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Modeling the Mode Choice of Peak Period Passenger Travel in the Windsor-Essex Area: A Mixed Logit Approach

By

Shakil Khan

A Thesis
Submitted to the Faculty of Graduate Studies
through the Department of Civil and Environmental Engineering
in Partial Fulfillment of the Requirements for
the Degree of Master of Applied Science at the
University of Windsor

Windsor, Ontario, Canada

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Modeling the Mode Choice of Peak Period Passenger Travel in the Windsor-Essex Area: A Mixed Logit Approach

By

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ABSTRACT

This thesis presents the research work that was conducted to model passenger mode choice behavior during the peak period in the Windsor-Essex area. The research focused on investigating the presence of preference heterogeneity in the mode choice process. While socio-economic characteristics are important variables influencing the type of chosen mode, identifying the presence of heterogeneity with regard to level-of-service (LOS) attributes across different socio-economic subgroups of population is also important. Using a dataset extracted from the 1997 Windsor-Essex Household Travel Survey, Multinomial and Mixed Logit models were developed. The results identified a number of significant socio-economic variables. Also, the results suggested the presence of heterogeneity among various population subgroups for work, non-work and shopping related trips. Simulations were performed to analyze the single and combined effects of various LOS and residential intensification initiatives on mode choice probabilities. The recommendations from this research provide useful insights about the factors influencing the choice of travel mode, as well as the impacts of policy initiatives on mode choice behavior.

DEDICATION

In the loving memory of my late father, Khalil Khan.

ACKNOWLEDGEMENTS

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INTRODUCTION

1.1 The Research Problem

The mode choice of transportation is one of the most significant aspects of daily travel. Understanding and predicting travelers' mode choice behavior is important to reduce the number of single-occupancy vehicle travel and encourage travelers to choose more sustainable modes such as public transit, walk, bicycle, etc. Travel demand is generated by individual travelers as a result of their choice of when, where and how to travel. Work related travel has long been considered as the major demand on the urban transportation network and a main contributor to the peak period severity. However, over the last two decades, changing life styles, increased auto ownership and time use patterns in many North American urban centers have resulted in a gradual increase in non-work travel during peak hours (Habib and Sasic, 2012). Non work travel demand is derived from activities that are not related to work and can partly be characterized by the need to make stops during the morning and evening commutes. It is obvious that understanding the mode choice behavior for both work and non work trips is essential to formulating efficient transportation control measures.

In the context of transportation modeling, mode choice models were the primary applications of discrete choice theory in the 1960s and 1970s (Hendrickson, 1984). A behavioral principal known as *Random Utility Maximization* is the foundation of discrete choice models. Through this principal, a mathematical expression, based on the utility functions, is developed for predicting a person's choice (Ben-Akiva and Lerman, 1985).

Mode choice models attempt to estimate trips between origin and destination for each travel mode. The models help analysts forecast the activity patterns of urban travel and levels of travel demand on a transportation network. In mode choice models, travelers' socio-economic characteristics, departure time, route choice and LOS variables (travel time and cost) are typically utilized to characterize the traveler, trip and chosen mode (Xie et. al, 2003 and Koppelman and Bhat ,2006). Based on these characteristics, the probability of choosing a particular mode can be predicted using discrete choice models (Ben-Akiva and Lerman, 1985).

Traditionally, Multinomial Logit (MNL) and Nested Logit (NL) models have been used to predict mode choice behavior. However, these models cannot capture the difference in preference towards attributes of a specific mode among socio-economic groups called "heterogeneity". To overcome this limitation, recent efforts have been focused on adapting more advanced discrete choice models such as Mixed Logit (MXL) model to predict mode choices. This research contributes to this emerging paradigm and attempts to address this knowledge gap by analyzing the choice of modes for work and non-work trips in the Windsor-Essex area of Ontario, Canada, using travelers' survey data for the year 1997. Accounting for preference heterogeneity in mode choice of travel may allow for realistic projections of the reduction in auto mode share and increase in the mode shares of public transit and non-motorized mode such as walking and bicycle (Habib and Sasic, 2012).

Efficient transportation network stimulates economic growth. In the context of the Windsor-Essex area, the inherent auto preference and the lack of public transit beyond the administrative boundaries of the City of Windsor are causing inefficient traffic operations, hurting local economy and contributing towards environmental pollution. In order to reduce single-occupancy vehicle travel and influence travelers to choose more sustainable modes, such as carpool, public transit, walk and bicycle etc., it is important to understand and predict traveler's mode choice behavior. With the advancements in Logit model estimation and availability of sophisticated simulation methods, renewed efforts are required to develop a state of the art independent and transferable mode choice model to analyze mode choice behavior for passenger travel in the Windsor-Essex area.

1.2 The Research Objectives

The objectives of this thesis are to develop mode choice models for work and non-work travel using the Mixed Logit model to identify the factors affecting travelers' mode choice behavior. Emphasis is placed on identifying the sources of heterogeneity in the random parameters of the Mixed Logit model. Mixed Logit models will be estimated to identify factors influencing work and non-work mode choice and to account the heterogeneity in mode choice preferences.

The specific objectives of this research are:

1. To investigate the socio-economic and level-of-service (LOS) factors influencing travelers' mode choice in the Windsor-Essex area;
2. To investigate the existence of preference heterogeneity in mode choice of passenger travel in peak period;

3. To employ the extended capabilities of Mixed Logit to estimate mode choice models for work and non-work related travel;
4. To gain in-depth understanding of the behavioral process of traveler's mode choice for work and non-work trips;
5. To evaluate the impacts of different policy initiatives on the mode choice probabilities.

These objectives will be achieved primarily by modeling the micro-data from the Windsor-Essex Household Survey, conducted in 1997. Windsor-Essex area land use, road transportation and public transit network datasets, provided by Desktop Mapping Technology Inc. (DMTI) and Statistics Canada will also be used to model the mode choice behavior of passenger travel in the Windsor-Essex area.

1.3 Thesis Outline

The thesis is organized as follows. Chapter II provides a description of choice behavior theory, elements of *Random Utility* discrete choice models, different types of Logit models and synthesis of literature concerning the mode choice modeling in transportation research. The chapter concludes with a summary of the models that have been commonly used in the past to model the mode choice behavior.

Chapter III outlines the methods of analysis used in this research. The chapter also describes the study area, lists the sources of data needed for the research and techniques for estimating LOS variables. The descriptive and preliminary analysis of the extracted dataset of Windsor- Essex Household Travel Survey is conducted in this chapter.

Chapter IV provides analysis of data representation, results of data exploration for work and non-work trips. Estimation results of Multinomial and Mixed Logit models for work, non-work trips and shopping trips are presented. Model predictions, model elasticities and model simulations are conducted.

In chapter V, the key findings of the research are summarized. Research contributions and transportation policy implications are discussed. Finally, the thesis concludes with some recommendations for future research.

CHAPTER II

LITERATURE REVIEW

2.1 Theory of Choice Behavior

According to Ben-Akiva and Lerman, (1985) an ideal choice behavioral theory has three main elements. It should be descriptive, abstract and operational. In other words, the theory should postulate how individuals behave, it should not be limited to specific circumstances and the variables of the estimated models should be quantifiable. However, there is no universally accepted choice theory the meets all three requirements Ben-Akiva and Lerman, (1985). Most theories differ in the level of conceptualization of the process that results in observed choices, however the sequential decision-making processes such as, definition of choice problem, generation of alternatives and evaluation of attributes of alternatives, and implementation of observed choice are common to most of the choice theories. Discrete choice models rely on behavioral theory which represents the choice behavior of an individual person or group of person. The elements of disaggregate discrete choice models are disused in the next section.

2.2 Elements of Disaggregate Discrete Choice Models

The following elements represent a set of procedures that define the basis of disaggregate discrete choice models (Ben-Akiva and Lerman, 1985):

The Decision-Maker

In disaggregate discrete choice models, individual person or group of persons such as families or households can be represented as an entity to take the role of decision maker. In general, the choice situations and tastes or preferences of individuals vary considerably. And these differences in decision-making processes need to be taken into consideration. Due to the disaggregate nature of these models, the socio-economic characteristics of the decision-makers, such as gender, age, income, employment etc. play a vital role in modeling the choice behavior of the decision makers.

The Alternatives

Alternatives are the choice options available to a decision-maker in a given situation. The choices are made from a non-empty set of alternatives. The universal set of alternatives is determined from the environment of the decision-maker. Based on the feasibility and prior knowledge of certain alternatives, the decision maker, considers a subset of universal set, termed as choice set. The feasibility of alternatives is directly related to personal and environmental constraints such income, time availability, lack of service (e.g. in case of transit service) or lack of information.

The Attributes

The attributes of an alternative form the general characterization of its attractiveness. The attractiveness is evaluated in terms of attribute value that could be ordinal (speed perception of the alternative, e.g. auto is the fastest mode) or cardinal (travel cost of the alternative e.g. $ 0.15/km). The choice of an alternative can vary among decision-makers and is largely conditional upon the attributes of each potential alternative.

The Decision Rule

Whenever the decision-maker is subjected to making a choice from a choice set containing two or more alternatives, a decision rule is needed. Essentially the decision rule is a mechanism, through which the decision maker processes all the available information pertaining to choice set and the attributes of the alternatives forming the choice set and selects an alternative. A wide array of decision rules have been used in discreet choice applications. In the field of travel demand and mode choice modeling, the most commonly used decision rule is based on utility maximization theory. This decision rule is based on a single objective function, *utility*, which expresses the attraction or preference of an alternative in terms of its attributes. A detail description of this theory is presented in next section.

2.2.1 Random Utility Maximization

Discrete choice models predict the probability of individual's choice among discrete alternatives (Train, 2009). Disaggregate discrete choice models allow for a more flexible representation of the policy variables. Unlike aggregate models, disaggregate models incorporate observed choices, made by individual travelers and can be applied at any aggregation level. Disaggregate models are probabilistic and less likely suffer from biases due to correlation between aggregate units (Train, 2009). *Random Utility Maximization* principle is the most common theoretical base for discrete choice models. The principle states:

A decision maker n chooses the alternative i that provides the greatest utility from a set of feasible discrete alternates (Train, 2009). The mathematical form of the utility is given as:

$$U_{ni} = V_{ni} + \varepsilon_{ni}$$

where U_{ni} is the utility for alternative i perceived by decision maker n; V_{ni} is the observable utility for alternative i by decision maker n (deterministic/measurable part of utility) and ε_{ni} is the estimation error for alternative i by decision maker n (random part of utility capturing uncertainty).

Utility functions

Utility functions, V_{ni} are related to the indirect utility of choosing a particular alternative, which is expressed as a function of variables, X_{ni} and corresponding coefficients, β_n . The general form of the utility functions is given below:

$$V_{ni} = \sum \beta_n X_{ni}$$

where β_n represent coefficients and X_{ni} represent the attributes of alternative *i* and decision maker *n*.

Utility functions incorporate attributes that are exclusively related to alternatives and socio-economic characteristics of the commuters and reveal interaction between attributes of alternatives and characteristics of the commuters. The alternative attributes are measureable and are helpful in understating the process of commuter's choice behavior among given alternatives, i.e. the commuters choose the mode with the highest utility.

Generic Variables

There are two types of variables (attributes), specified in utility functions, $V_{ni.}$ When the utility value of variables is deemed to be identical across the available alternatives, then the variables are treated as generic variables. Generic variables are used for all the alternatives with same weight or coefficients.

Alternative-Specific Variables

Conversely, when variables with attributes specific to a certain alternatives are used in the model, then they are termed as alternative-specific variables. Alternative-specific variables with different weights are used for different alternatives. In certain situations travel time and travel cost are used as generic variables, with the assumption that *a minute/a cent* has same marginal (dis)utility whether it is incurred on auto or transit mode.

Consider the following three alternative mode choice scenario: 1-Auto drive, 2- Auto Passenger, 3-Transit. The functional form of utility functions is given below:

$V_1 = \alpha_1 TT_1 + \gamma TC_1$; $V_2 = \alpha_2 TT_2 + \gamma TC_2$; $V_3 = \alpha_3 TT_3 + \gamma TC_3$

where, TT_1, *TT2 and TT3* are alternative specific variables; TC_1, TC_2 *and* TC_3 are generic variables; TT = Travel time; TC = Travel cost *and* α, γ *are* weights or coefficients of the variables.

Alternative-specific constants

The presence of an alternative-specific constant in the utility functions is related to the systematic preference for each alternative. In other words it captures the average effect on the utility of all factors that are not included in the model. For *n* number of alternatives, *(n-1)* alternative-specific constant are needed in the Logit model. One constant is normalized to zero by not including in the model. The other constants in the utility functions of the model are interpreted relative to the constant which is normalized (Train, 2009).

Specification of the utility in the presence of an alternative-specific constant takes the following form:

$$V_1 = \Theta_1 + \alpha_1 TT_1 + \gamma TC_1$$

where, Θ_1= Alternative-specific constant

2.3 The Logit Model

The Logit probability, $P_{ni,}$ of choosing an alternative *i by* a decision maker *n* from choice set C_n , is given as (Train, 2009):

$$P_{ni} = Prob\ (V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}\ ,\ )\ where\ j \neq i\ and\ \ i,j \in C_n$$

$$P_{ni} = Prob\ (\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}\ )$$

The Logit Model is obtained by assuming that error components $(\varepsilon_{nj} - \varepsilon_{ni})$, are independently (no covariance) and identically (same variance) distributed across alternatives and/or individuals (Koppelman and Bhat, 2006). The implications of this assumption are that there is no covariance between errors for alternatives *i* and *j*, i.e. $Cov\ (\varepsilon_{nj} - \varepsilon_{ni}) = 0$ and error structure is identical for decision maker *n* and both alternatives *i* and *j*. The logistic distribution (or Gumbel) is used to derive the probability. The succinct closed form expression of Logit model for two alternatives is as follow:

$$P_{n1} = \frac{exp(V_{n1})}{exp(V_{n1}) + exp(V_{n2})} \quad ; \quad P_{n2} = 1 - P_{n1} = \frac{exp(V_{n2})}{exp(V_{n1}) + exp(V_{n2})}$$

These expressions are defined as a Binary Logit model, i.e. model with two alternatives. As shown in *Figure 2.1*, Gumbel distribution of error components $(\varepsilon_{nj} - \varepsilon_{ni})$, closely approximates Normal distribution.

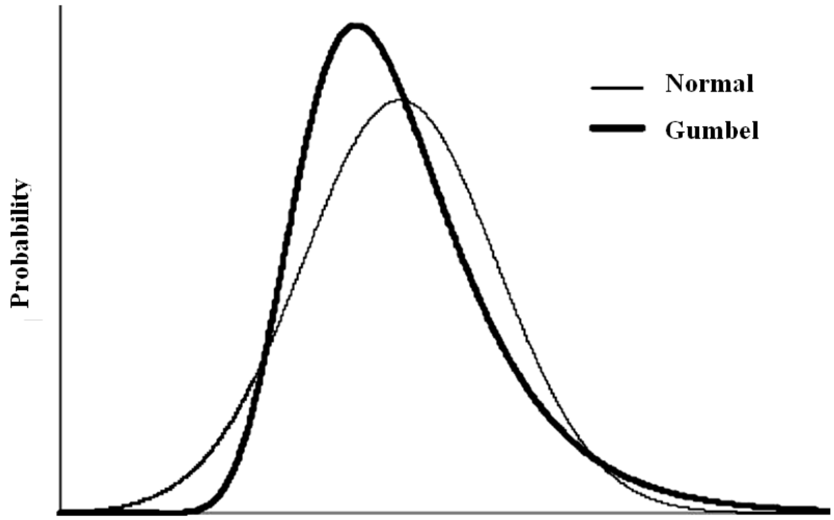


Figure 2.1 Gumbel and Normal Distributions for same Mean and Variance

(Koppelman and Bhat, 2006)

The Normal distribution assumption for error terms results in Multinomial Probit model (MNP). However, due to numerical and interpretation problems, the use of MNP in choice analysis is limited (Koppelman and Bhat, 2006). The variance of Gumbel distribution is □□ / 6 □whereas the mean is not zero. The mean μ and variance σ^2 indicate the location and spread of the Gumbel distribution (Koppelman and Bhat, 2006).

Figure 2.2 shows the sigmoid (S-shaped) relationship of Logit probability P_{ni} to alternative i's utility. Relative to other alternatives, the sigmoid shape limits the probabilities between 0 (when the utility of alternative i is very low) and 1 (when the utility of alternative i is very high). This implies that when the utility of an alternative is relatively very high or very low, a small increase in the utility of this alternative will not substantially affect its probability of being chosen. When the probability is close to 0.5 (maximum slope along the sigmoid curve), the greatest effect of an increase in utility, on choice probability is observed. A small improvement in attributes of an alternative can shift the mode choice resulting in larger change in probability (Train, 2009).

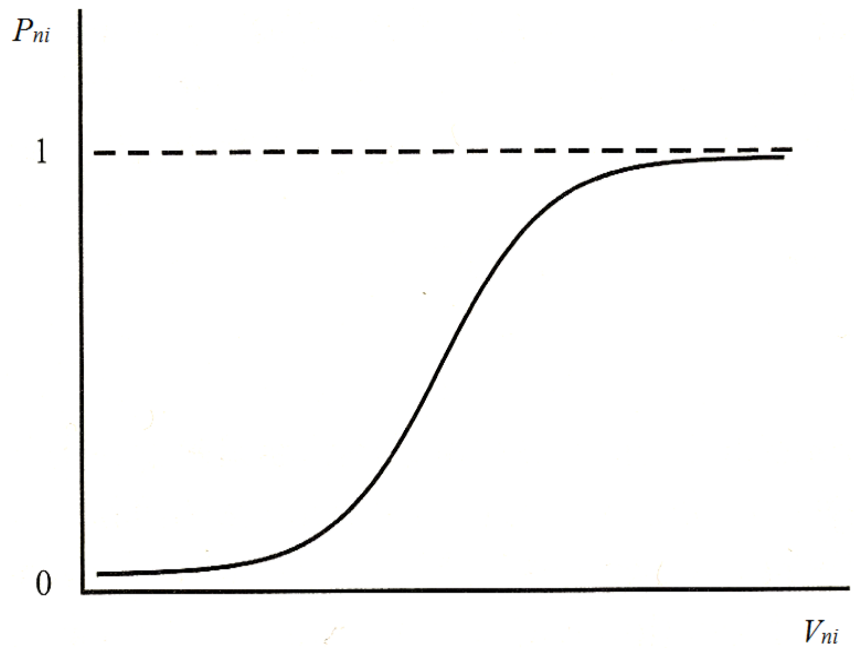


Figure 2.2 The Sigmoid Logit Curve (Train, 2009)

2.3.1 Multinomial Logit Model

Logit model with more than two alternatives is referred to as the Multinomial Logit (MNL) model. The form of MNL model is given below:

$$P_{ni} = \frac{exp(V_{ni})}{\sum_{j \in C_n} exp(V_{nj})}$$

Multinomial Logit model is also derived under the same assumption that the error terms of the utility functions are independent and identically Gumbel distributed (Train, 2009). MNL model has been a very popular choice for mode choice analysis since the probabilities can be calculated without use of numerical integration or simulation methods.

Independence from Irrelevant Alternatives (IIA) property

The Independence from Irrelevant Alternatives (IIA) property is the main disadvantage of Logit model. This property implies that relative probability of choosing an alternative is independent of mode choice set. More explicitly the property states:

"The ratio of Logit probabilities for any pair of alternative *i* and *k* is independent of any other alternative other than *i* and *k*." (Train, 2009). The property is expressed mathematically as follow:

$$P_{ni}/P_{nk} = exp\ (\ V_{ni} - V_{nk}\ )$$

In other words relative odds of choosing alternative *i* over alternative *k* will remain unchanged even if new alternatives are made available. To elaborate the undesirable effect of IIA, consider the famous *Red-Bus – Blue-Bus* problem (Train, 2009)**.** Say commuters' mode choice shares for car and bus modes are 50% each. When a blue bus with the same utility as of red bus, is made available as an additional travel alternative $(\varepsilon_b = \varepsilon_r)$, common sense and logic suggests that bus ridership should split evenly between red and blue bus (25% each) leaving car mode share unchanged. But Logit model predicts 33% modes share for each of the three alternatives. Logit model assumes that the error terms in the utility are independent and there are zero correlations between the error terms. In the above problem, by assuming proportionality, Logit model under predicts car mode share and over predicts bus mode shares.

