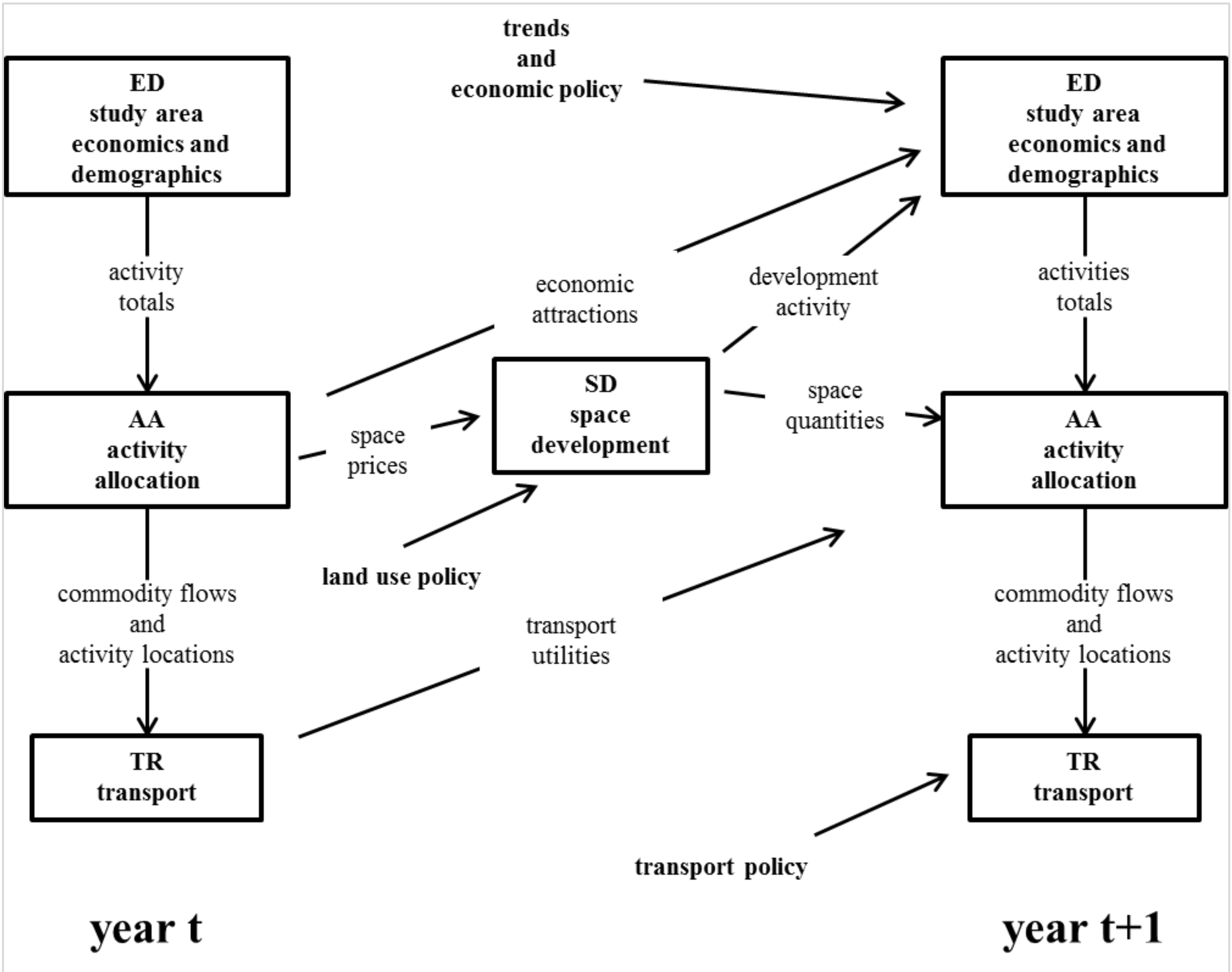


Figure 6-2: PECAS Structure (Adapted from: Hunt et al. 2009)

6.3 Recommendation for improved land use planning for residential and workplace location choices

The literature shows that land use models use unsegmented residential and work place location choice models. Though there are number of latent choices present that unsegmented models are not able to capture the effect, segmented models can potentially improve the accuracy of residential and workplace location choices. Future research is needed to compare the performance of unsegmented and segmented land use models in predicting land use model outcomes.