McFadden's analysis paved the way of Generalized Extreme Value (GEV) family of models, which allow more flexible covariance structures (McFadden, 2000). By late seventies, McFadden, Ben-Akiva and Lerman and other researchers were able to develop independent random utility maximization specifications for GEV models. The main advantage of GEV models is that they partially relax the independence from irrelevant alternatives (IIA) assumption and yet have a closed form. The most widely used extension of GEV family of Logit models is Nested Logit model (Train, 2009).

2.3.2 Nested Logit Model

Nested Logit (NL) model was developed to avoid the restrictive assumption of estimation errors being independent of each other. GEV models such as NL model offers variety of substitution pattern and assumes that the estimation errors for all alternatives are jointly distributed as generalized extreme value (Train, 2009). The structural form of Nested Logit model (*Figure 2.3*) for estimating mode choice of a decision maker *n*, between private or public modes (with grouped lower level modes) of transportation is given below:

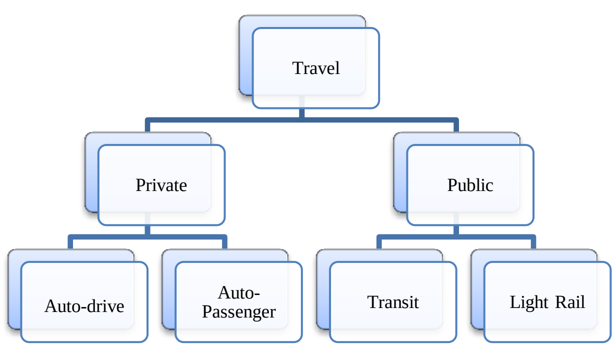


Figure 2.3 Two-Levels Nesting Structure for Nested Logit Model

The resulting probabilities are given as:

$$P_{ni|j} = \frac{\exp(V_{ni|j})}{\sum_k \exp(V_{nk|j})} \qquad ; \qquad P_{nj} = \frac{\exp(V_{nj}+\delta_j I_{nj})}{\sum_k \exp(V_{nk}+\delta_k I_{nk})}$$

where $P_{ni|j}$ is the probability that decision maker n chooses mode i for a given mode type j, $V_{ni|j}$ is the observable utility of mode i for decision maker n for a given mode type (private and public) j, P_{nj} is the probability that decision maker n chooses mode type j and I_{nj} is the inclusive value of mode type j for decision maker n:

$$I_{nj} = Ln\left[\sum_k \exp(V_{ni|j})\right]$$

δ_j is the scale parameter, representing sensitivity for lower level mode choice to upper level mode choice for mode type j. The value of scale parameter δ_j can vary from 0 to 1. $\delta_j = 1$ implies zero correlation among nested mode pairs and NL model reduces to MNL model. $0< \delta_j <1$ *implies* non-zero correlation among nested mode pairs with low values of δ_j indicating increased substitution among nested modes whereas $\delta_j =0$ *indicates* perfect correlation among nested mode pairs resulting in deterministic mode choice. The values of $\delta_j<0$ *or* $\delta_j>1$ results in rejection of Nested Logit model as the values are not consistent with the theoretical derivation of Nested Logit.

2.3.3 Estimation Technique

Since the Logit probabilities take a closed form, the traditional maximum-likelihood estimation (MLE) method is used to maximize the probability, that choices predicted by model are indeed the observed choice. The following detail of Logit model estimation is adapted from Train, 2009.

The probability of decision-maker *n* choosing the alternative that was actually observed to be chosen is given as:

$$P_{ni} = \prod_{i} (P_{ni})^{y_{ni}}$$

where y_{ni}=1, if decision-maker chose alternative *i* and 0 otherwise. Assuming that choice made by the decision-maker *n* is independent of that of other decision-makers, the probability of each decision-maker's actual choice in sample *N* can be expressed as:

$$L(\beta) = \prod_{n=1}^{N} \prod_{i} (P_{ni})^{y_{ni}}$$

where β is a vector containing model parameters. To simplify the computational process, the natural logarithm of L is maximized instead of L and the log-likelihood function can be given as:

$$LL(\beta) = \sum_{n=1}^{N} \sum_{i} y_{ni} \ln(P_{ni})$$

The maximization of $LL(\beta)$ is based on the assumption that the observed choice is the choice made in reality. The maximum likelihood estimates are the values of β that satisfy the first order condition, i.e. $\frac{dLL(\beta)}{d\beta} = 0$. And these values of β explain the effect of the specified variables in the utility functions of the choice, i.e. the alternative.

2.3.4 Goodness-of-fit

Statistical significance of model parameters (t-statistics) at specified confidence level and overall goodness-of-fit measures are criteria for Logit model validation. At a 90%

confidence level, if standard t-statistics is greater than or equal to 1.65, the variable is statistically significant.

Likelihood ratio index is a statistic, widely used to explain the data-fit of the discrete choice models, such as Logit models. The model fit, interpreted in terms of Log-likelihood ratio index, ρ^2 is given as:

$$(\rho^2) = 1 - \frac{L^*(\beta)}{L^*(0)}$$

where, $L^*(\beta)$ is the Log-likelihood at convergence (i.e. with explanatory variables) and $L^*(0)$ is the Log-likelihood /restricted likelihood (i.e. without explanatory variables). ρ^2 vary from 0 to 1. Typically a value of ρ^2 in the range of 0.3 – 0.5 suggest a good model fit.

2.4 Mode Choice and Urban Transport Modeling System

Mode choice modeling is the third sequential stage of the Urban Transportation Modeling System (UTMS). UTMS is a traditional trip-based four-phase modeling package used throughout North America and around the globe (Maoh et al., 2009). Each phase of UTMS consists of estimating a specific model for that particular phase. UTMS is mostly used to critically evaluate the impacts of land use patterns and transportation infrastructure on peak period, work related travel (Maoh et al., 2009). In the past years two UTMS models were estimated for Windsor-Essex area. The details of these models are presented in section 3.2 of Chapter III. The operational sequence of UTMS is depicted in *Figure 2.4.*

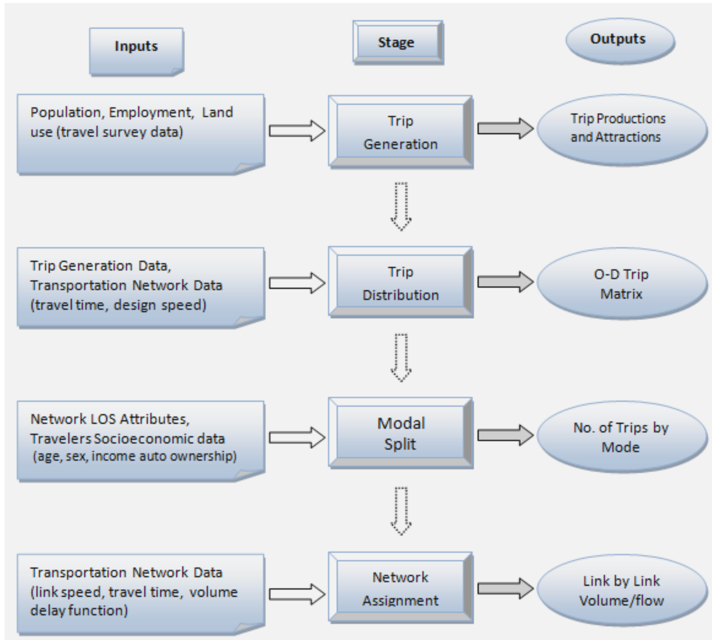


Figure 2.4 Operational Sequence of Urban Transportation Modeling System (UTMS)

The Modal Split stage predicts the percentages of flow by different modes for trips between origin and destination. Logit family of models is a very popular method of choice for implementing the modal split phase of UTMS.

2.5 Application of Discrete Choice Models in Mode Choice Modeling

2.5.1 Work Trips

Discrete choice models offer a comprehensive analysis framework for identifying socio-economic and transportation level-of-service (LOS) attributes affecting mode choice. The literature on mode choice for work related travel is extensive and covers wide range of modeling issues. Past research employed the Binary Logit model in mode choice analysis of work trips with two modes. For instance, Brown and Kahkeshan (1989) calibrated a Binary Logit model choice model for auto and transit work trips in Vancouver, Canada. The study concluded that both socio-economic variables and LOS variables (excluding cost) influence mode choice. Similarly, Vega and Reynolds-Feighan (2008) investigated mode choice for work trips to key employment sub-centers using the binary Logit model. Substantial differences in travel mode choice probabilities between central and suburban employment locations were reported. The results also suggested that female commuters are less likely to use the private car than male commuters.

By comparison, Multinomial Logit (MNL) models have been used when the number of modes is more than two. Commins and Nolan (2011) analyzed the effect of socio-economic characteristics on the work trip mode choice. Travelers' characteristics were incorporated in a Conditional Logit model (an extension of the MNL). The results showed that household composition, availability of public transport, journey time and work location are important factors in explaining the choice of mode to work.

Lucas et al., (2007) developed MNL models to investigate the mode choice behavior of elderly travelers. Five consolidated trip purposes namely, work, shopping, personal, eating out, and "other" were considered in the analysis. The results suggested that seniors are more likely to travel by transit as opposed to drive alone, car-pooling and walk. Their study also concluded that the elderly are more sensitive to travel cost than travel time – when choosing auto or transit.

Rieser-Schüssler and Axhausen (2012) incorporated latent variables representing attitudes, perceptions and preferences into their MNL model. The results suggested a correlation between the latent variables and travelers' socio-economic characteristics.

Bernetti et al., (2008) developed a MNL model to study the relationship between socio-demographic factors and mode choice in Trieste, Italy. The results indicated that different socio-demographic groups react differently to various LOS initiatives. Cherian and Sargious (1977) forecasted mode choice for work trips in Toronto using MNL models and concluded that socio-economic data was essential for developing a realistic mode choice model.

Wilson et al., (1990) developed MNL models for intercity, business and non-business passenger travel in eastern and western regions of Canada. The study emphasized the significance of LOS variables in determining the mode choice. Day et al., (2010) investigated commuter trip timing and mode choice of work trips using MNL models. The study pointed to the existence of differences in the mode choice preferences among various occupation groups.

While using the MNL model has been commonplace in mode choice analysis, the model is incapable of accounting for correlation among alternative modes. To overcome this limitation, the Nested Logit (NL) models have also been used in mode choice modeling. Shahangian et al., (2012) developed generalized NL models to investigate population heterogeneity and the significance of socio-economic variables affecting mode choice under LOS-oriented policies. The study identified gender-based differences in mode choice. Consequently, the authors concluded that gender factors need to be taken into consideration when designing modal shift policies.

Patterson et al., (2005) estimated MNL and NL models to analyze the gender difference in mode choice for work trips. Separate MNL and NL models were developed for whole population, male population and female population. Estimated inclusive value (IV) or scale parameters of all NL models were either outside the theoretical bound of 0 to 1, or very close to 1, implying unsuitable nesting structure. For all three categories of populations, the MNL models appeared to provide the best results. Female travelers were less inclined to use public transit and less sensitive to travel time than male travelers. Furthermore, female travelers were found to have higher preference for shared ride than male travelers.

Zaman and Habib (2011) studied commuters' mode choice, in the context of travel demand management (TDM) policies by estimating NL models. The model results revealed that commuters' choice of transit-oriented modes was highly sensitive to in-vehicle travel time, out-of-vehicle travel time and fare.

Although the NL model addresses some of the limitations of the MNL model, it cannot account for taste variation in the estimated parameters. In this regard, McFadden (2000) introduced simulation methods for practical estimation of open-form discrete choice models such as the Probit model and the Mixed Logit (MXL) model. The latter Logit relaxes the underlying behavioral assumptions used in the estimation of discrete choice models by allowing random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train, 2009). The MXL model can estimate the extent to which individuals differ in their preferences for attributes of a given alternative, thus providing more information than MNL and NL models (Train, 2009) MXL is also capable of both , identifying sources of heterogeneity associated with the mean of population parameters, and the variances associated with random parameter distributions as well. Detailed information about the MXL model is provided in Chapter III.

The review of the literature suggests a limited number of studies which used the MXL in mode choice analysis. Most of the existing studies have been focused on applications of the MXL to stated preference data. The use of MXL in the context of UTMS is not commonplace in the literature. Also, the emergence of the activity-based paradigm in travel demand modeling has benefited from the MXL model. For instance, Wan et al., (2011) developed an agent-based micro simulation model to simulate the mode choice decisions made by members of a household as part of the activities undertaken by those members in one day. The authors exploited the capabilities of the MXL model in their framework to estimate some of their mode choice models. Among several key findings, the results from the MXL analysis suggest a strong influence of unobserved preference heterogeneity.

On the other hand, Cherchi and Cirillo (2008) estimated MXL mode choice models using panel data from a six-week travel diary. The authors report the presence of significant variability in the preferences for the different alternatives. Also, the estimates from their LOS variables (i.e. travel time and travel cost) exhibited a significant variation around the mean values.

2.5.2 Non Work Trips

There have been numerous studies on mode choice for non-work trips using discrete choice models. In general, these studies have focused on mode choice behavior for a specific type of non-work trips such as shopping and recreational trips. The following section briefly summarizes the key findings of these studies.

Some studies have analyzed mode choice for shopping trips. Hamed and Easa (1998) used disaggregate data collected in Amman, Jordan to develop MNL mode choice models for three categories of shopping activities - during home-to-work, during work-to-home and after work-to-home. The results suggested that the household socioeconomic characteristics such as auto ownership and household income greatly influence the commuter's mode choice for shopping trips. Auto was the preferred choice for shopping trips to non-local shops whereas taxi cabs were preferred for shopping trips to the downtown area. The study also found that travel time, origin of shopping trips and type of post-shopping activity had significant effects on mode choice.

Bhat (1998) analyzed travel mode and departure time choice for urban shopping trips using MNL and ordered generalized extreme value (OGEV) models. The data for the analysis was obtained from the 1990 San Francisco Bay area travel survey. Socio-economic factors such as gender, age and employment were significantly related to the mode choice. The effect of gender on mode choice indicated that females prefer to shop during the off peak (mid-day) and PM peak periods than the AM peak and evening periods. It was also found that females were more likely to use transit than males. Older individuals were more likely to drive alone when shopping but individuals over 65 years of age were less likely to drive alone in the evening. Employed individuals were more likely to use auto for shopping than unemployed individuals.

Su et al., (2009) studied elderly travelers' mode choice behavior for shopping trips in London, United Kingdom using MNL and NL models for four travel modes, auto, auto passenger, public transit and walk. The results suggest that elderly travelers with high income prefer auto. The study also found out that elderly travelers considered higher number of stops on a given transit route more important than service frequency and they do not frequently choose two or more modes.

Wang et al., (2010) analyzed the effect of socio-economic and LOS factors on mode choice for shopping trips in the cities of Shanghai and Shenzhen, China using binary and NL models. Model results show the effect of commuters' attitude and trip-related factors on their mode choice.

On the other hand, some studies analyzed traveler's choice behavior for recreational trips. Agrawal and Schimek (2007) estimated Binary Logit models to study the correlations between different socio-economic factors and recreational walk trips. It was found that the people in the areas with extremely high and low population densities were more likely to walk when making recreational trips. Higher income and education also had a positive effect on recreational walking trips.

Pozsgay and Bhat (2001) estimated destination choice models for home-based recreational trips. The non-linear-in-parameters MNL model was estimated using the 1996 Dallas-Fort Worth household activity survey. The result of the model indicated that older individuals were more sensitive to travel time and cost since they prefer closer recreational destinations. However, individuals with higher numbers of cars in households were less sensitive to travel time and cost.

Some studies attempted to identify the heterogeneity for non-work trips using advanced discrete choice models. For instance, Habib and Sasic (2012) investigated commuter's mode choice behavior for non-work trips during the peak period in the Greater Toronto and Hamilton Area (GTHA) using a generalized extreme value (GEV) model. The proposed model captured the influence of mobility tool (auto and transit pass ownerships) on non-work trips. Results suggested that providing incentives for higher transit pass ownership levels would be beneficial for social welfare. The study also concluded that better spatial coverage of transit service rather than increasing transit frequency, would attract more commuters for transit use.

Greene et al., (2006) investigated the heterogeneity in the variance of unobserved effects using MXL models. The estimated heteroscedastic MXL model decomposed the variance heterogeneity in the random parameter estimates through an interaction with commuter's socio-economic characteristics. The study indicated that accounting for variance heterogeneity within the random parameter distributions not only improves the explanatory power of the model, but also provides behaviorally more sensible outputs in terms of travel time saving (VTTS) distributions.

Bhat and Gossen (2004) examined the effects of household and individual socio-demographics, land-use and density variables on recreational activity episodes by estimating a MXL model. Socio-demographic variables such as household size, income and family types had significant correlations with recreational activity. Land-use and density variables had no substantial impact on recreational trips on weekends. It was found that individuals in high-income households and with higher number of bicycles were more likely to only make recreational trips as oppose to mixed types of travel activities. It was also found that younger individuals were more likely to prefer recreational trips than older individuals. Furthermore individuals who reside in duplex dwelling units were more likely to make outdoor recreational trips but single parents were less likely to participate in pure recreation than the other individuals.

Based on the literature review, there has been no comprehensive study on mode choice for non-work trips using MXL model. Accounting for heterogeneity in non-work trips helps formulate better traffic congestion control measures as non-work trips significantly contribute to total travel during peak periods. Thus, this thesis will employ the Mixed Logit model to investigate the preference heterogeneity in mode choice of individual trip makers for peak period work, non-work and shopping related travel in the Windsor-Essex area.

2.6 Chapter Summary

The literature review offers valuable insight to the issues faced by researchers in mode choice modeling. These issues range from choice set consideration to model specifications issues. Collectively, in all the studies reviewed, tackling the model specifications issues represented a significant challenge for the researchers. Although many researchers have predicted mode choice using discrete choice models, there is limited number of studies which investigated variation in taste and the heterogeneity through the MXL model.

An appropriately specified MXL model can effectively portray the complexities of travel behavior and improve the predictive ability of the model. Furthermore, MXL has not been used in the development of the UTMS. Efforts towards bridging this gap will be attempted by developing MXL-based mode choice models for the peak period passenger travel in the Windsor-Essex area as will be discussed in the next two chapters.

CHAPTER III

METHODS OF ANALYSIS

3.1 Introduction

This chapter presents the method of analysis used to accomplish the objectives of this thesis as outlined in section 1.2. A brief overview of study area and past modeling efforts is provided in next section. Section 3.3 introduces the dataset and provides description of different types of variables used in model estimation. Details about GIS based road network, Transit Windsor network and estimation process of level-of-service (LOS) variables are also included in this section three. Preliminary analysis of dataset is presented in section 3.4.

Section 3.5 describes in details, the theoretical back ground of MXL model, used to develop the mode choice model for the Windsor-Essex Area. The last two section presents model specifications and information about modeling apparatus.

3.2 Study Area and Past Modeling Efforts

The city of Windsor, located in Southwestern Ontario, is the southernmost city in Canada and is administrated separately from the Essex county government. The population of Windsor Essex area in 2011 was 319,246 (Statistics Canada, 2012). Famously known as the automotive capital of Canada, Windsor has long been associated with higher auto mode usage. Windsor’s auto dependent culture is rooted mainly in its automotive manufacturing sector. Economic growth and rising employment opportunities across the border in neighboring Detroit, Michigan have also led to the almost unsustainable auto reliance trend. Auto accounts for about 81% of the all the trips (work and non-work) during the afternoon peak period (WALTS Report-1, 1999). In Windsor-Essex area, the non-work passenger trips accounts for about 30% of afternoon peak period trips. The afternoon peak period for passenger travel in Windsor is observed between 3:30 PM and 6:30 PM whereas the morning peak period is about half the duration of afternoon peak period. The map of the study area in presented in *Figure 3.1*.

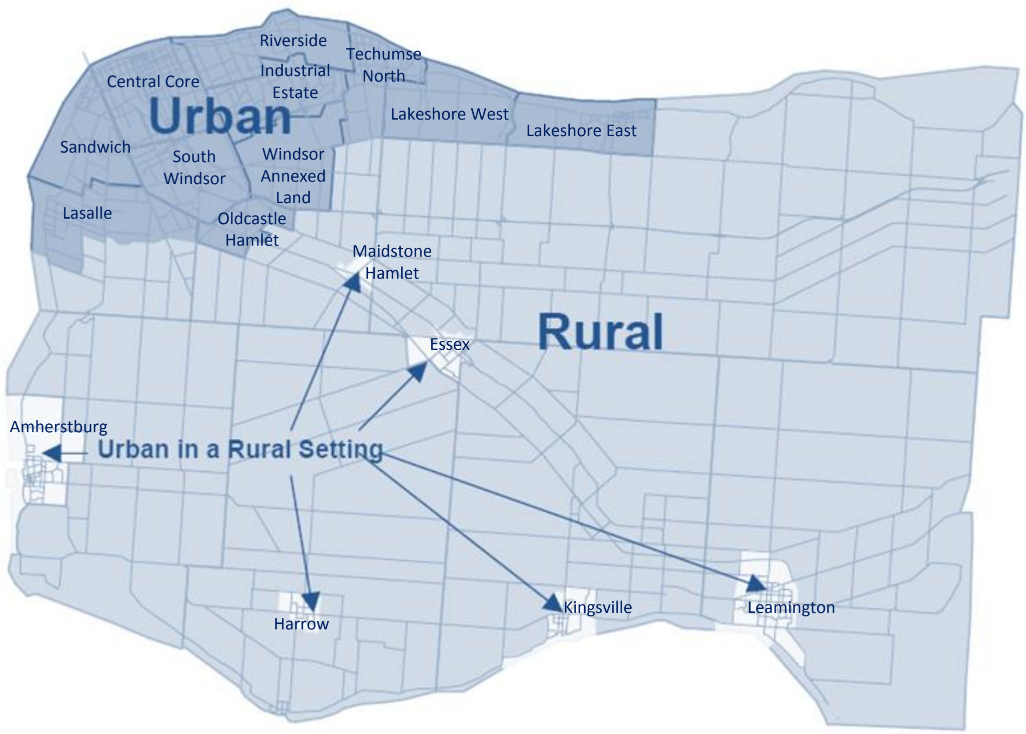


Figure 3.1 Map of the Windsor-Essex Area (IBI Group, 2006)

Future development of transportation services in the Windsor-Essex area is perceived in the context of a master plan formulated with the findings of The Windsor Area Long Range Transportation Study (WALTS), conducted in 1997 and 1998 (WALTS Report-1, 1999). The master plan was to provide guidelines for development of future transportation services /infrastructure in the Windsor-Essex area by year 2016. The study area of WALTS included the City of Windsor, Towns of LaSalle and Tecumseh, Townships of Sandwich South and Maidstone, and the Village of St. Clair Beach. After establishing existing transportation conditions through WALTS study, SYSTEM II traffic forecasting model was developed as a future forecast for planning purpose (WALTS Report-1, 1999). Data from household travel survey of 1997, cordon survey and *Average Annual Daily Traffic* (AADT) count on the Windsor- Essex road network, was used for model estimation.

The model forecasted traffic volumes based on the existing transportation conditions, land use and socio-economic characteristics of the Windsor Essex residents. Based on the forecast certain travel demand management strategies, such as car pooling, expansion of transit service, bike and recreational way provisioning, were recommended to reduce auto mode share from an existing level of 85 % to 76% and to increase public transit ridership from 3% to 6 % by the year 2016. Targeted auto occupancy for the year 2016, was established at 1.4 passenger /vehicle.

In May 2002 WALTS Steering Committee and Essex County Council decided to develop the Essex-Windsor Regional Transportation Master Plan (EWRTMP). The regional plan inherited the policy guidelines from WALTS. In a technical report published by IBI Group and Paradigm Transportation Solutions (2005) on EWRTMP, *TransCad*, a computerized UTMS model, was used for transportation forecasting in the Windsor-Essex area. The model effectively replicated the actual conditions. It was deemed as a valuable tool for forecasting future travel demands under various transportation network alternatives. The model simulated the allocation of trips to cars, transit buses, cycling and walking. The model employed WALTS household travel survey data. The model took into account the impact of service provided by each mode such as auto, transit, cycling, and walking, based on the relative attractiveness of the mode.

The above two studies employed *SYSTEM II* and *TransCad* UTMS models to forecast travel demand in Windsor-Essex Area. The mode choice modeling phase implemented in these studies lacked the use of zonal characteristics of origins and destinations as additional variables.

Mode choice modeling requires traveler, trip and mode related data. This data is often obtained through household travel survey of concerned population. Quality and quantity of socio-economic, mode and trip related data directly relates to the extent of behavioral realism that can be reflected with Logit models (Hensher and Greene, 2002). In order to estimate MNL and MXL mode choice models for Windsor-Essex area, the research made use of the data from various sources.

3.3 Data for Analysis

3.3.1 The Windsor- Essex Household Travel Survey -1997

To assess the present day travel demand, detailed information about travel characteristics of the Windsor-Essex's residents is needed. This research made use of the Windsor-Essex household travel survey (telephonic) that was conducted for one month from April 14 to May 14, 1997 from 3:00 PM to 6:00 PM. A specialized database software was used to generate geographically stratified, randomly generated, residential telephone number database. Data checks such as built-in logic and range were incorporated in the software to improve the quality of the collected data. The selected residents were requested to respond to a questionnaire that contained socio-economic characteristics, trip-making and various LOS attributes (traffic congestion, road system, bicycle network) of the Windsor-Essex transportation network. The responses of residents were then recorded directly into the software. A total of 6,300 households were contacted during the survey. A copy of original WALTS questionnaire obtained from municipal archives section of Windsor Central Public Library, Windsor is provided in Appendix A (see *Figure A-1*).

At the time of survey that estimated population in the study area was about 230,000 persons with nearly 85,000 households (WALTS Report-1, 1999). Collected data contained traveler's socio-economic characteristic such as age, sex, employment status, dwelling type and vehicle ownership. Information on number of trips made by each household, reason for trip, travel mode used and origin and destination for each trip was also recorded.

After needful noise cleaning, the dataset extracted from the survey contained 2679 records of individual trips makers. Four travel modes were identified namely, auto, public transit, walking and bicycle. *Table 3.1* provides a detailed list of the categorical and continuous variables included in the extracted data set for model estimations. The table includes variables from, WALTS' survey and additional zonal variables that were introduced in the dataset from external sources.

Table 3.1 Description of Variables used in Estimated Logit Models

Variable	Definition of variables
t_i	trip maker
mode	1 – auto, 2 – transit, 3 – walk/bicycle
choice	1 – selected mode, 0 – otherwise
gender	trip maker's gender (1 – female, 0 – male)
hhsize	number of persons in the trip maker's household
AGE	
age1	1 if trip maker's age is less than16 years, 0 otherwise
age2	1 if trip maker's age is between 16-25 years, 0 otherwise
age3	1 if trip maker's age is between 26-35 years, 0 otherwise
age4	1 if trip maker's age is between 36-45 years, 0 otherwise
age5	1 if trip maker's age is between 46-55 years, 0 otherwise
age6	1 if trip maker's age is between 56-65 years, 0 otherwise
age7	1 if trip maker's age is over 65 years, 0 otherwise (Reference Category)
MOBILTY	
nveh	number of vehicles in the trip maker's household
nbic	number of bicycles in trip maker's household
DWELLING	
dwlapt	1 if trip maker reside in an apartment, 0 otherwise
dwldplx	1 if trip maker reside in a duplex, 0 otherwise
sfam	1 if trip maker reside in a single family dwelling, 0 otherwise
dwlth	1 if trip maker reside in a townhouse dwelling, 0 otherwise
dwlothr	1 if trip maker reside in other dwellings, 0 otherwise (Reference Category)
EMPLOYMENT	
empstd	1 if trip maker is employed student, 0 otherwise
fltemp	1 if trip maker is employed fulltime, 0 otherwise
hmkr	1 if trip maker is homemaker, 0 otherwise
emppt	1 if trip maker is employed part time, 0 otherwise
selfemp	1 if trip maker is self-employed, 0 otherwise
studnt	1 if trip maker's is student, 0 otherwise
unemp	1 if trip maker is not employed, 0 otherwise
emprtd	1 if trip maker is retired, 0 otherwise(Reference Category)
PEAK PERIOD	
pktime1	1 if trip is made between 3:00 pm-3:29 pm, 0 otherwise
pktime2	1 if trip is made between 3:30 pm-3:59 pm, 0 otherwise
pktime3	1 if trip is made between 4:00 pm-4:29 pm, 0 otherwise
pktime4	1 if trip is made between 4:29 pm-4:59 pm, 0 otherwise
pktime5	1 if trip is made between 5:00 pm-5:29 pm, 0 otherwise
pktime6	1 if trip is made between 5:29 pm-6:00 pm, 0 otherwise (Reference Category)
DERIVED	
femsfam	1 if trip maker is female and reside in a single family dwelling, 0 otherwise
tpshop	1 if trip is made for shopping purpose, 0 otherwise
age4sfam	1 if trip maker's age is between 36-45 years and resides in a single family, 0 otherwise
studnt_ag12	1 of trip maker is student with age less than 26 years, 0 otherwise
rvehocup	ratio of number of vehicle to number of occupants in trip maker's household for auto mode
LOS	
ttime	in-vehicle travel time for Auto and Transit and Walk/Bicycle(min)
trc	travel cost for auto and transit modes (dollars)
ZONAL	
hhinc	average household income of trip maker in 1997(thousand dollars)
eindex	land use entropy index for Windsor-Essex area
tc/hhinc	ratio of travel cost to trip maker's household income for auto and transit mode

These variables form the basis of the statistical analysis of this thesis. Model estimation in the initial phase of this research included the unrestricted choice set of four modes of travel. These modes were auto, transit, walk and bicycle. However, at later phase, the walking and bicycle modes were combined to represent a non-motorized mode. The combination of the two modes was deemed more appropriate since each mode on its own did not have a good representation in terms of the mode share.

3.3.2 Zonal Variables

House hold Income

Average household income of the travelers in the WALTS survey was not recorded. Number of mode choice studies have concluded that travelers with higher household income are likely to afford car(s), and are less concerned with travel cost associated with auto mode. To represent this behavior in the model estimation, the average household income at Enumeration/Dissemination area level for the year 1997, was estimated using 2006 and 2001 census information from Statistics Canada. The travel cost by auto mode was divided by the average household income. The derived variable *tc/hhinc* was introduced in model estimation to reflect the relative importance of cost, an individual trip makers places on the choice probability of certain mode.

Entropy Index

Entropy index, a measure of land use mixing was introduced in the model estimation in the study area, with the hypothesis that higher mixed land use (at census tract level) decreases automobile ownership in households and results in lower auto mode choice probability (Maoh and Tang, 2012). Conversely, travelers in more homogenous areas would rely more on auto. The land use categories in the study area include commercial, industrial, government and recreation land use. Entropy index for census tract *i* is calculated using the expression:

$$EI_i = \frac{-\sum_{K=1}^{K} P_K ln P_K}{ln(K)}$$

where,

$$P_K = \frac{Area\ of\ type\ K\ land\ use\ in\ TAZ_i}{Total\ area\ of\ TAZ_i}$$

and *K* = total number of land-use categories in the study area.

Entropy Index ranges from 0 to 1. A value 0 means perfectly homogeneous land use in census tract *i*. Conversely, 1 indicates a perfectly heterogeneous and an even distribution of all land use categories. An illustration of Entropy index of the Windsor-Essex area in 1996 provided in Appendix B (see *Figure B-4*).

Additional zonal variables such as ratio of travel cost to house hold income and entropy were introduced in the dataset to make the dataset more robust. However, these variables proved to be statistically insignificant and did not add to the explanatory power of estimated models.

3.3.3 GIS Data

Travel time for individual travelers, for different modes of transportation, is normally calculated from network models and has great significance in model estimation (Bhatta and Larsen, 2011). Network models are developed by coding the existing road network in computerized UTMS such as *TransCad*, *VISUM* and implementing the network assignment stage of UTMS which yields link by link traffic flow and link travel time. The resulting travel time is then used to calculate travel cost for individual travelers.

The WALTS survey data did not contain travel time for the individual trips made by various travel modes. The travel times for auto, public transit, walk and bicycle modes were calculated using the *Network Analyst*, an extension of ArcGIS® Geographical Information System (GIS) software (ESRI, 2012). Given mild traffic congestion during peak period in the study area, free-flow travel time was deemed as a reasonable estimate of in-vehicle travel time.

Trips were geo-coded using address locator (specifying the X-coordinates and Y-coordinates of origin and destinations in GIS). GIS based Windsor-Essex road network and Transit Windsor datasets consist of pre-calculated lengths all freeways, major and minor urban and rural roads and specified speed limits. The *New Route* assignment was employed in Network Analyst. The *New Route* assignment estimates the shortest routes for given trips. This is done by first calculating the shortest road network distances between origin and destination on different segments of road lengths that define the route, and then these distances are divided by the specified speed limits for all the roads segments of the route. The resulting summed up travel time is free flow travel time.

Illustration of travel time estimation for auto mode is provided in Appendix B (*see Figure B-1*).

Transit Windsor formed in 1977 is an important mode of travel for Windsor's existing transportation network. The new transit terminal was opened in the summer of 2007. According to Transit Windsor, (2011) Transit Windsor operates 7 days a week and provides transportation to over 6 million passengers each year. The transit service coverage area is nearly 313 square kilometers and a population base of 209,000. The basic fleet size is 105 vehicles, 10% of which is off road, at any time for maintenance.

In order to estimate the transit travel time more accurately Windsor Transit routes map published in March 1997 was acquired from municipal archives section of Windsor Central Public Library. Information on operating statistics, routes and service hours and fleet size were collected. To better reflect the transit conditions that existed at the time of household travel survey in 1997, present day transit routes were compared with the routes existed in 1997. Transit Windsor maps for the year 1997 and 2011 are provided in Appendix A (*see Figure A-2 and Figure A-3*).

In 1997, Windsor Transit operated 13 transit routes. Presently few of those routes have been merged together to form one single route (routes *Dominion-B* and *Dominion-C* were combined under one single route *Dominion-5*) and a new *Transway 1c Express* service has been introduced. Fleet size has marginally increased from 100 busses to 105 busses over a period of 15 years. Transit Windsor's service population also increased from

200,000 in 1997 to 217,249 in 2011. The in-vehicle travel time for transit mode was estimated by using ArcGIS® Network Analyst. An illustration of travel time estimation for transit mode is provided in Appendix B (see *Figure B-2*).

The performance of any public transit, over time, is greatly influenced by socio-economic, geographic and political environment. Windsor Transit lost ridership during mid-1990s, but it has been experiencing a slow recovery since 2000, with about a 3% increase in ridership from 2002 to 2003 (WALTS Report-1, 1999). WALTS study concluded that Transit Windsor system had a high revenue/cost (R/C) ratio with fares higher than average, when compared to transit operations in Brampton, Kitchener and London. According to Detroit River International Crossing Study Report (2005), from travel demands management (TDM) perspective, extension of Transit Windsor service into Tecumseh and LaSalle, is the most likely expansion. In WALTS study, a 6% transit mode share of peak hour trips was set as a target for year 2016 (WALTS Report-2, 1999).

In order to calculate travel time for the walk and bicycle mode, the Windsor-Essex road network speeds were modified. Based on a study of the walking speed data on 7,123 pedestrians, Knoblauch et al., (1996) recommended mean walking speeds of 1.46 m/sec (5.26 km/hr) for pedestrians under 65 years and 1.20 m/sec (4.32 km/hr) for older pedestrians. Taking into consideration the relative proportions of pedestrians' under and over the age of 65, a mean walking speed of 5 km/hr was adopted to calculate the travel time for walking trips. Different speeds for bicycle have been sighted in the academic literature. Typical average cruising speeds for bicycle vary from 14.3 km/hr to 26.6 km/hr whereas for intersection crossing, bicycle speeds may vary from 8.4 km/hr to 14 km/hr

(Pline, 1999). In Vancouver, the speed limit on bicycle boulevards is 30 km/hr (Pucher et al., 2011). The bicycle trips were mostly distributed in the downtown areas of Windsor-Essex and since the road condition in downtown area is not great, a lower average speed of 15 km/hr was specified for calculating travel time for bicycle trips. Travel time for walk and bicycle trips were calculated separately. The travel time for a single trip made by the non-motorized mode i.e. walk/bicycle was calculated by averaging the travel times by walk and bicycle. Illustration of travel time estimation for walk/bicycle mode is provided in Appendix B (*see Figure B-3*).

For travel cost estimation, the average annual per kilometer operating costs for various models of passenger vehicles, as suggested by the Canadian Automobile Association, were considered (CAA, 2011). The breakdown of per year operating cost of these vehicles is provided in *Table 3.2*. Assuming that the shares of auto trips by the three models of passenger vehicles (Mid Size SUV, Mini Van and Sedan) were equal, the average annual operating cost of \$0.145/km was used for calculating the travel cost of trips using the auto mode. Network Analyst, was used to generate Origin-Destination (OD) cost matrix for auto trips in the Windsor-Essex transportation network.

Table 3.2 Average Annual Vehicle Operating Costs per km (CAA, 2011)

	Average Annual Operating Costs Per Kilometer		
Vehicle Model	Cruze 1lt	Grand Caravan	Toyota Prius
Fuel	10.10 Cents	14.47 Cents	4.74 Cents
Maintenance	2.43 Cents	2.98 Cents	2.73 Cents
Tires	2.17 Cents	2.20 Cents	1.73 Cents
Total	14.70 Cents	19.65 Cents	9.20 Cents

Note: The costs were calculated based on 18,000 km of driving in the year 2011.

Based on the average trip distance by transit mode, it was assumed that a trip was made on a single route. Thus, a fixed travel cost of $2.75 was specified for transit. Since the monetary cost does not incur for trips by the walk/bicycle mode (excluding the purchase cost of bicycles), travel cost of these trips was assumed to be zero.

3.4 Descriptive and Preliminary Analysis of Extracted Dataset

Socio-economic characteristics such as age, gender, household size and type, vehicle and bicycle ownership, trip purpose and employment status of trip makers in the dataset (sample) extracted from Windsor- Essex households travel survey are summarized *in Table 3.3.* Male accounted for an approximate 54% of the extracted sample. For the three-hour afternoon peak period, auto mode was favored choice among travel alternatives dominating with 83% of the trips. GIS spatial analysis revealed that auto trips were well distributed across the Windsor as would be expected. Nearly 95% of all area households had at least one car.

Walking was second with 12% mode share. Walking trips were shown to occur mainly over short distances especially in the University of Windsor area. The rest of 5% was composed of Transit Windsor (3%) and bicycle (2%). Lower than average public transit can be attributed to the lack of transit operations beyond the City of Windsor. Public transit use was higher in employment areas including the downtown.