CHAPTER 7: CONCLUSION

Simple discrete choice models use deterministic rules regarding the availability of alternatives whereas latent choice models provide significant behavioral improvements by adequately incorporating traits of the market segments. The Manski model that assumes a two-stage representation of decision making served as the mainstay model for latent choice set modeling. However, estimation of the Manski model is not always feasible because calculation of the resulting likelihood function requires enumeration of all possible choice sets and weighted average of alternative probabilities over these choice set probabilities. In this context, researchers tried to develop implicit choice set models that directly tweak the utility functions of alternatives that are considered probabilistically to approximate the likelihood function in the Manski model. The advantage of these implicit choice set models is that evaluation of the likelihood function in these models has linear complexity with respect to the number of alternatives in the universal choice set.

The proposed model offers significant behavioral advantages by identifying market segments with differential sensitivities to various attributes and characteristics for household and workplace location choices to assist targeted policy programs can be designed by planning agencies. From a forecasting standpoint, latent class models can substantially improve the model fit and serve as a significant and necessary step towards developing adequate residential and workplace choices to be further used for land use and transportation planning. Latent class segmentation can help provide crucial insights into spatial characteristics, geographic boundaries, multimodal accessibilities, land-use preferences along with socioeconomic attributes to understand location choices and travel behavior for medium and long term planning.

Latent choice modeling has served as a valuable modeling method for identifying population segments with significant behavioral heterogeneity, probabilistic choice sets, decision rule heterogeneity, and alternate dependency pathways among inter-dependent choices. However, studies that used latent choice methods in the context of location choices are relatively rare. This is primarily because of large choice sets in zonal-level destination choice models that make it unwieldy for estimating latent class models. This paper developed a latent class model that explicitly accounts for probabilistic nature of choice sets by using a two-stage modeling framework that assumes people first pick a neighborhood and then look for specific locations within the chosen neighborhood. The expected utility from the second stage zonal choice model component was used as an explanatory variable in the utility specification of neighborhood choice model to link the two models. The model was used to analyze residential and work location decisions in Nashville, Tennessee. The model results indicate significant heterogeneity in the consideration probability of different neighborhood alternatives both in the residential and work location choices. Also, the latent class neighborhood models were found to outperform standard MNL models that assume all decision makers consider the complete universal choice set in their decision making. The model applicability was demonstrated by calculating elasticity effects and identifying demographic groups with considerably different residential and work location preferences.