Table 3.3 Socio-economic Characteristics of the Extracted Dataset

Socio-economic Characteristics	Proportions		Socio-economic Characteristics	Proportions	
Gender			Trip Purpose		
Male	1443	(54)	Returning Home	1690	(63)
Female	1236	(46)	Shopping	374	(14)
			Recreation	148	(6)
Travel Mode			Other	179	(7)
Auto	2213	(83)	Work	149	(6)
Transit	92	(3)	Passenger	111	(4)
Walk	325	(12)	School	28	(1)
Bicycle	49	(2)			
			Age		
Household Size			0 - 15 years	269	(10)
1	411	(15)	16 - 25 years	383	(14)
2	739	(28)	26 -35 years	493	(18)
3	504	(19)	36 - 45 years	576	(22)
4 and over	1025	(38)	46 - 55 years	378	(14)
			56 - 65 years	236	(9)
Household Type			over 65 years	344	(13)
Apartment	342	(13)			
Duplex	93	(3)	Vehicle Ownership		
Other	33	(1)	0	146	(5)
Single Family	2143	(80)	1	1007	(38)
Townhouse	68	(3)	2	1170	(44)
			3	254	(9)
Employment Status			4 and over	102	(4)
Homemaker	107	(4)			
Full Time	1329	(50)	Bicycle Ownership		
Part-Time	177	(7)	0	1051	(39)
Retired	456	(17)	1	417	(16)
Self Employed	47	(2)	2	538	(20)
Student	443	(17)	3	297	(11)
Employed Student	7	(0)	4 and over	376	(14)
Unemployed	113	(4)			

Total Number of Observations	2679

Note: Values in parenthesis are percentages rounded off to the significant digits.

Work to home trips accounted for 63% of total trips followed by home based shopping trips at 14%. Single occupant household constitutes 15% of total extracted dataset. Household with two occupants accounted for 28% and nearly 38% households had 4 or more occupants. Nearly 80 % of the households were single family dwellings while 13% of the household resided in apartments. Rest of the remaining household (7%) resided in duplexes, townhouses and other dwellings.

36-45 years age group represented nearly 22% of all trip makers followed second by 26-35 years age group with 18% of total extracted dataset. Senior citizens constituted third sizeable proportion of at 13%. Only 5% of household did not have any vehicle which suggests auto dominance for Windsor area whereas 39% of sample had no bicycle in household. Regarding the distribution of employment status for the extracted sample, nearly one half of residents had full time employment. Students and retirees accounted for 17% each of the extracted sample with third significant employment status being part time (7%).

3.5 Modeling Approach

3.5.1 Mixed Logit Model Formulation

Development of simulation methods such as simulated maximum likelihood estimation paved the way of estimation of open-form discrete choice models. Mixed Logit model, a highly flexible random utility model allows correlation in unobserved factors over time and is not restricted to Gumbel distribution (Train, 2009). Fast processing computers and sophisticated simulation methods have helped realize the true potential of Mixed Logit model (Train, 2009).

Under the random utility maximization principle, an individual n chooses alternative mode i that provides the greatest utility from a set of feasible discrete alternatives $J = \{1, 2, \ldots, j\}$. Following the work of Train (2009), the utility function of mode i for decision maker n, is specified as follows:

$$\boldsymbol{U}_{ni} = \boldsymbol{V}_{ni} + \boldsymbol{\varepsilon}_{ni} \qquad (3.5.1.1)$$

where $\boldsymbol{V}_{ni}$ is the observed (deterministic) component of the utility, and $\boldsymbol{\varepsilon}_{ni}$ is the unobserved (random) component of the utility. The observed component is known to the researcher and, is typically a linear-in-parameter function that takes the form $\boldsymbol{V}_{ni} = \boldsymbol{\beta}_n \boldsymbol{x}_{ni}$, where $\boldsymbol{\beta}_n$ is a vector of coefficients (β_1, β_2 , …, β_n) of observed variables representing the taste of individual n, and $\boldsymbol{x}_{ni}$ represents observed variables (x_{1i} , x_{2i} , …, x_{ni}) related to the individual and alternative. The random terms account for all those attributes that have not been considered in the deterministic part of the utility. These terms represent model misspecification, unobserved factors and taste variations not controlled for in the estimated utility (Ben-Akiva and Lerman, 1985; Train, 2009; Hensher et al., 2005).

The values of both, observed and unobserved components $\boldsymbol{\beta}_{n,}$ and $\boldsymbol{\varepsilon}_{ni}$ of the utility $\boldsymbol{U}_{ni}$ are known to the individual, choosing the alternative. In contrast, the researcher is only aware of the observed values forming the utility$\boldsymbol{V}_{ni}$. Starting from the assumption that $\boldsymbol{\varepsilon}_{ni}$'s are independently and identically distributed (iid extreme value), the choice probability of alternative *i* conditional on β_n can be formulated to the well-known Multinomial Logit model, that is:

$$P_{ni/\beta_n} = \frac{\exp(V_{ni/\beta_n})}{\sum_j \exp(V_{nj/\beta_n})} \tag{3.5.1.2}$$

Since a coefficients like β_n of a given observed variable represents individual *n*'s taste with respect to that variable, it becomes obvious that each individual n will have a particular conditional probability P_{ni/β_n} that depends on a particular value β_n. Consequently, it is convenient to assume the existence of a range of β_n values (i.e. $\beta_1, \beta_2, \dots, \beta_t$) which correspond to various heterogeneous groups exhibiting taste variation in the population of travelers.

Typically, the analyst cannot observe the actual tastes or heterogeneous groups responsible for the variation in the taste. Instead, he can intuitively specify the probability distribution to which $\beta_1, \beta_2, \dots, \beta_t$ will likely follow. As such, β_n is thought of as a random parameter where the probability of having a particular β_n value can be derived from a known probability density function like $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$, where $\boldsymbol{\Omega}$ is a vector of the parameters characterizing the probability distribution $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$. Using $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$, the probability of each plausible random parameter β_n value can be calculated, that is: $P(\beta_1|\boldsymbol{\Omega})$, $P(\beta_2|\boldsymbol{\Omega})$, …, $P(\beta_t|\boldsymbol{\Omega})$. Consequently, the unconditional choice probability P_{ni} can be thought of as the weighted average of the MNL formula from equation 3.5.1.2 evaluated at different values of β_n, with weights given by the density $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$, that is,

$$P_{ni} = \sum_{n=1}^{t} P_{ni/\beta_n} P(\boldsymbol{\beta}_n|\boldsymbol{\Omega}) \tag{3.5.1.3}$$

The above formulation assumes that the probability density function $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$ is discrete. However, if the probability density $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$ is a continuous function, the unconditional choice probability can be expressed as the integral of P_{ni/β_n} over all possible values of β. Such integral is known in the literature as the Mixed Logit model (MXL) (Train, 2009).

The estimation of the MXL generally involves estimating the mean value μ of $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$, as well as the standard deviation σ. The choice probabilities in the Multinomial Mixed Logit model can now be written as:

$$P_{ni} = \int_{\beta} P_{ni/\beta_n} \; P(\boldsymbol{\beta}|\boldsymbol{\Omega}) d\boldsymbol{\beta} \tag{3.5.1.4}$$

It should be noted that equation 3.5.1.4 would collapse to the conventional MNL if $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$ is equal to 1. That is, β is fixed rather than being random and does not vary across a range of values as described above.

3.5.2 Estimation Technique - Simulated Log Likelihood

Due to its non-closed form, the integral in equation 3.5.1.4 cannot be evaluated analytically. Instead, simulations are performed in which the conditional choice probability P_{ni/β_n} is calculated at various β_n values that are randomly drawn R times from the distribution $P(\boldsymbol{\beta}|\boldsymbol{\Omega})$. Following this treatment, the choice probability P_{ni} is approximated by $\hat{P}_{ni}$ such that:

$$\hat{P}_{ni} = \frac{1}{R}\sum_{r=1}^{R} P_{ni/\beta_r} \tag{3.5.2.1}$$

The resulting simulated choice probability $\hat{P}_{ni}$ is then used to construct simulated log-likelihood (SLL) function:

$$SLL = \sum_n \sum_i y_{ni} \ln(\hat{P}_{ni}) \tag{3.5.2.2}$$

where y_{ni} equals 1, if individual n chooses alterative i, 0 otherwise. The value of $\mathbf{\Omega}$ which maximizes SLL is referred to as maximum simulated likelihood estimator.

3.5.3 Mixed Logit Model Specifications

Appropriate specification of random parameters and their distribution is key to identifying the existence of preference heterogeneity in the sample population (Hensher and Greene, 2003). LOS variables are deemed as prime candidates for random parameters as they vary across individuals and alternatives. Furthermore, the interaction of LOS and different socio-economic variables identifies the covariates, responsible for preference heterogeneity.

Distributions are approximate representation of real behavioral process (Hensher and Greene, 2003). The distribution of selected random parameters can be specified with many functional forms, such as normal, uniform and lognormal. The normal and lognormal forms are commonly used. Lognormal form is useful when the specified parameter needs to be a non-negative whereas a uniform distribution is more suited to represent dummy variables.

The variables listed in *Table 3.1* of section 3.3 are used to specify the utilities of the Logit models estimated in this thesis. With regards to LOS variables (i.e. travel time and travel cost), the a priori expectation is a negative sign indicating a disutility. This implies that an increase in travel time or travel cost for will lower the choice probability even further. With respect age and gender varying preferences for mode choice are reported in the mode choice literature. It is expected that female travelers in general are likely to prefer transit or walk/bicycle more than their male counterparts. Older travelers are less likely to use auto mode. Regarding mobility tools, auto ownership is associated with positive effect on auto mode choice probabilities and a positive and statistically significant coefficient is expected for this parameter. Similarly bicycle ownership should also have a positive effect of walk/bicycle mode choice.

With regard to trips makers' housing or dwellings status, it is likely that travelers from single family (detached housed) from outer suburbs of the city will have higher preference for auto. Hence, a positive coefficient is expected for this parameter in the utility function of auto mode. On other hand, the trip makers living in apartment in inner suburbs of city in apartment dwellings, are likely choose transit

In age and employment effects, the travelers in 26-35 years and 36-45 years age groups having full time employment are likely to have higher preference for auto as auto offers highest travel time reliability, which is an important consideration for travelers with full time jobs. On the other hand travelers who are either student or unemployed will more likely prefer cheaper transportation modes such as transit and walk/bicycle. A positive coefficient is expected for this parameter in the utility functions of transit and walk/bicycle mode.

Generally speaking, more occupants in the household are likely to generate higher auto trips, and hence higher preference for auto mode. A positive coefficient is expected for this parameter in the utility function of auto mode. The specifications and utility functions of estimated MNL and MXL models are provided in Appendix C.

3.6 Modeling Apparatus

NLOGIT 4.0, an extension of LIMDEP (Econometric Software, Inc. 2011), commonly used to specify, estimate and validate discrete choice models was used to develop MNL and MXL mode choice models for passenger travel in the Windsor-Essex area. NLOGIT 4.0 extends the capabilities of LIMDEP, the original discrete choice command. It can estimate up to four- level Nested Logit models as well as state of the art Mixed (random parameter) Logit model. Estimation of mode choice models in NLOGIT follows as distinctive pattern of data structures. Data structure consists of set of multiple observations of each individual incorporating socio-economic and LOS attributes of individual travelers and alternatives.

CHAPTER IV

RESULT AND DISCUSSIONS

4.1 Data Representation-Results

Linear regression models were estimated to check if the work trips mode shares in extracted dataset are representative of mode shares of the 1996 census data. The regression model takes the following form:

$$Y^m_i(Census) = \beta\, Y^m_i\,(WALTS)$$

where $Y^m_i(Census)$ is the share of mode m in census tract i according to the 1996 census data, $Y^m_i\,(WALTS)$ is the share of mode m in census tract i according to the WALTS-197 data and β is a parameter to be estimated.

Theoretically, if the WALTS data is representative of the census data, then the value of β should be equal to 1 for any given mode m. The results of the linear regression models are presented in *Table 4.1*.

Table 4.1 Result of Regression Models

Model No.	Regression Model	β	t-statistics	R^2
1	Auto Mode	0.95	41.37	0.97
2	Transit Mode	0.82	3.26	0.16
3	Walk/Bicycle Mode	0.30	6.01	0.40

The results suggest that auto and transit modes had better representation than the walk/bicycle. However, the model fit (R^2 value) for the transit mode was the lowest among other two modes. Furthermore, the variability in the walk/bicycle mode was higher when compared to transit mode. Over all the results of the regression model indicate acceptable level of data representation. A table containing modes shares percentages for auto, transit and walk/bicycle (at census tract level) for 1996 census and WALTS data is provided in Appendix B (see *Table B-1*). Furthermore, the mode shares of 1996 census and WALTS data, presented in graphical context, are also provided in Appendix B (see *Figure B-5* to *Figure B-10*).

4.2 Descriptive Analysis of Work Trips Dataset

In this thesis, subsets of the dataset extracted from Windsor-Essex household travel survey were used to model mode choice for peak period work, non-work and shopping trips in the Windsor-Essex area in Ontario, Canada. The subsets contained traveler's socio-economic characteristics such as age, sex, employment status, dwelling type and, vehicle and bicycle ownership. Information on the number of trips made by each household, and trip purpose, travel mode, origin and destination for each trip was also recorded. Two motorized travel modes – auto (A), public transit (T) and one non-motorized mode – walk/bicycle (O) were identified to model mode choice.

The work trip subset contains trip records of 812 trip makers returning home from work. *Table 4.2* shows the summary of cross tabulations of socio-economic characteristics and travel modes. The shares of auto, transit and walk/bicycle were 92.8%, 1.5%, and 5.7%, respectively. Male accounted for an approximate 56% of the sample. Travelers in the 26-35 and 36-45 years age groups accounted for nearly 60% of the sample. 84% of the households were single family dwellings while 9% of the travelers resided in apartments. 88% of the travelers had full time employment.

Table 4.2 Statistics of Mode Shares by Socio-economic Factors of the Work Trips Dataset

Socio-economic Characteristics	Mode: Auto		Transit		Walk/Bicycle		Totals	
Gender								
Male	423	(52.09)	6	(0.74)	25	(3.08)	454	(55.91)
Female	331	(40.76)	6	(0.74)	21	(2.59)	358	(44.09)
Total	754	(92.86)	12	(1.48)	46	(5.67)	812	(100.00)
Age								
0 - 15 years	1	(0.12)	0	(0.00)	4	(0.49)	5	(0.62)
16 - 25 years	86	(10.59)	3	(0.37)	8	(0.99)	97	(11.95)
26 -35 years	207	(25.49)	1	(0.12)	16	(1.97)	224	(27.59)
36 - 45 years	243	(29.93)	4	(0.49)	12	(1.48)	259	(31.90)
46 - 55 years	179	(22.04)	2	(0.25)	5	(0.62)	186	(22.91)
56 - 65 years	35	(4.31)	2	(0.25)	1	(0.12)	38	(4.68)
over 65 years	3	(0.37)	0	(0.00)	0	(0.00)	3	(0.37)
Total	754	(92.86)	12	(1.48)	46	(5.67)	812	(100.00)
Dwelling Type								
Apartment	60	(7.39)	0	(0.00)	15	(1.85)	75	(9.24)
Duplex	23	(2.83)	0	(0.00)	3	(0.37)	26	(3.20)
Other	6	(0.74)	0	(0.00)	3	(0.37)	9	(1.11)
Single Family	646	(79.56)	12	(1.48)	24	(2.96)	682	(83.99)
Townhouse	19	(2.34)	0	(0.00)	1	(0.12)	20	(2.46)
Total	754	(92.86)	12	(1.48)	46	(5.67)	812	(100.00)
Employment Status								
Employed Student	1	(0.12)	0	(0.00)	0	(0.00)	1	(0.12)
Full Time	674	(83.00)	8	(0.99)	33	(4.06)	715	(88.05)
Homemaker	3	(0.37)	0	(0.00)	1	(0.12)	4	(0.49)
Part-Time	41	(5.05)	2	(0.25)	5	(0.62)	48	(5.91)
Retired	5	(0.62)	0	(0.00)	0	(0.00)	5	(0.62)
Self Employed	15	(1.85)	0	(0.00)	0	(0.00)	15	(1.85)
Student	12	(1.48)	2	(0.25)	7	(0.86)	21	(2.59)
Unemployed	3	(0.37)	0	(0.00)	0	(0.00)	3	(0.37)
Total	754	(92.86)	12	(1.48)	46	(5.67)	812	(100.00)
Household Size								
1	87	(10.71)	1	(0.12)	15	(1.85)	103	(12.68)
2	190	(23.40)	4	(0.49)	3	(0.37)	197	(24.26)
3	148	(18.23)	1	(0.12)	16	(1.97)	165	(20.32)
4 and over	329	(40.52)	6	(0.74)	12	(1.48)	347	(42.73)
Total	754	(92.86)	12	(1.48)	46	(5.67)	812	(100.00)
Auto Ownership								
0	8	(0.99)	2	(0.25)	11	(1.35)	21	(2.59)
1	222	(27.34)	4	(0.49)	25	(3.08)	251	(30.91)
2	371	(45.69)	5	(0.62)	9	(1.11)	385	(47.41)
3	102	(12.56)	0	(0.00)	1	(0.12)	103	(12.68)
4 and over	51	(6.28)	1	(0.12)	0	(0.00)	52	(6.40)
Total	754	(92.86)	12	(1.48)	46	(5.67)	812	(100.00)

Note: Values in parenthesis are percentages.

Households with two occupants constituted nearly 25% of the sample with 43% of dataset consisted of households with four or more occupants. 97% of households had at least one car. Multiple trips were recorded for households with more than one occupant.

Auto mode shares were the highest among all modes for both male and female - 52% and 41%, respectively. Travelers in age group 36-45 years accounted for 32% (243/754) of total trips by auto mode shares and were the highest among all modes.

Nearly 86% (646/754) of auto users had single family dwelling and 89% (674/754) of auto users had full-time employment. On the other hand, the total walk/bicycle mode share of 5.67% was fairly split between male and female (3.08% and 2.59% respectively). Travelers in age group of 26-35 years of age accounted for nearly 35% (16/46) of total trips by walk/bicycle.

The temporal distribution of work trips by mode is presented in *Figure 4.1*. For the three-hour afternoon peak period, shares of each mode were generally consistent. Highest auto trips were observed during 5:00-5:29 PM in the three hour peak period.

The trip distances for work trips made by the three modes of travel were analyzed. Auto trips had the highest standard deviation (8.30) of trip distance among all modes whereas the standard deviations for transit and walk/bicycle trips were nearly similar (4.34 and 4.14 respectively). The average trips distance by auto, transit and walk/bicycle modes were 10.0 km, 8.5 km and 2.9 km respectively. The statistics of trip distances by different modes are summarized in *Table 4.3*.

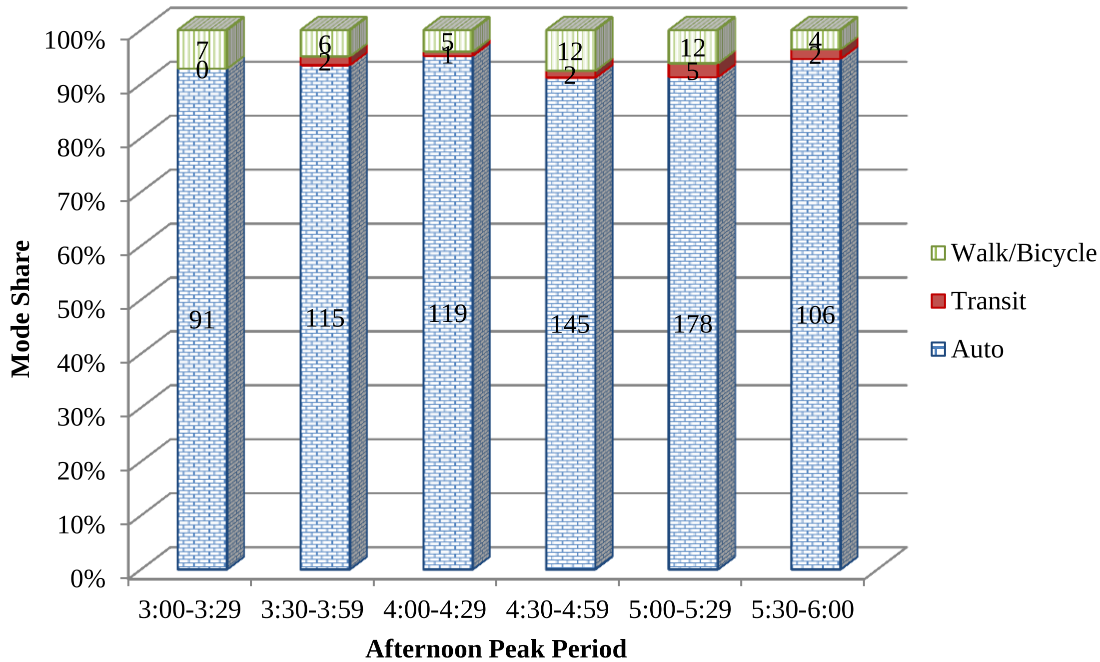


Figure 4.1 Temporal Distribution of Work Trips by Mode.

Note: Values within the stacked bars are the number of trips by respective modes.

Table 4.3 Statistics of Trip Distance (km) by Modes for Work Trips

Measure	Auto	Transit	Walk/Bicycle
Minimum	0.09	2.43	0.17
Maximum	61.45	16.27	21.92
Mean	10.02	8.51	2.91
Standard Deviation	8.30	4.34	4.14
No. of Trips	754	12	46

4.3 Descriptive Analysis of Non Work Trips Dataset

The non work subset contains the trip records of 448 trip makers making home based non-work (shopping, recreational and other) trips.

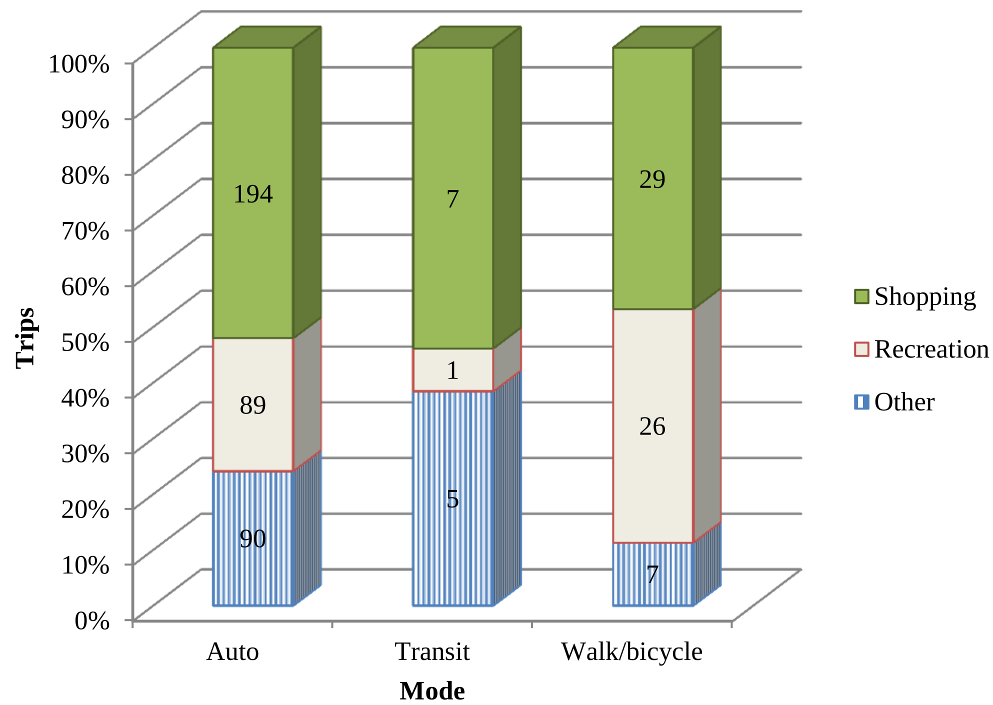


Figure 4.2 Mode Shares of Non Work Trips by Trip Purpose.

Note: Values within the stacked bars are the number of trips by respective modes

Figure 4.2 shows the proportions of shopping, recreational and other trips by three modes of travel. Shopping trips accounted for nearly 51% of total trips while the recreational and other trips had shares of 26% and 23% respectively. Auto was the by far the most favored choice of mode for three trip purposes. Nearly 83% of all non-work trips were made by auto, followed by walk/bicycle at 14%, while the transit accounted for only 3% of total trips.

Table 4.4 shows the summary of cross tabulations of socio-economic characteristics and travel modes for non work trips. Females were in majority and accounted for an approximate 56% of the subset sample. Travelers older than 65 years accounted for nearly 31% of the total subset sample followed by 36 - 45 years age group with 16% and 56 -65 years group with nearly 14% of all travelers. Nearly 76% of the trips makers resided in single family dwellings while approximately 16% of the travelers resided in apartments. About 40% of the travelers were retirees followed second by fulltime employed travelers with 27% share of total sample.

Households with two occupants constituted nearly 38% of the sample with 22% of subset consisted of households with four or more occupants. Nearly 92% of households owned at least one car. Auto mode shares were the highest among all modes for males and females - 36% and 47%, respectively. Nearly 30% (113/373) of auto trips were attributed to travelers over 65 years of age. Nearly 81% (301/373) of auto users lived in single family dwellings and 40 % (148/373) of auto users were retirees. On the other hand, walk/bicycle mode shares for male and female were 6.5% and 7% of total trips respectively. Travelers over 65 years of age accounted for nearly 34% (21/62) of total walk/bicycle trips.

Table 4.4 Statistics of Mode Shares by Socio-economic Factors of Non-work Trips Dataset

Socio-economic Characteristics	Mode Distributions							
	Auto		Transit		Walk/Bicycle		Totals	
Gender								
Male	163	(36.38)	4	(0.89)	30	(6.70)	197	(43.97)
Female	210	(46.88)	9	(2.01)	32	(7.14)	251	(56.03)
Total	373	(83.26)	13	(2.90)	62	(13.84)	448	(100.00)
Age								
0 - 15 years	22	(4.91)	0	(0.00)	6	(1.34)	28	(6.25)
16 - 25 years	34	(7.59)	2	(0.45)	10	(2.23)	46	(10.27)
26 -35 years	52	(11.61)	1	(0.22)	6	(1.34)	59	(13.17)
36 - 45 years	61	(13.62)	1	(0.22)	10	(2.23)	72	(16.07)
46 - 55 years	39	(8.71)	1	(0.22)	3	(0.67)	43	(9.60)
56 - 65 years	52	(11.61)	3	(0.67)	6	(1.34)	61	(13.62)
over 65 years	113	(25.22)	5	(1.12)	21	(4.69)	139	(31.03)
Total	373	(83.26)	13	(2.90)	62	(13.84)	448	(100.00)
Trip Purpose								
Shopping	194	(43.30)	7	(1.56)	29	(6.47)	230	(51.34)
Recreation	89	(19.87)	1	(0.22)	26	(5.80)	116	(25.89)
Other	90	(20.09)	5	(1.12)	7	(1.56)	102	(22.77)
Total	373	(83.26)	13	(2.90)	62	(13.84)	448	(100.00)
Dwelling Type								
Apartment	43	(9.60)	7	(1.56)	21	(4.69)	71	(15.85)
Condo	1	(0.22)	0	(0.00)	0	(0.00)	1	(0.22)
Duplex	11	(2.46)	0	(0.00)	3	(0.67)	14	(3.13)
Triplex	1	(0.22)	0	(0.00)	0	(0.00)	1	(0.22)
Single Family	301	(67.19)	5	(1.12)	35	(7.81)	341	(76.12)
Townhouse	10	(2.23)	1	(0.22)	1	(0.22)	12	(2.68)
Other	6	(1.34)	0	(0.00)	2	(0.45)	8	(1.79)
Total	373	(83.26)	13	(2.90)	62	(13.84)	448	(100.00)
Employment Status								
Employed Student	2	(0.45)	0	(0.00)	0	(0.00)	2	(0.45)
Full Time	113	(25.22)	1	(0.22)	7	(1.56)	121	(27.01)
Homemaker	34	(7.59)	1	(0.22)	1	(0.22)	36	(8.04)
Part-Time	18	(4.02)	0	(0.00)	5	(1.12)	23	(5.13)
Retired	148	(33.04)	5	(1.12)	27	(6.03)	180	(40.18)
Self Employed	8	(1.79)	0	(0.00)	1	(0.22)	9	(2.01)
Student	27	(6.03)	2	(0.45)	10	(2.23)	39	(8.71)
Unemployed	23	(5.13)	4	(0.89)	11	(2.46)	38	(8.48)
Total	373	(83.26)	13	(2.90)	62	(13.84)	448	(100.00)

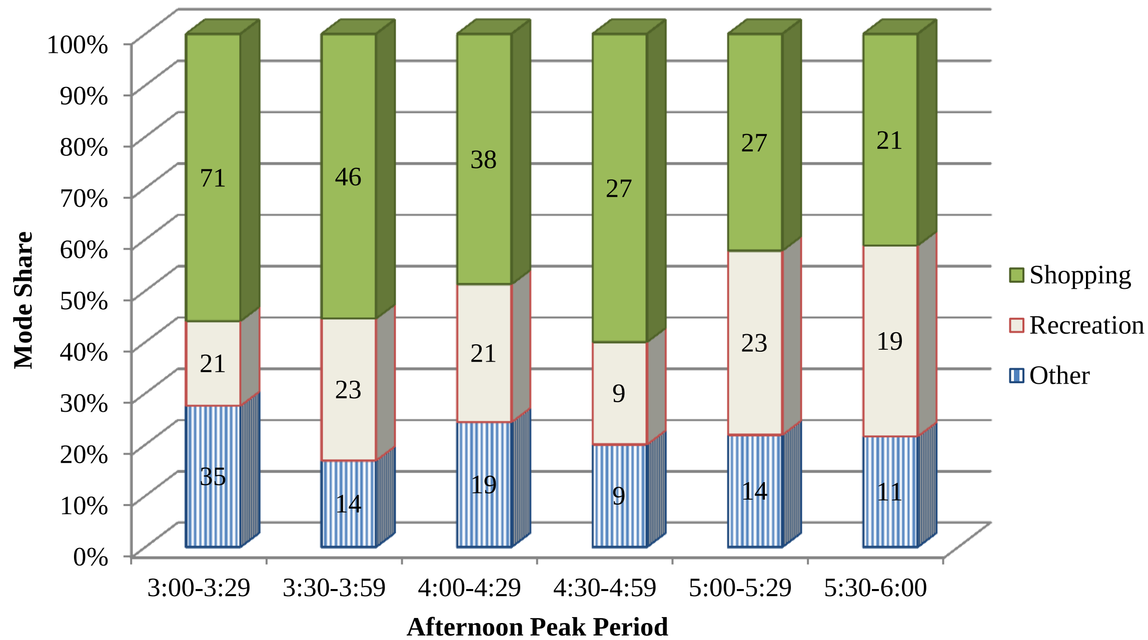
Table 4.4 - Continued

Socio-economic Characteristics	Mode Distributions							
	Auto		Transit		Walk/Bicycle		Totals	
Household Size								
1	59	(13.17)	8	(1.79)	27	(6.03)	94	(20.98)
2	152	(33.93)	2	(0.45)	16	(3.57)	170	(37.95)
3	78	(17.41)	0	(0.00)	8	(1.79)	86	(19.20)
4 and over	84	(18.75)	3	(0.67)	11	(2.46)	98	(21.88)
Total	373	(83.26)	13	(2.90)	62	(13.84)	448	(100.00)
Auto Ownership								
0	5	(1.12)	9	(2.01)	22	(4.91)	36	(8.04)
1	171	(38.17)	2	(0.45)	29	(6.47)	202	(45.09)
2	158	(35.27)	2	(0.45)	11	(2.46)	171	(38.17)
3	31	(6.92)	0	(0.00)	0	(0.00)	31	(6.92)
4 and over	8	(1.79)	0	(0.00)	0	(0.00)	8	(1.79)
Total	373	(83.26)	13	(2.90)	62	(13.84)	448	(100.00)

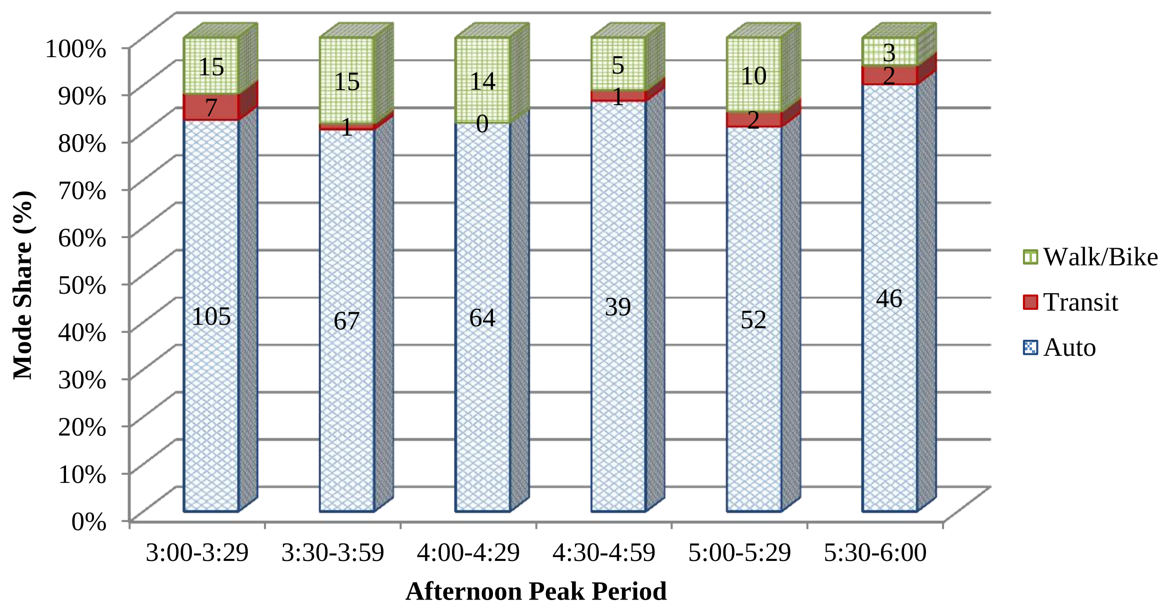
Note: Values in parenthesis are percentages.

The temporal distribution of non-work trips by purpose is presented in *Figure 4.3(a)*. Highest trips (28%) were observed in the first half hour of peak period. Nearly 47% of all non-work trips were made in the first half of peak period i.e from 3:00 pm to 4:29 PM.

The temporal distribution of non-work trips by mode is presented in *Figure 4.3(b)*. Highest auto trips were made in the first half hour of peak period. For the remaining afternoon peak period, shares of auto trips show a gradual decline. Apart from the first half hour of peak period, the shares of transit and walk/bicycle trips were generally consistent for the rest of peak period.



(a)



(b)

Figure 4.3 Temporal Distributions of Non Work Trips by (a) Trip purpose (b) Mode

Note: Values within the stacked bars are the number of trips by respective modes

The statistics of non work trip distances by the three modes are summarized in *Table 4.5* As observed in the case of work trips, for non work trips, auto mode had the highest standard deviation (7.84) of trip distance among all modes whereas the standard deviations for trips made by transit and walk/bicycle modes were 4.86 and 4.48 respectively. The average trips distance by auto, transit and walk/bicycle modes were 7.84 km, 8.87 km and 2.76 km respectively.

Table 4.5 Statistics of Trip Distance (km) by Modes for Non Work Trips

Measure	Auto	Transit	Walk/Bicycle
Minimum	0.05	1.47	0.01
Maximum	62.14	13.12	21.67
Mean	7.85	8.88	2.76
Standard Deviation	8.11	3.86	4.27
No. of Trips	373	13	62

4.4 Model Estimation for Work Trips

4.4.1 Results - Multinomial Logit Model

The results pertaining to the MNL model in *Table 4.6* indicate that travel time, travel cost, automobile ownership, full-time employment and dwelling type are statistically significant. A positive alternative-specific constant for walk/bicycle mode ($ASC_{walk/bic}$) suggests travelers' general preference for walking/bicycling, other things being equal. Only one constant was used in the model as no other constants were statistically significant. The estimated model is also well behaved with a ρ^2 value of 0.33. The coefficients of the LOS variables (travel time and travel cost) for motorized travel modes (auto and transit) are negative as expected. Likewise, the coefficient of travel time for non-motorized travel mode (walk/bicycle) is also negative and noticeably significant.

Auto ownership emerged as a significant factor for choosing the auto mode to commute. A higher number of automobiles in the household will increase the propensity of choosing the car. Similarly, more bikes in the household increases the propensity of choosing walk/bicycle as the preferred mode for transportation. Fulltime employees value travel time reliability and as such are more likely to choose auto over other modes of transportation. Furthermore, no age-related variables were found to be statistically significant in the MNL model. This result suggests that age is not a dominant predictor of mode choice for work trips in the study area.

Travelers living in a single family dwelling are more likely to also use auto and transit. This could be because a disproportional number of single family dwellings in Windsor are located in the inner and outer suburbs. Given the large spatial extent of Windsor and the sprawling nature of its residential land use, workers living in the suburbs will be more prone to choosing auto to commute especially given that the transit service does not cover suburban areas. On the other hand, workers living in the inner suburbs might choose transit or drive to/from work. Furthermore, the results suggest that students are more likely to travel by transit. This is likely because many students have low income and potentially do not own vehicles. Also travel cost for transit is cheaper. Likewise, the model shows that students are more likely to travel by walk/bicycle to work.