APPENDIX A: OVERVIEW OF CASE STUDY DATA

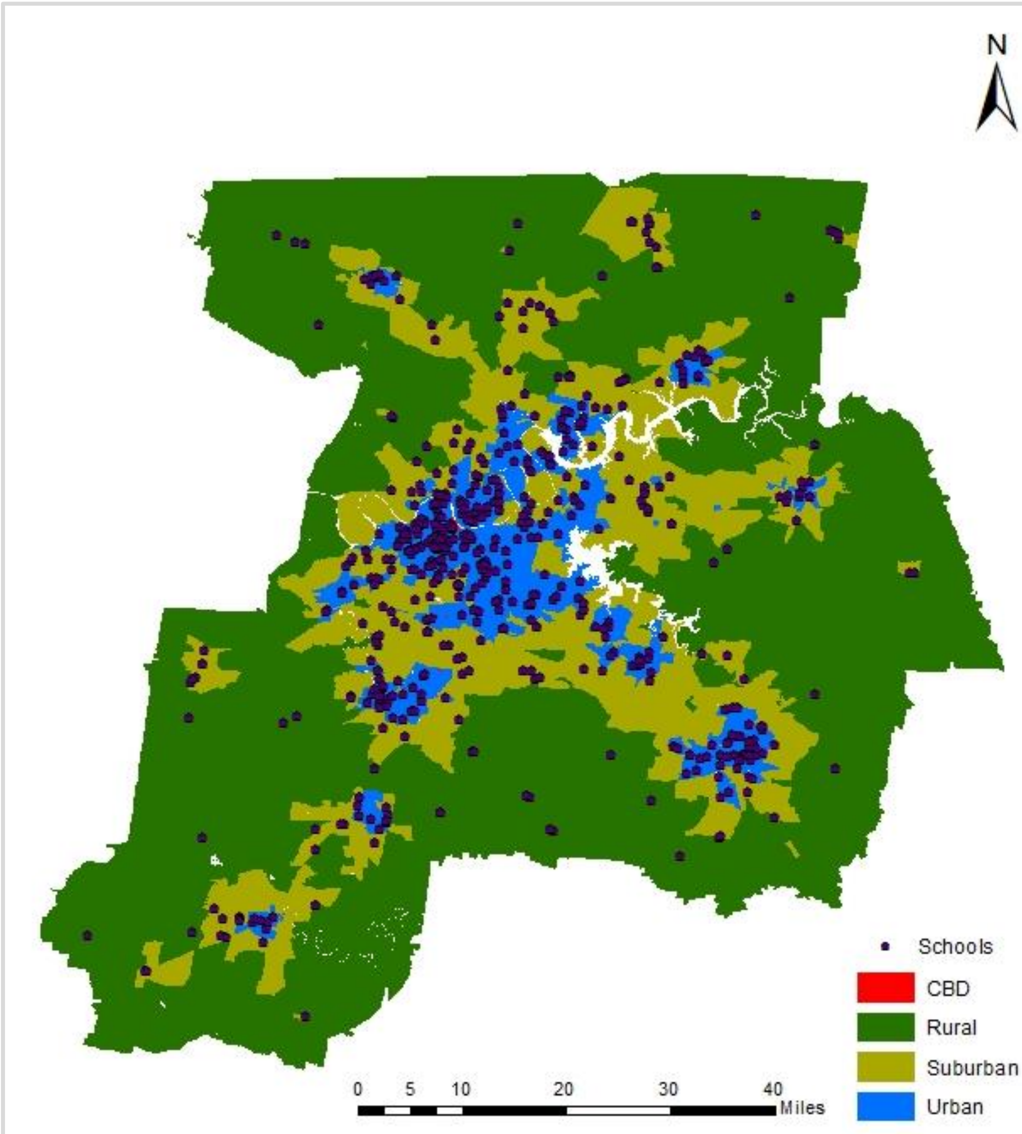


Figure