Table 4.6 Estimated Parameters of MNL and MXL Models for Work Trips

Variable	Utility Functions	MNL Value	MNL (t-stat)	MXL Value	MXL (t-stat)
Non-Random Parameters					
$ASC_{walk/bic}$	*O*	2.208	(3.56)	3.717	(4.42)
β_{ttnm}	*O*	-0.079	(-3.97)	–	–
β_{ttm}	*A,T*	-0.141	(-1.80)	-0.172	(-1.83)
β_{trc}	*A,T*	-0.994	(-2.12)	-1.169	(-2.08)
β_{nveh}	*A*	1.679	(5.91)	1.831	(5.79)
β_{nbic}	*O*	0.352	(2.88)	0.356	(2.44)
β_{fltemp}	*A*	0.965	(2.14)	1.033	(2.01)
β_{sfam_A}	*A*	1.083	(2.65)	1.704	(3.28)
β_{sfam_T}	*T*	2.751	(2.42)	4.062	(2.80)
β_{studn_T}	*T*	2.867	(2.95)	2.964	(2.95)
β_{studnt_O}	*O*	1.994	(2.48)	1.385	(1.23)*
Random Parameter (Normally Distributed)					
μ_{ttnm}	*O*	–		-0.161	(-4.28)
Heterogeneity in mean, Parameter: Variable					
$\gamma_{ttnm:age1}$		–		0.130	(2.43)
$\lambda_{ttnm:femsfam}$		–		0.032	(2.35)
Derived standard deviation of parameter distributions					
σ_{ttnm}		–		0.043	(3.19)
Number of observations		812		812	
Number of explanatory variables		11		14	
Log-likelihood at convergence		-160.43		-147.62	
Log-likelihood at $\beta=0$		-238.51		-238.51	
Log-likelihood ratio index (ρ^2)		0.33		0.38	

Note: All parameters are significant at 10 % significance level, *A*: Auto, *T*: Transit, *O*: Walk/Bicycle, * : Not significant at 10% significance level

4.4.2 Results - Mixed Logit Model

As shown in *Table 4.6*, with the exception for the variable representing students using non-motorized mode of travel (i.e. β_{studnt_O}), the results of the MXL model are consistent with those reported for the MNL model in terms of expected signs and statistical significance. The different LOS variables were specified as random parameters to identify variation in taste with respect to these variables. The random parameters were estimated from the modeled population over a number of draws (Halton sequences) with 20 replications. These parameters are termed as unconditional random parameters as they are not conditioned on any individual choice level, but rather on the sample population as a whole (Hensher at al., 2005). The analysis suggests variation in taste in only the travel time for the non-motorized mode. The mean of the estimated random parameter for this LOS variable, μ_{ttnm}, is negative and statistically significant. The coefficient of the derived standard deviation of the parameter distribution, σ_{ttnm}, is also statistically significant, suggesting the presence of heterogeneity among the modeled travelers. This implies that travelers' preference towards travel time by non-motorized mode varies among different socio-economic subgroups. The decomposition of heterogeneity represented by its mean and standard deviation is depicted in *Figure 4.4.*

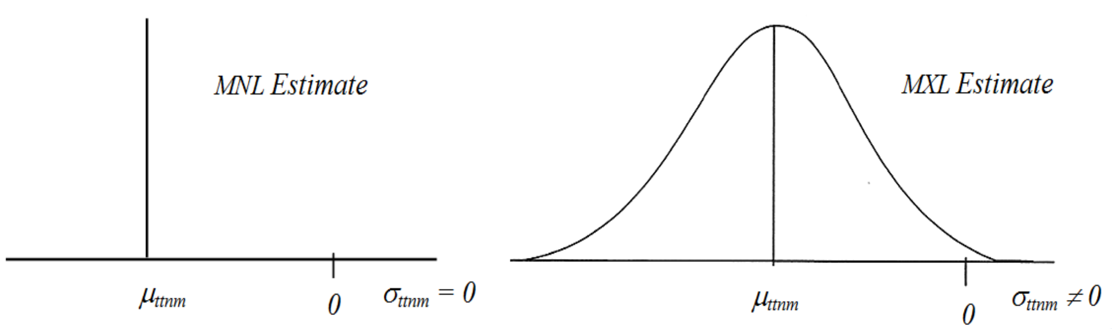


Figure 4.4 Preference Heterogeneity in tt_{nm} Parameter

In order to identify the source of this heterogeneity, the interaction between various socio-economic attributes with the random parameter was investigated. In the final model specifications, age and gender were sensitive to travel time for non-motorized modes. The positive coefficient for the interaction between *ttnm* and *age1* suggests that travelers with age less than 16 years have stronger preference of choosing walk/bicycle mode than the other age groups. Similarly, female travelers living in single family dwellings *(femsfam)* show a stronger preference to non-motorized modes as indicated by the positive coefficient $\lambda_{ttnm:femsfam}$. An explanation of the heterogeneity results maybe that these socio-economic groups prefer short-distance work trips (i.e. they prefer working closer to their houses) which makes it possible for them to walk or bike to work. Another explanation could be that some of these workers are less likely to afford driving auto or taking transit compared to the other socio-economic groups.

Overall, the MXL model provides a better model fit ($\rho^2 = 0.38$) than MNL model as it is able to capture the heterogeneity of travelers' preferences.

Model Predictions for Work Trips

Accuracy of model estimation was evaluated by comparing predicted and observed mode choices as shown in *Table 4.7*. The diagonal values represent the number of correct predictions of mode choices by the model. The percentage of correct prediction of auto mode (95%) was higher than transit (8%) and walk/bicycle mode (43%). This is potentially due to lower observations of trips by transit and walk/bicycle modes in the dataset. The overall percentage of correct predictions was 91%.

Table 4.7 MXL Model Predictions for Work Trips

Mode	Predicted Mode Choices			Observed Mode Choices		
	Auto	Transit	Walk/Bicycle	Auto	Transit	Walk/Bicycle
Auto	717 (95)	11	26	754 (100)	0	0
Transit	10	1 (8)	1	0	12 (100)	0
Walk/Bicycle	25	1	20 (43)	0	0	46 (100)

Note: The numbers in parenthesis are percentages.

4.5 Sensitivity Analysis of Work Trips Mode Choice

4.5.1 Direct and Cross Elasticities of LOS Variables

Understanding and quantifying the response to changes in attributes of alternatives has practical use in mode choice modeling. Logit choice probabilities are function of the values of the attributes that define the utility of the alternatives and have the capability of reflecting the response to changes in attributes of alternatives (Koppelman and Bhat, 2006). Often it is desired to know the likely gain in the choice probability of an alternative in response to a policy action (such as decreased fare/increased frequency). In the context of Logit models, Direct Elasticity, $\eta_D{}^{P_i}_{X_{in}}$, is expressed as change in choice probability (the response variable) of alternative *i* for unit changes in the value of attributes (the explanatory variable) of that particular alternative (Koppelman and Bhat, 2006).

$$\eta_D{}^{P_i}_{X_{in}} = \beta_n X_{in}(1 - P_i)$$

where, β_n = parameter value, for the attribute in the utility; X_{in} = the attribute level at which the elasticity is being computed; P_i= choice probability of an alternative *i.*

Whereas Cross Elasticity, $\eta_C {}^{P_k}_{X_{in}}$, is expressed as change in choice probability (the response variable) of an alternative k for unit changes in the value of attributes (the explanatory variable) associated with other alternative *i* (Koppelman and Bhat, 2006).

$$\eta_C {}^{P_k}_{X_{in}} = \beta_n X_{in}(P_i)$$

where, P_k = choice probability of an alternative *k.*

Sensitivities of mode choice to different variables were analyzed based on elasticities of the mode choices predicted by the MXL model. Aggregate direct and cross elasticities of travel time and cost for the three modes are presented in *Table 4.8*. Due to their small magnitudes, the elasticities were multiplied by 100. The values represent averages of 812 observed individual mode choices.

Table 4.8 Aggregate Direct Elasticities of LOS variables for Work Trips

	Aggregate Direct Elasticity	
Mode	Travel time	Travel cost
Auto	-0.05	-0.05
Transit	-2.78	-3.20
Walk/Bicycle	-5.15	□

Table 4.9 Aggregate Cross Elasticities of LOS variables for Work Trips

Mode	Aggregate Cross Elasticity				
	Travel time			Travel cost	
	Auto	Transit	Walk/Bicycle	Auto	Transit
Auto	–	0.42	0.10	–	0.05
Transit	1.58	–	0.10	1.60	–
Walk/Bicycle	1.41	0.03	–	1.40	0.04

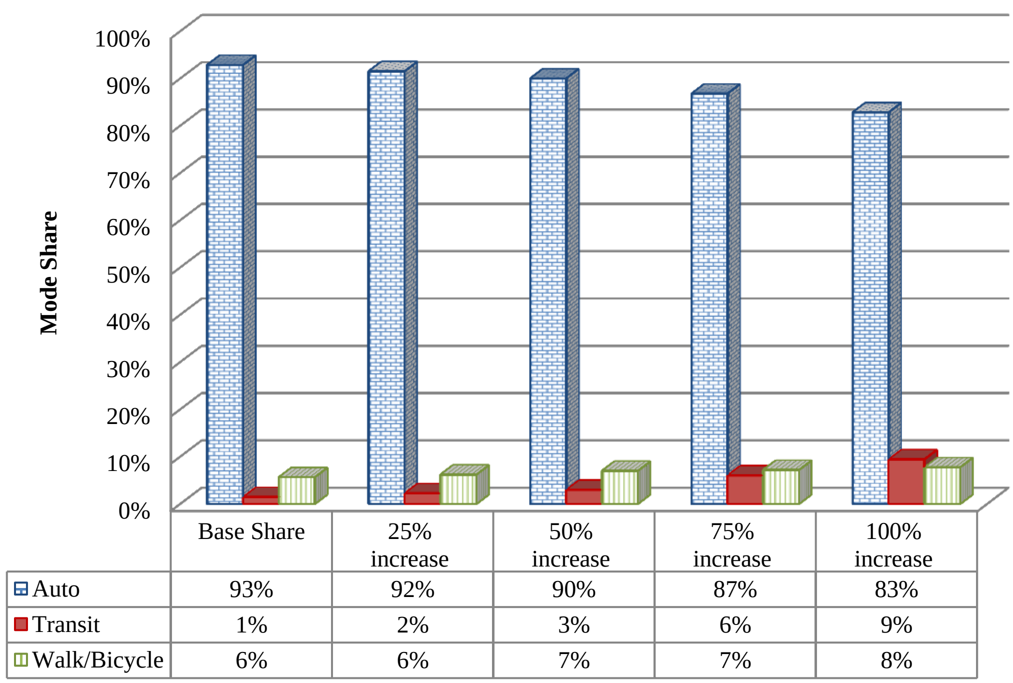
The direct elasticities of mode choice to travel time and travel cost were the lowest for auto among the three modes as shown in *Table 4.8*. This shows that auto users are less sensitive to travel time and travel cost than users who travel by transit and walk/bicycle. On the other hand, the cross elasticities of mode choice to travel time and cost by auto were higher for transit and walk/bicycle as indicated in *Table 4.9*. This implies that the people who travel by transit and walk/bicycle perceive auto as a more competitive mode than non-auto modes (i.e. transit or walk/bicycle) and their mode choice is more sensitive to attributes of auto.

4.5.2 Model Simulations for Work Trips

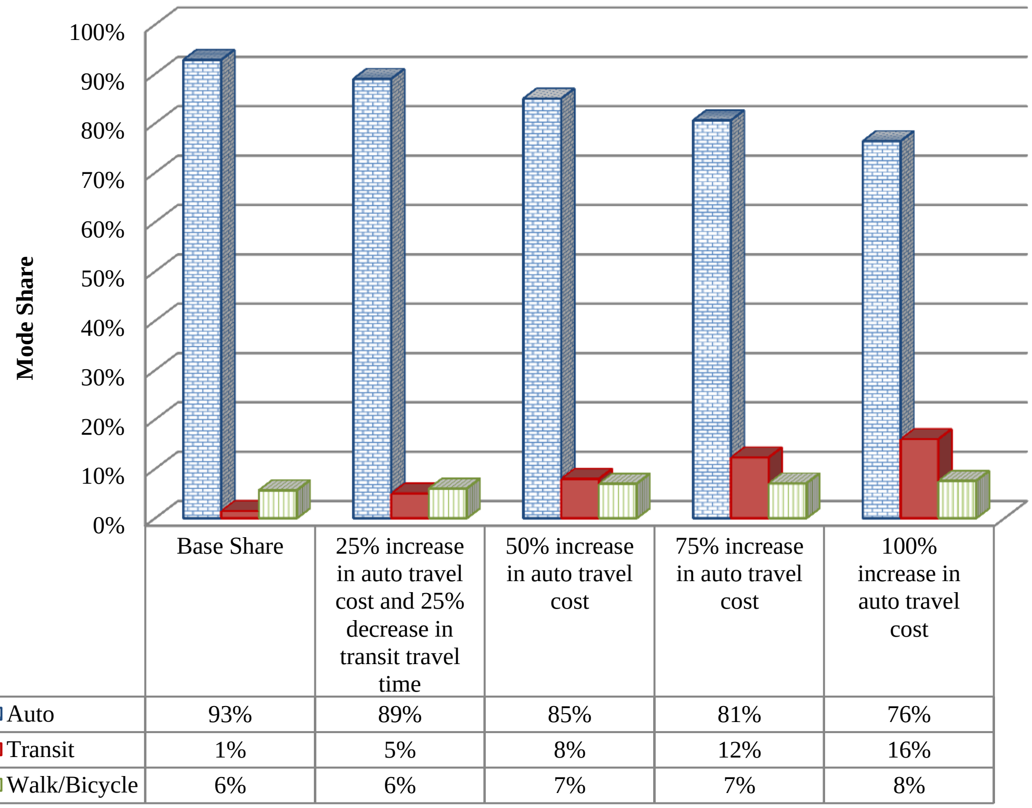
Model simulation (what-if-analysis) is another powerful tool offered by NLOGIT. The simulators of NLOGIT are used to re-compute the mode shares under the effects of change in attributes on the choice probability. NLOGIT allows the analysis of model elasticities through simulation of simple and compound scenario.

The scenarios are used to quantify traveler's response to specific mode choice when a particular attribute is changed in a specified way. In essence, these simulations help to analyze the effect of policy measures on mode choice probabilities

Various LOS scenarios were created to quantify traveler's response to choice of specific mode when a particular attribute was increased or decreased. In the simple scenario, sensitivity of mode shares to the travel cost for auto was examined. According to *Figure 4.5 (a)*, as the travel cost for auto was increased in the increments of 25%, 50%, 75% and 100%, auto mode share was decreased by 1%, 3%, 6% and 10%, respectively. A 100% increase in travel cost for auto mode resulted in a gain of 8% and 2% in mode shares by transit and walk/bicycle modes, respectively.



(a)



(b)

Figure 4.5 Predicted Mode Shares in the (a) Simple and (b) Compound Scenarios.

In the compound scenario, sensitivity of mode shares to the travel cost for auto and the travel time for transit was examined. According to *Figure 4.5 (b),* as the travel cost for auto was increased in increments of 25%, 50%, 75% and 100% and the travel time for transit was reduced by 25%, auto mode share was decreased by 4%, 8%, 12% and 17%, respectively. A 100% increase in auto travel cost with 25% reduction in transit travel time resulted in a gain of 15% and 2% in mode shares by transit and walk/bicycle mode, respectively.

4.6 Model Estimation for Non Work Trips

4.6.1 Results - Multinomial Logit Model

Table 4.10 presents results of estimated MNL and MXL models for non-work trips. In the results pertaining to the MNL model, the coefficient of the travel time for motorized travel modes, β_{ttm} (auto and transit) is of expected negative sign but statistically insignificant, whereas for non-motorized mode (walk/bicycle), the coefficient of travel time, β_{ttnm} is noticeably significant and of expected negative sign as well. This suggests that travel time reliability for motorized modes (auto and public transit), is not an important consideration in mode choice decisions for non-work trips in the study area. The coefficient of travel cost for the motorized travel modes, β_{trc} is statistically significant and of negative sign as expected.

The coefficients of travelers' mobility status, β_{nveh} (automobile ownership), employment status β_{fltemp}, β_{hmkr} (full-time, home-maker) and dwelling type β_{dwlapt} (apartment dwelling) are statistically significant. The results pertaining to these socio-economic indicators are intuitive and plausible. Auto ownership has always been deemed as a significant factor for choosing the auto mode to commute. A higher number of automobiles in the household will increase the propensity of making non-work trips. Fulltime employees are generally concerned with travel time reliability and as such are more likely to choose auto over other modes of transportation. A negative coefficient of home-maker variable for transit mode can be attributed to the fact that the travelers with home-maker status are more committed to fulfilling family obligations and are likely to have travel time constraints, thereby demonstrating their lower preference for transit mode.

Table 4.10 Estimated Parameters of MNL and MXL Models for Non Work Trips

Variable	Utility Functions	MNL Value	MNL (t-stat)	MXL Value	MXL (t-stat)
$ASC_{walk/bic}$	*O*	1.912	(4.46)	4.443	(4.62)
β_{ttnm}	*O*	-0.045	(-4.08)	–	–
β_{ttm}	*A,T*	-0.044	(-1.22)*	-0.012	(-0.30)*
β_{trc}	*A,T*	-0.616	(-2.50)	-0.446	(-1.66)
β_{nveh}	*A*	1.813	(6.53)	2.541	(5.85)
β_{hmkr}	*O*	-1.993	(-1.85)	-2.461	(-1.89)
β_{fltemp}	*A*	0.834	(1.91)	0.575	(0.97)*
β_{studnt}	*T*	1.227	(1.48)*	2.001	(2.14)
β_{dwlapt}	*T*	1.409	(2.29)	1.489	(2.23)
β_{tpshop}	*A*	0.708	(2.28)	0.823	(1.91)
Random Parameter (Normally Distributed)					
μ_{ttnm}	*O*		–	-0.21	(-3.11)
Heterogeneity in mean, Parameter: Variable					
$\gamma_{ttnm:unemp}$			–	0.094	(2.78)
$\lambda_{ttnm:studnt\_ag12}$			–	0.116	(2.60)
Derived standard deviations of parameter distributions					
σ_{ttnm}				0.110	(2.63)
Number of observations		448		448	
No. of explanatory Variables		10		13	
Log-likelihood at convergence		-167.88		-146.29	
Log-likelihood at $\beta=0$		-236.97		-236.97	
Log-likelihood ratio index (ρ^2)		0.29		0.38	

Note: All parameters are significant at 10 % significance level, *A*: Auto, *T*: Transit, *O*: Walk/Bicycle, * : Not significant at 10% significance level

Travelers living in apartments dwelling are more likely to also use transit than any other mode. This could be because most of these dwellings in Windsor are located in the inner suburbs and have immediate access to transit. A positive coefficient of *tpshop* variable for auto mode indicates travelers' preference for the particular mode, when the trip is made specifically for shopping purpose.

The findings suggest that travelers' mobility and employment status, dwelling type and trip purpose are the key predicator of mode choice for non-work trips in the study area. ρ^2 value reflects the quality of the estimated Logit model. A ρ^2 value of 0.29 implies that the estimated MNL model provides satisfactory data fit.

4.6.2 Results - Mixed Logit Model

As shown in *Table 4.10,* with the exception of estimates of β_{fltemp} and β_{studnt} for auto and transit modes respectively, the results of the MXL model for non-work trips are generally consistent (in terms of expected signs and statistical significance) with those reported for the MNL model. The coefficient of travel cost for auto and transit modes is marginally insignificant. This result is justifiable as travelers are often perceived to trade-off travel cost with trip purpose when it comes to non-work travel such as shopping and recreational trips.

Travel time for non-motorized mode was specified as random parameter to identify preference heterogeneity in taste for different population subgroups. The random parameter was estimated from the modeled population over a number of draws (*Halton Sequences*) with 15 replications. The analysis suggests variation in taste in the travel time for the non-motorized walk/bicycle mode. The mean of the estimated random parameter (for non-motorized travel time), μ_{ttnm}, is negative and statistically significant. The coefficient of the derived standard deviation of the parameter distribution, σ_{ttnm}, is also statistically significant, suggesting the presence of heterogeneity among the modeled travelers. This implies that travelers' preference towards travel time by non-motorized mode varies among different socio-economic subgroups.

In order to identify the source of this preference heterogeneity, the interaction between various socio-economic attributes with the random parameter was investigated. In the final model specifications, employment status and age proved sensitive to travel time for non-motorized modes. The positive coefficient of the interaction term *ttnm* and *unemp* suggests that travelers with no employment are less sensitive to travel time for walk/bicycle mode than other socio-economic subgroups. Similarly, students with age less than 26 years *(studnt_ag12)* demonstrate a stronger preference towards non-motorized modes as indicated by the positive coefficient of $\lambda_{ttnm:studnt\_ag12}$. As evident from the results, the of MXL model provide a much richer interpretation of influence of LOS and socio-economic variables on mode choice for population subgroups. Overall, the MXL model provides a better model fit (ρ^2 = 0.38) than MNL model as it is able to capture the heterogeneity of travelers' preferences.

Model Predictions for Non Work Trips

Accuracy of parameters estimates of MXL model for non-work trips was evaluated by comparing predicted and observed mode shares as shown in *Figure 4.6*. The percentage of correct predictions of auto mode (89%) was higher than transit (23%) and walk/bicycle mode (48%). This is potentially due to lower observations of trips by transit and walk/bicycle modes in the dataset. The overall percentage of correct predictions was 81.5%.