A-1. Distribution of schools in Nashville MPO area

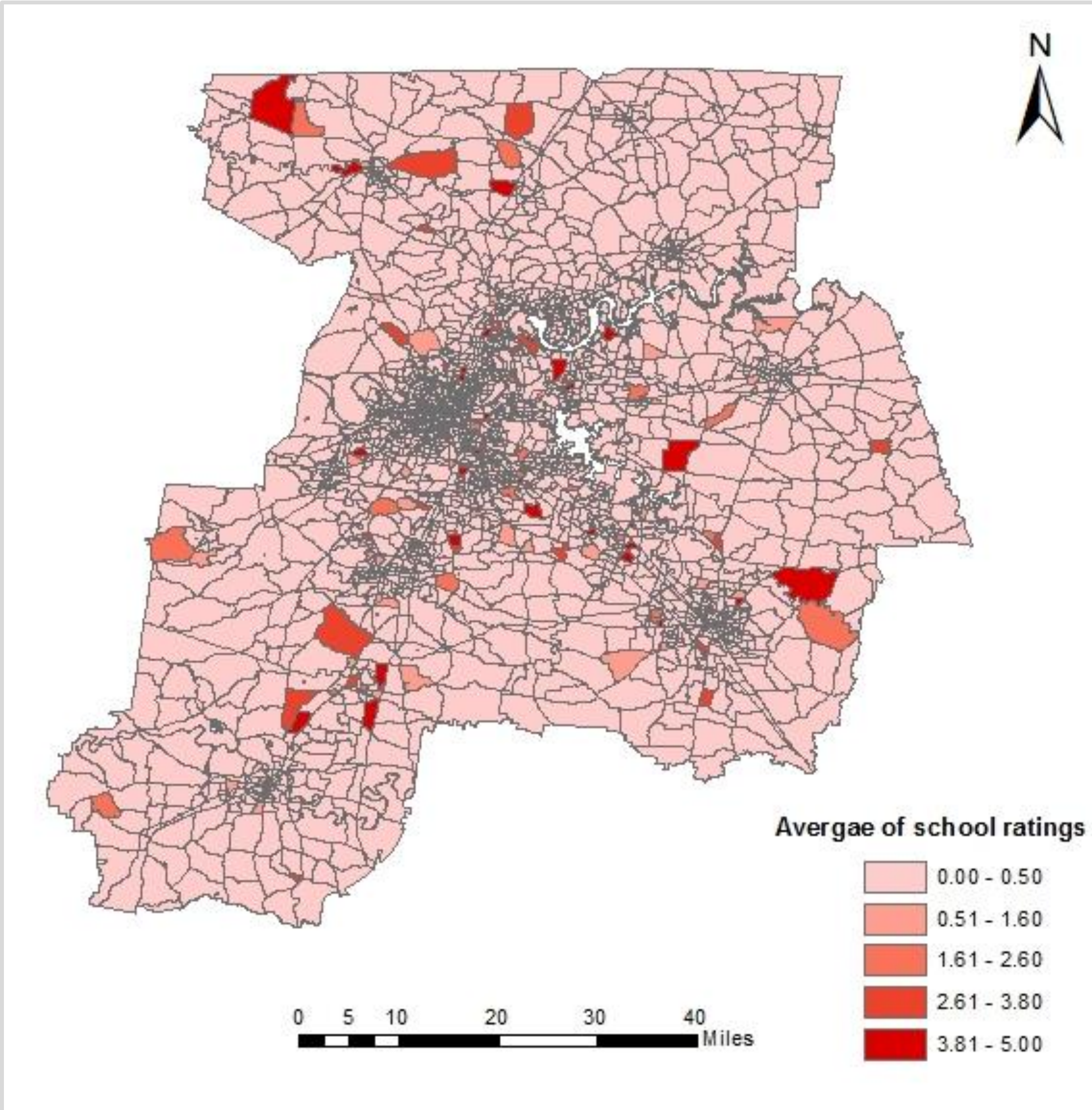