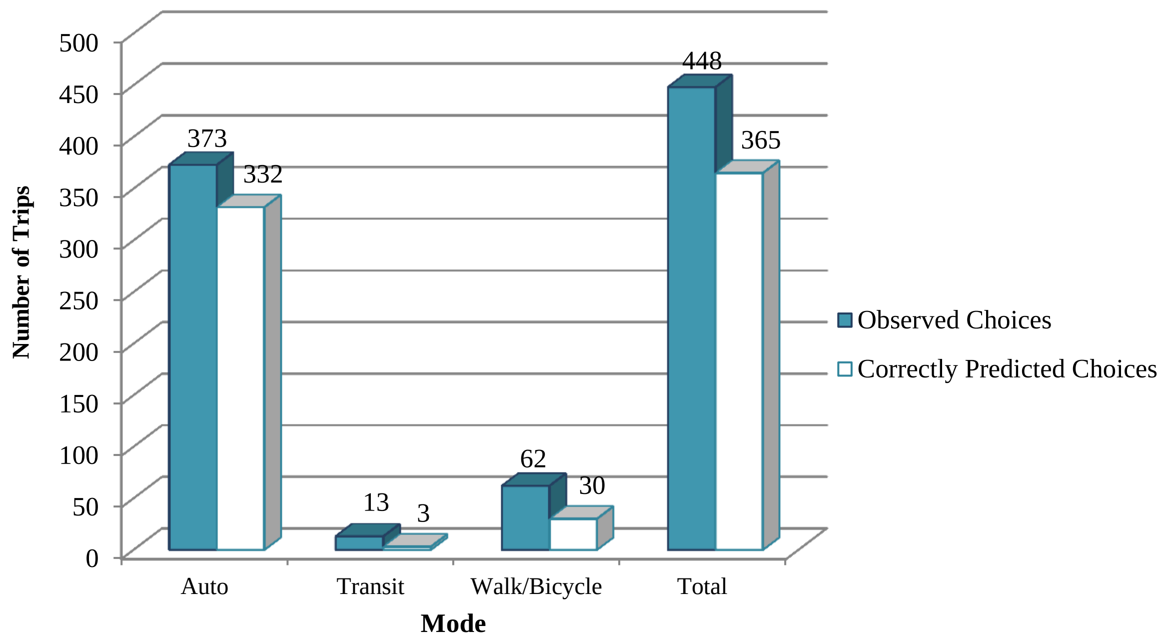


Figure 4.6 MXL Model Predictions for Non Work Trips

<u>4.7 Sensitivity Analysis of Non Work Trips Mode Choice</u>

Sensitivities of mode choice to different variables were analyzed based on elasticities of the mode choices predicted by the MXL model for non work trips.

4.7.1 Direct and Cross Elasticities of LOS and Socio-economic variables.

Aggregate direct and cross elasticities of LOS variables for the three modes of travel are presented in *Table 4.11* and *Table 4.12*. Due to their small magnitudes, the elasticities were multiplied by 100. The values represent averages of 448 observed individual mode choices.

Table 4.11 Aggregate Direct Elasticities of LOS Variables for Non Work Trips

Mode	Aggregate Direct Elasticity	
	Travel time	Travel cost
Auto	-0.006	-0.030
Transit	-0.144	-1.184
Walk/Bicycle	-1.360	□

Table 4.12 Aggregate Cross Elasticities of LOS Variables for Non Work Trips

Mode	Aggregate Cross Elasticity				
	Travel time			Travel cost	
	Auto	Transit	Walk/Bicycle	Auto	Transit
Auto	–	0.006	0.145	–	0.042
Transit	0.079	–	0.145	0.434	–
Walk/Bicycle	0.042	0.003	–	–	–

The direct elasticities of mode choice to travel time and travel cost for auto mode were the lowest among the three modes as shown in *Table 4.11*. This shows that auto users are less sensitive to travel time and travel cost than people who travel by transit and walk/bicycle.

On the other hand, the cross elasticities of mode choice to travel time by walk/bicycle were higher for auto and transit as shown in *Table 4.12.* This implies that the people who travel by motorized modes perceive walk/bicycle as a more competitive mode than the other motorized mode (i.e. auto or transit) and their mode choice is sensitive to attributes of walk/bicycle.

Aggregate direct and cross elasticities of LOS variables for the three modes of travel are presented in *Table 4.13* and *Table 4.14.* The direct elasticities of mode choice to vehicle

Table 4.13 Aggregate Direct Elasticities of Socio-economic Variables for Non Work Trips

Change in Socio-economic Attributes	Aggregate Direct Elasticity		
	Auto	Transit	Walk/Bicycle
Auto Ownership	0.252	–	–
Apartment Dwellings	–	0.208	–

Table 4.14 Aggregate Cross Elasticities of Socio-economic Variables for Non Work Trips

Change in Socio-economic Attributes	Aggregate Cross Elasticity		
	Auto	Transit	Walk/Bicycle
Auto Ownership	–	-3.554	-2.321
Apartment Dwellings	-0.029	–	-0.012

ownership and apartment dwellings are reasonably high as indicated in *Table 4.13* suggesting their potential impact in residential intensification process. As shown in *Table 4.14*, the cross elasticities of auto ownership by auto mode for transit and walk/bicycle are significantly higher. This indicates that vehicle ownership in the study area is strongly correlated with auto mode choice.

4.7.2 Model Simulations for Non Work Trips

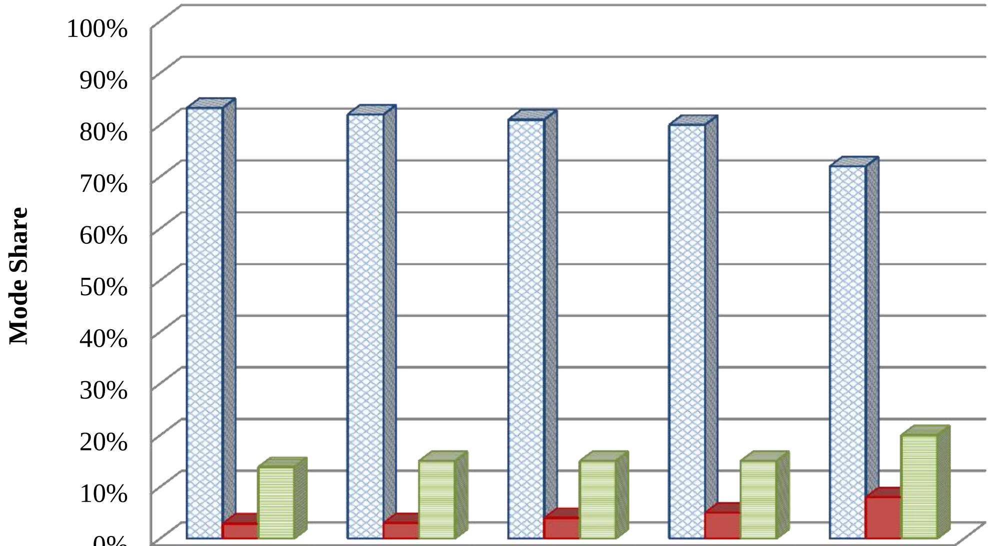
NLOGIT allows the analysis of model elasticities through simulation of scenarios accommodating various LOS initiatives. These simulations help to analyze the effect of policy measures on mode choice probabilities. Various scenarios were tested to quantify traveler's response to choice of specific mode when particular attributes were increased or decreased. The results are presented in *Figure 4.7*. In scenarios 1 and 2, sensitivity of mode shares to the travel cost for auto and the travel time for transit was examined.

In scenario-1 the travel cost for auto was increased by 25%. In scenario 2, the travel cost for auto was increased by 25% and travel time for transit was decreased by 10%. No appreciable mode share changes were observed in both scenarios.

In scenario-3, travel time for transit was decreased by 10% and a 25% growth of residential dwellings was assumed. The measures resulted in auto mode share reduction of 3% and subsequent gains of 2% and 1% for transit and walk/bicycle.

In scenario-4, travel cost of auto was increased by 25%, travel time for transit and walk/bicycle was decreased by 10% and 5% respectively. Furthermore a simultaneous 2.5% reduction in auto ownership and a 25% growth in apartment dwellings were also assumed for the same scenario.

The combined effect of these LOS and residential intensification initiatives in scenario-4, demonstrated significant reduction in mode share of auto (11%) and increase in mode shares of transit (5%) and walk/bicycle (6%).



	Base Share	Scenario-1	Scenario-2	Scenario-3	Scenario-4
Auto	83%	82%	81%	80%	72%
Transit	3%	3%	4%	5%	8%
Walk/Bicycle	14%	15%	15%	15%	20%

Figure 4.7 Predicted Mode Shares for Non Work Trips under Various Scenarios

<u>4.8 Model Estimation for Shopping Trips</u>

Shopping trips constituted more than 50% of the total non work trips. A separate MXL model for shopping trips was estimated to investigate the mode choice behavior of travelers for this specific trip purpose.

4.8.1 Results - Mixed Logit Model for Shopping Trips

The results of estimated MXL model are presented in *Table 4.15*. Estimates for LOS variables, i.e. travel time and travel cost for motorized modes (auto and transit) are of expected negative sign but statistically insignificant. Parameter estimates for vehicle ownership and employment status ($\beta_{nveh,}$ β_{studnt}) are intuitive and consistent with the findings of MXL model for non-work trips. The positive coefficients of variable *hsize_T* *and hsize_O* (household size) for transit and walk/bicycle suggest that households with higher number of persons are conducive to making more transit and walk/bicycle shopping trips as oppose to auto shopping trips. This unique finding is specific to the study area and can be explained by the relatively lower proportion (21%) of auto mode share for households with four or more persons.

The estimates of random parameter *ttnm*, of non-motorized travel time, μ_{ttnm} and σ_{ttnm}, are of expected sign and are statistically significant. The LOS results indicate that choice of motorized modes (i.e. auto and transit) for shopping trips is not governed by LOS variables (travel time and travel cost) and preference heterogeneity exists among the modeled travelers in the study area.

The source of preference heterogeneity in non-motorized travel time was traced back to age, employment and dwelling status. The negative coefficient of the interaction term *ttnm and fltemp* suggests that travelers with full time employment have lower preference of choosing walk/bicycle mode than traveler in the other socio-economic subgroups. An explanation of this behavior maybe that trips makers with this specific attribute, are more likely to afford automobiles, which makes it possible for them use auto as a favored mode of transport for making shopping trips. On the other hand the positive coefficient for the interaction between *ttnm and age4sfam* implies that travelers age 36-45 years residing in single family dwellings are less sensitive to non-motorized travel time and show a stronger preference of choosing walk/bicycle mode than the other age groups with any other dwelling status.

Table 4.15 Estimated Parameters of MXL Models for Shopping Trips

Variable	Utility Functions	MXL	
		Value	(t-stat)
$ASC_{walk/bic}$	*O*	7.861	(3.30)
β_{ttnm}	*O*	–	–
β_{ttm}	*A,T*	-0.049	(-0.48)*
β_{trc}	*A,T*	-0.679	(-1.19)*
β_{nveh}	*A*	5.536	(3.94)
β_{dwlapt}	*T*	1.986	(1.51)*
β_{hsize_T}	*T*	0.926	(1.96)
β_{hsize_O}	*O*	0.997	(1.74)
$\beta_{fspouse}$	*A*	4.717	(2.26)
β_{studnt}	*O*	5.186	(1.80)
Random Parameter (Normally Distributed)			
μ_{ttnm}	*O*	-0.845	(-2.54)
Heterogeneity in mean, Parameter: Variable			
$\lambda_{ttnm:fltemp}$		-0.235	(-1.70)
$\gamma_{ttnm:age4sfam}$		0.218	(1.65)
Derived standard deviations of parameter distributions			
σ_{ttnm}		0.451	(2.47)
Number of observations		230	
No. of explanatory Variables		13	
Log-likelihood at convergence		-57.53	
Log-likelihood at $\beta=0$		-117.52	
Log-likelihood ratio index (ρ^2)		0.51	

Note: All parameters are significant at 10 % significance level, *A*: Auto, *T*: Transit, *O*: Walk/Bicycle, * : Not significant at 10% significance level

A spatial analysis of trip origins of this particular socio-economic group indicates that travelers are located mostly in the inner suburbs of city and are likely to prefer walk or use bicycle for going to shopping places that are in close proximity to their dwellings. The estimated MXL mode has a ρ^2 value of 0.51 which indicates excellent data fit.

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

This thesis presents the findings from the research conducted to model the mode choice behavior of passenger travel in the Windsor-Essex area, with a focus on investigating preference heterogeneity in the mode choice.

State of the art random parameter Mixed Logit approach was used to model the travel behavior. The dataset for model estimation was extracted from the Windsor-Essex household survey conducted in 1997. Level-of-service (LOS) variables, household income and entropy index variable, for the study area were calculated from external sources. Passenger travel was categorized mainly into two categories, work and non-work. The following objectives have been accomplished by this thesis:

1. Investigate the socio-economic characteristics and LOS variables influencing travelers' mode choice in the Windsor-Essex area;
2. Investigate the existence of preference heterogeneity in mode choice for work and non-work trips;
3. Utilize the extended capabilities of Mixed Logit to estimate mode choice models for work and non-work related travel;
4. Gain in-depth understanding of the behavioral process of traveler's mode choice for work and non-work trips;
5. Evaluate the impacts of different policy initiatives on the mode choice probabilities.

Findings from work and non-work MXL models are summarized in the next section. The last two sections highlight the contributions of this thesis and recommendations for future research.

5.1 Summary of Findings

5.1.1 Work Trips

This thesis analyzed mode choice of work trips for the Windsor-Essex area in Ontario, Canada using Multinomial and Mixed Logit models. The models predicted mode choice based on socio-economic characteristics of individual travelers and trip characteristics obtained from a subset of the Windsor-Essex Household Travel Survey. Results pertaining to LOS variable (travel time and travel cost) are consistent with those found in mode choice literature. The results showed that traveller's age, dwelling type, vehicle and bicycle ownership and employment type, and travel time and cost for each mode are significantly associated with mode choice. The results also showed that housing type, employment status and vehicle ownership are correlated with the auto mode.

Although both Multinomial and Mixed Logit models showed similar results, Mixed Logit model provided better model fit. The latter model was also able to identify "heterogeneity" of traveler's preference towards attributes of a specific mode among different socio-economic groups. It was found that travelers younger than 16 years and female travelers with single family dwelling are more sensitive to travel time by non-motorized modes (walk or bicycle) than the other socio-economic groups. This indicates that variation in taste exists among travelers and can be accounted for using the Mixed

Logit model. These findings are in line with the findings of Day et al., 2010. However, caution should be exercised in generalizing these findings. Overall, the Mixed Logit model in thesis context helped to better explain the travel behavior of workers. Furthermore, the simulation results conducted with the estimated Mixed Logit model provided insights about the consequences of particular transportation initiatives.

The model was used to examine the impacts of enhancing transit services while accounting for an inevitable increase in auto travel cost. An appreciable reduction of 17% in auto mode share was observed in a scenario accommodating LOS initiatives. Such analysis can help predict the likely shifts in mode as was illustrated in the previous section.

5.1.2 Non Work trips

This thesis estimated Multinomial and Mixed Logit models for non work trips in the Windsor-Essex area in Ontario, Canada. Socio-economic and trip characteristics of 448 individual travelers for non-work trips were obtained from a dataset extracted from the Windsor-Essex Household Travel Survey conducted in 1997 and were considered for modeling the mode choice behavior. A Mixed Logit model for shopping trips (230 observations from non work subset) was also estimated separately.

The model results showed that the travel time reliability for motorized modes (auto and public transit), is not an important consideration in mode choice decisions for both non-work and shopping trips whereas the opposite was true for non-motorized mode

(Walk/Bicycle). Travel cost for motorized mode is marginally significant for non-work trips but for shopping trips it has no bearing on auto and transit mode choice. Vehicle ownership was significantly associated with auto mode choice for both non-work and shopping trips.

Although the parameter estimates of both Multinomial and Mixed Logit models for non work trips were largely consistent, Mixed Logit model provided a much richer interpretation of commuter's mode choice behavior by identifying preference heterogeneity of traveler's towards the attributes of Walk/bicycle mode among different socio-economic groups.

Preference heterogeneity analysis for non-work trips revealed that the unemployed trip makers and students (age less than 26 years) are less sensitive to travel time by non-motorized modes (walk or bicycle) than other socio-economic groups. Both subgroups show a show a higher preference to non-motorized modes. Variation in taste for non-motorized mode for shopping trips exists among travelers with full time employment and travelers residing in single family dwellings, aged 36-45 years. The former are more sensitive to travel time by non-motorized mode, whereas the later show a higher preference towards non-motorized modes. These unique findings are relevant to study area, but can be generalized in broader context.

Accounting for the heterogeneity in non-motorized mode for non-work tips may allow for more realistic projections of the reduction in auto mode share and increase in the mode shares of transit and non-motorized mode such as walking/bicycle. The MXL model for non-work trips was used to examine the impacts different policy initiatives, such as improving transit services, promoting residential intensification, while accounting for an inevitable increase in auto travel cost. Under the combined effect of various initiatives, a significant reduction (11%) in auto mode share was observed whereas transit share increased from 3% to 8%. The simulation results provide insights about the effects of particular policy initiatives. Finally, in order to reduce auto dependence and purse travelers to choose more sustainable modes such transit, walk and bicycle for non-work travel, the research recommends that the impacts of transportation and residential initiatives on mode choice, targeted at specific socio-economic groups be evaluated.

5.2 Research Contributions

5.2.1 Methodological Contributions

The lack of applications of the Mixed Logit (MXL) model in travel mode choice analysis was part of the motivation of this thesis. This thesis employed the MXL approach to model the mode choice behavior of passenger travelers during the peak period in the Windsor-Essex Area, and thereby contributes to this emerging paradigm in the field of transportation research. Mixed Logit model is the least restrictive in its behavioral assumptions when compared to its predecessors, i.e. the traditional Multinomial Logit (MNL) and Nested Logit (NL) models. Due to inherent rigid assumptions, MNL and NL models provide single point coefficients for the whole sample population. Therefore, these conventional models cannot capture the difference in preference towards attributes of a specific mode among various socio-economic groups, also known as “heterogeneity” in choice behavior. By accounting for this heterogeneity in preference, the MXL model provides a richer and significantly better representation of the travelers' mode choice behavior. This can be discerned from the consistently higher ρ^2 values of the estimated MXL models in this thesis. The source of this superior explanatory power resides in the ability of the MXL model to explicitly estimate the mean and variance of the randomly specified variables, thereby taking into account both the observed and unobserved effects in the revealed choices. Furthermore, the novel and unique findings from this thesis pave the way for future research while the rest add credence to the existing knowledge found in mode choice modeling literature.

5.2.2 Formulation of Policy Initiatives

Formulation of efficient transportation demand initiatives and polices is a very important aspect of transportation planning. It requires understanding on how to influence people to reduce auto use and choose more sustainable modes such as, shared ride, public transit, walk, bicycle etc. The simulations carried out in this thesis helped to analyze the effect of policy measures on mode choice probabilities. By simulating the changes in LOS and/or socio-economic attributes that are envisioned in the different scenarios, the mode share probabilities can be re-calculated and the response to the proposed policy initiative can be quantified.

In this thesis, the mode share probabilities for work and non-work travel were simulated in simple and compound scenarios. Various LOS scenarios were created to quantify traveler's response to choice of specific mode, when a particular attribute increases or decreases. The results of simulations for work related travel revealed that the increase in mode share of transit mode was primarily due to induction of auto mode commuters who were persuaded to switch to transit mode due to not only the higher cost of auto mode but also the lowered travel time for transit mode. The results reinforce the idea that, a reliable transit system with a good spatial coverage in the Windsor-Essex Area is critical for the success of any transportation demand initiatives. Over all, the simulation results were intuitive and plausible and could be used to formulate LOS initiatives in conjunction with ever increasing fuel costs.

With regard to non-work travel, simulations were performed to analyze the single and combined effects of various LOS and residential intensification initiatives on mode choice probabilities. The results suggest that under the combined effect of increasing fuel costs, measures such as improvements in transit service, extra provisioning of walk/bicycle facilities and availability of more apartment dwellings in the inner suburbs can lead to appreciable decline in the auto dependence in the Windsor-Essex area.