Figure A-2. Average school ratings in each TAZ

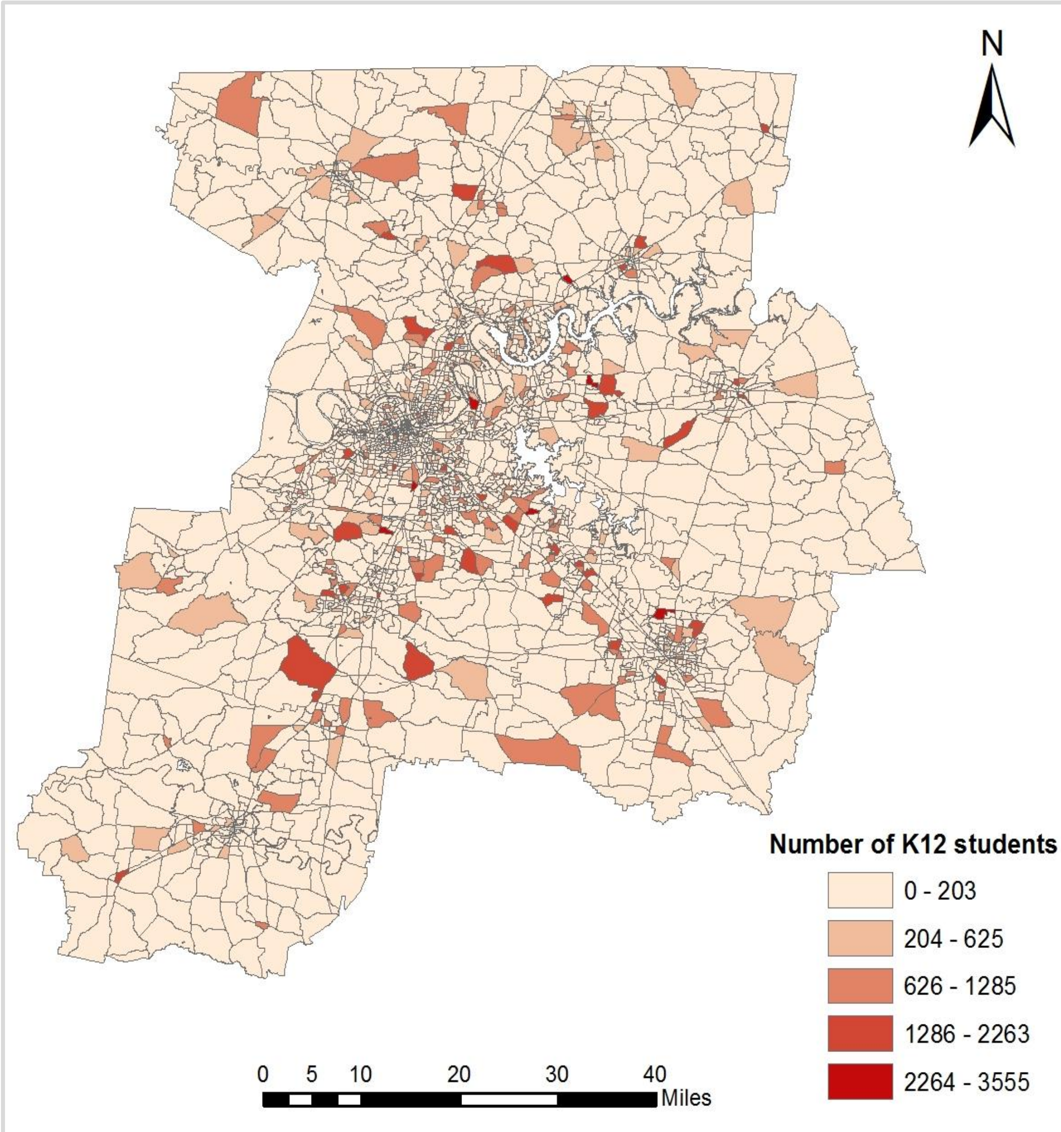


Figure A-3. K12 Students in each TAZ

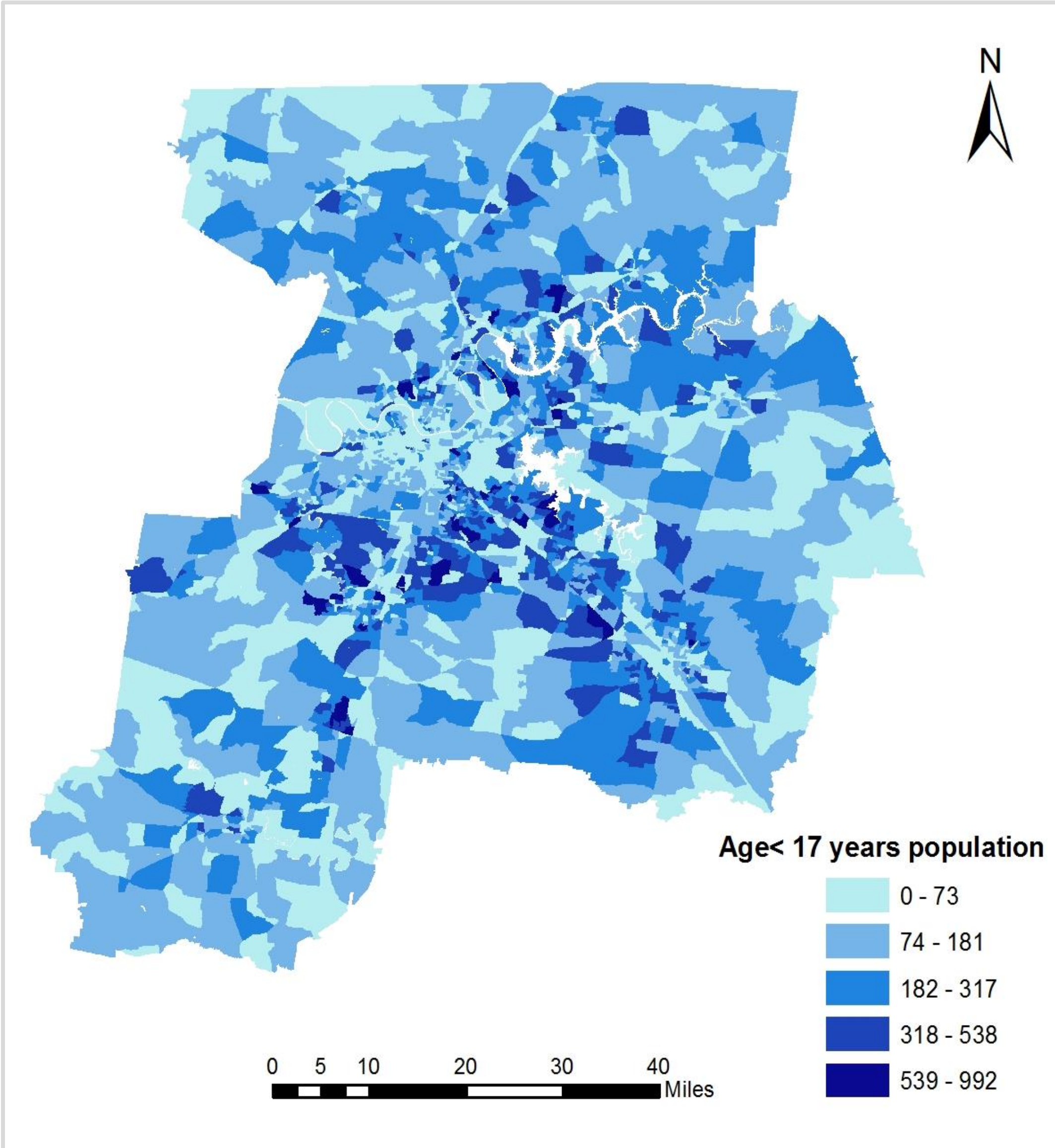
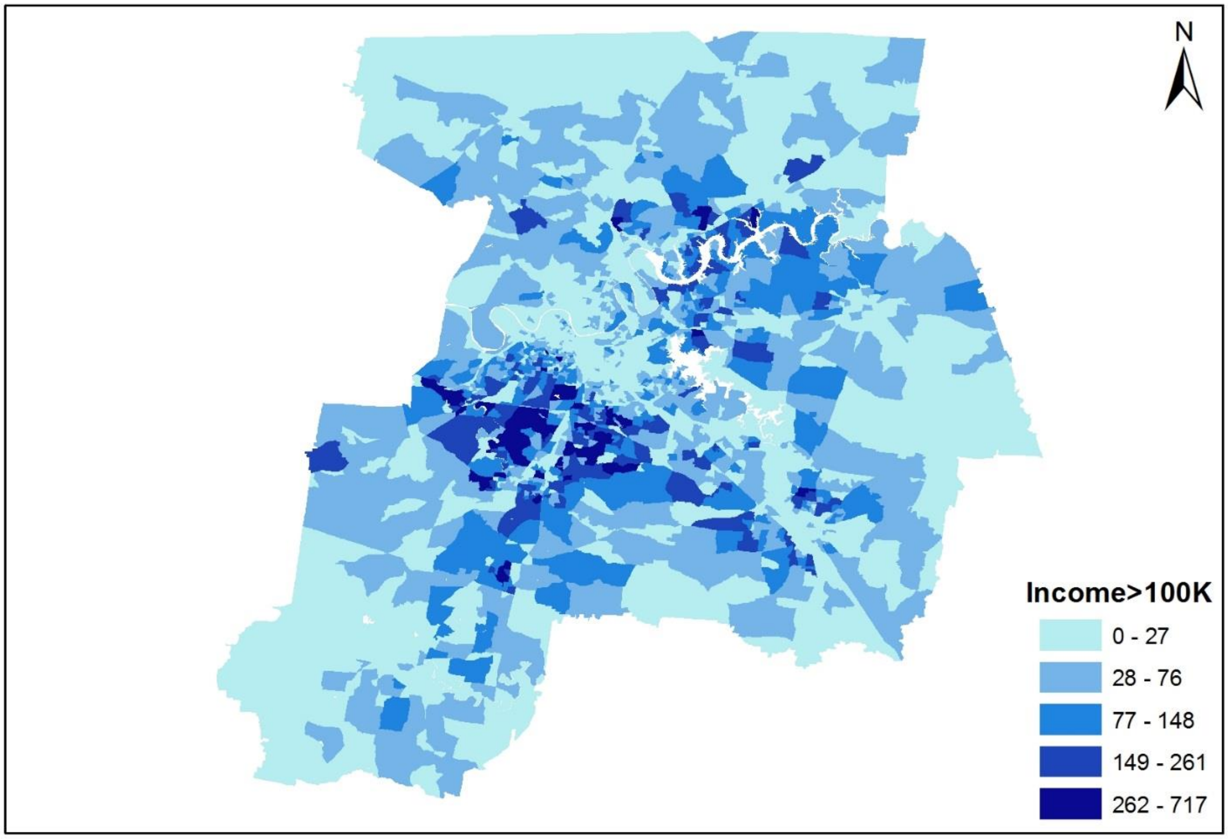


Figure A-4. Population: Age<17 years



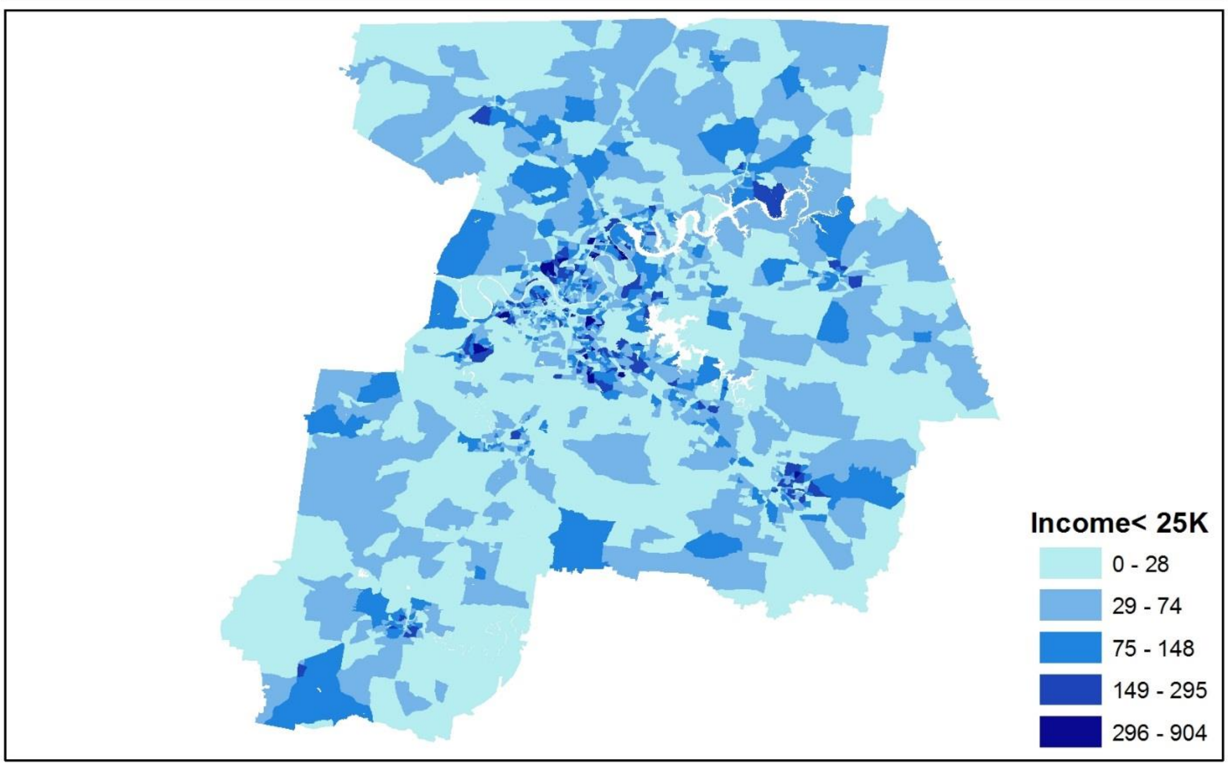


Figure A-5. High and Low-income category households

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