5.3 Research Limitations and Future Research

Accurate estimation of LOS attributes such as travel time and travel cost for different travel modes at the micro level is very important. The limitations in this research are primarily due to the absence of actual travel time and cost perceived by travelers in the travel survey data. The research had to rely on calculated values which might not reflect the actual in-vehicle travel time for the observed trips. The same could be said about the vehicle operating costs, which was also calculated from external sources. Despite these limitations, the results of estimated MXL models are useful to policy makers as they provide insight into traveler’s behavior and identify factors influencing transport mode choice of passenger travel in the study area. With regard to these limitations, it is therefore recommended that any future travel survey should include the LOS variables.

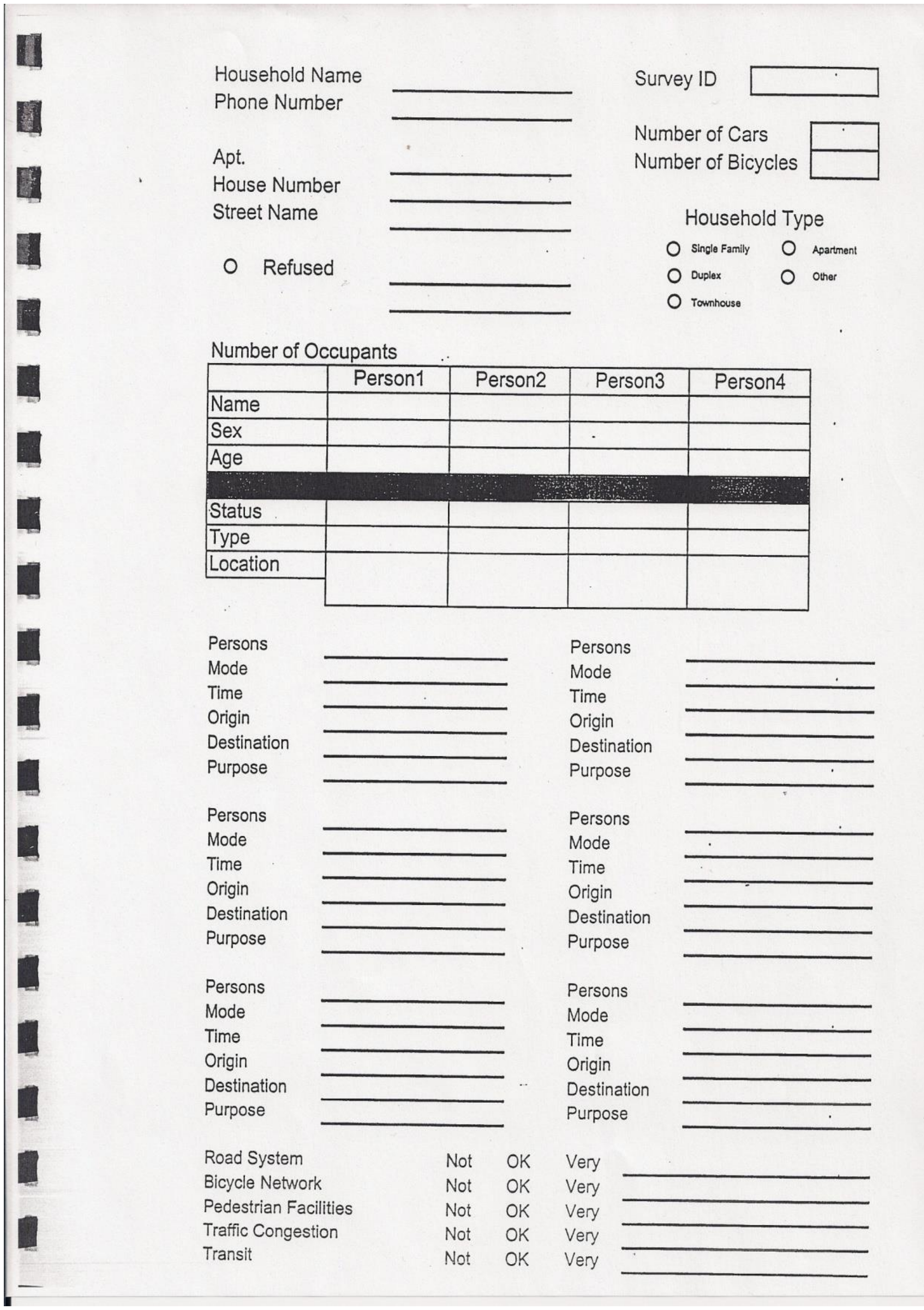
The Windsor-Essex Household survery-1997 data used in this thesis was based on the revealed preferences of travelers. Revealed preference data reflects the actual choices that existed at the time of survey. However in order to gauge travelers’ response to planned (hypothetical) choice situations, stated preference data is commonly used to record travelers’ preference or choices (Train, 2009). Stated perfect data can be used to reflect any level of variation in the attributes of an alternative. Combining both revealed and stated preference data in choice behavior analysis provides desired level of variation in attributes and actual predicted choices (Train, 200). It is therefore, recommended that the future travel surveys should also incorporate stated preference data. The prospects of recording panel data (travel diaries), in which repeated choices for each traveler are obtained over time, should also be explored. The use of panel data enables MXL model to capture even the slight daily variation in mode choice behavior.

As for the recommendation of the modeling approach for future research, this research recommends the application of the MXL model in mode choice analysis, due to its ability to overcome the limitations of the MNL and NL models and to identify the preference heterogeneity in the sub-groups of a sample population.

APPENDICES

APPENDIX A

WALTS Questionnaire and Transit Windsor Maps for the Years 1997 and 2012



Household Name
Phone Number

Survey ID

Apt.
House Number
Street Name

Number of Cars
Number of Bicycles

O Refused

Household Type

O Single Family O Apartment
O Duplex O Other
O Townhouse

Number of Occupants

	Person1	Person2	Person3	Person4
Name				
Sex				
Age				
[redacted]				
Status				
Type				
Location				

Persons
Mode
Time
Origin
Destination
Purpose

Persons
Mode
Time
Origin
Destination
Purpose

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Purpose

Persons
Mode
Time
Origin
Destination
Purpose

Road System	Not	OK	Very
Bicycle Network	Not	OK	Very
Pedestrian Facilities	Not	OK	Very
Traffic Congestion	Not	OK	Very
Transit	Not	OK	Very

Figure A-1 Original WALTS Questionnaire (Windsor Public Library, 2011)

Figure A-2 Transit Windsor – 1996 Routes (Windsor Public Library, 2011)

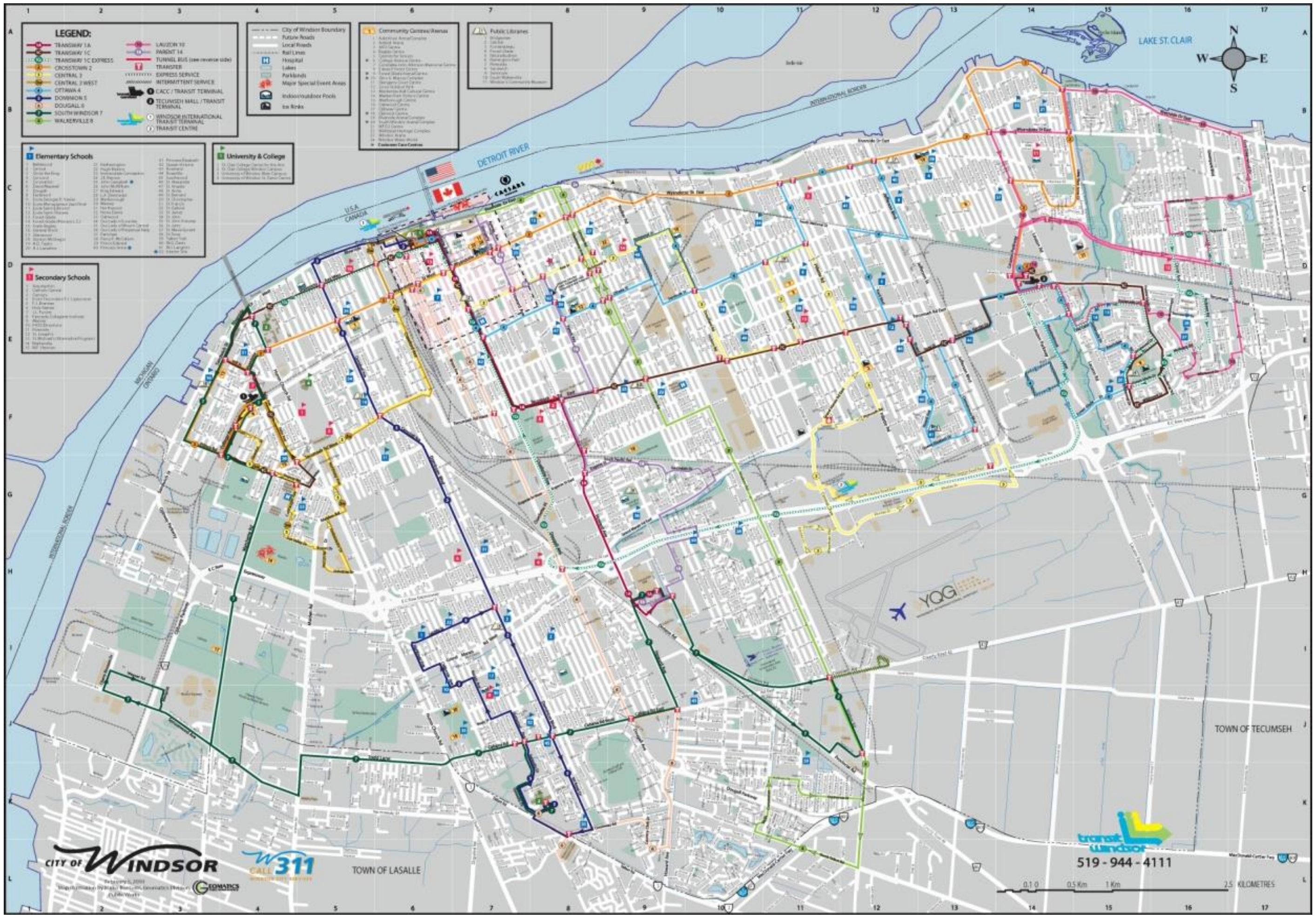

Figure A-3 Transit Windsor – 2011 Routes (Transit Windsor, 2011)

APPENDIX B

LOS Estimation, Entropy Index and Data Representation Analysis

Figure B-1 Illustration of Travel Time Estimation using Network Analyst for Auto Trips in the Windsor-Essex Area

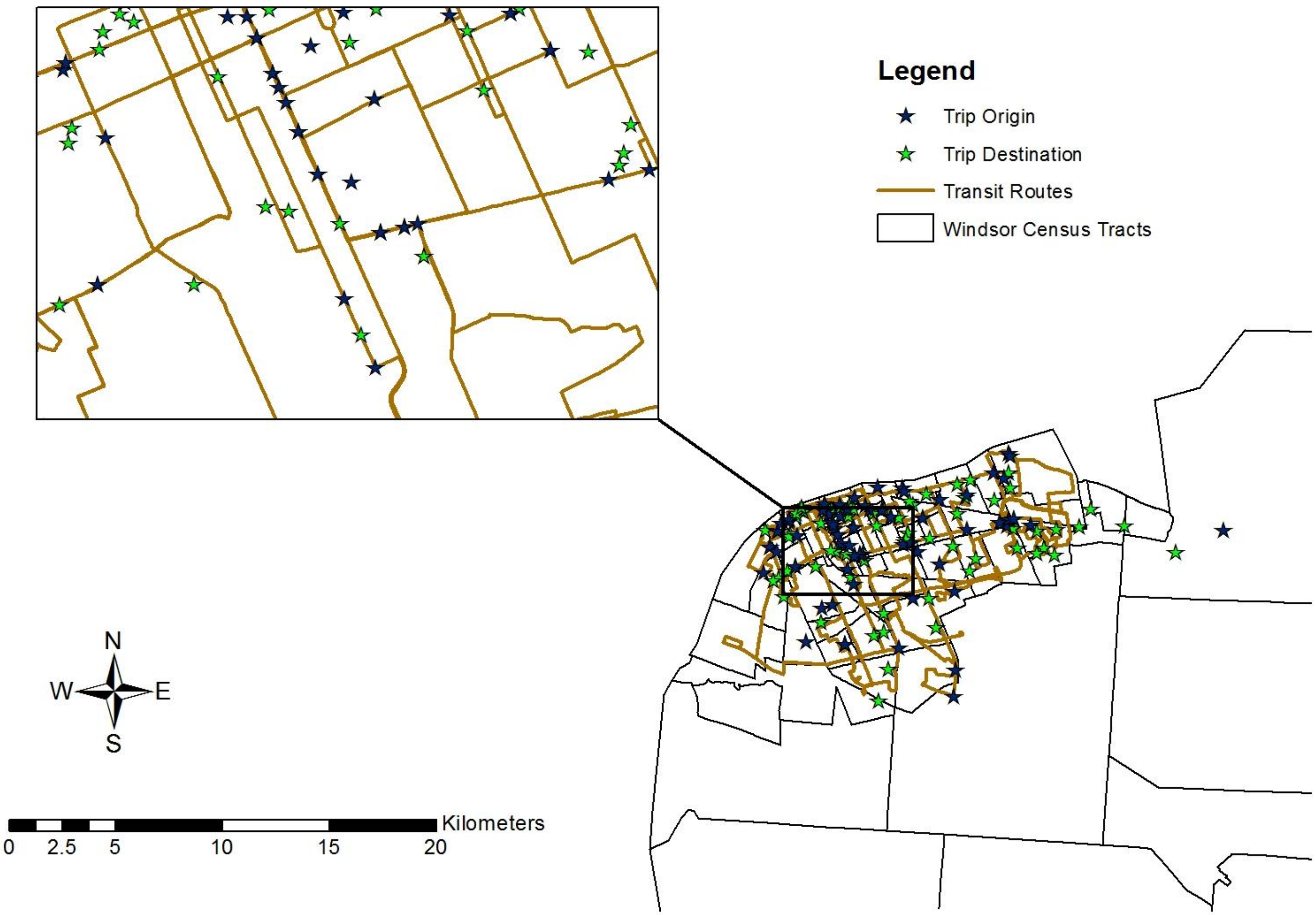

Figure B-2 Illustration of Travel Time Estimation using Network Analyst for Transit Trips in the Windsor-Essex Area

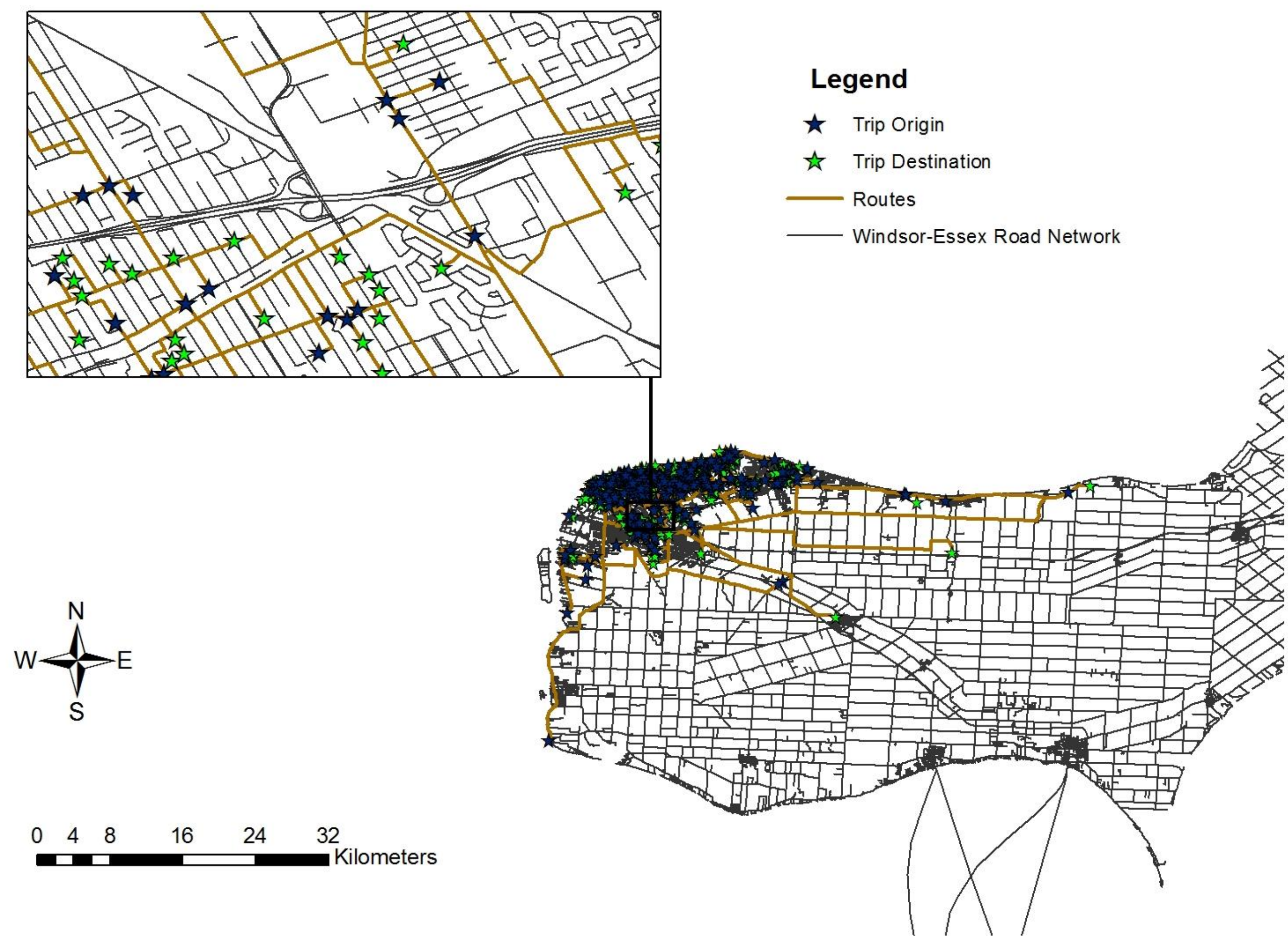

Figure B-3 Illustration of Travel Time Estimation using Network Analyst for Walk/Bicycle Trips in the Windsor-Essex Area

Table B-1 Data Representation – Work Trips Mode Shares Comparison

	Stats Canada 1996			WALTS 1997		
CTUID	Auto(%)	Transit(%)	W/B(%)	Auto(%)	Transit(%)	W/B(%)
5590000	0.903	0.034	0.063	0.929	0.015	0.057
5590001	0.966	0.013	0.021	1.000	0.000	0.000
5590002	0.986	0.014	0.000	1.000	0.000	0.000
5590003	0.956	0.009	0.034	0.913	0.043	0.043
5590004	0.953	0.013	0.034	0.935	0.000	0.065
5590005	0.966	0.006	0.028	0.962	0.000	0.038
5590006	0.941	0.000	0.059	1.000	0.000	0.000
5590007	1.000	0.000	0.000	1.000	0.000	0.000
5590008	0.884	0.000	0.116	0.000	0.000	1.000
5590009	0.772	0.110	0.118	0.833	0.000	0.167
5590010	0.873	0.043	0.084	0.895	0.053	0.053
5590011	0.951	0.022	0.027	0.917	0.000	0.083
5590013	0.812	0.074	0.113	0.778	0.000	0.222
5590014	0.854	0.060	0.086	1.000	0.000	0.000
5590015	0.950	0.020	0.030	0.875	0.000	0.125
5590016	0.899	0.006	0.095	1.000	0.000	0.000
5590017	0.850	0.034	0.116	0.923	0.077	0.000
5590018.01	0.908	0.044	0.048	0.955	0.045	0.000
5590018.02	0.868	0.070	0.062	1.000	0.000	0.000
5590019.01	0.934	0.042	0.024	1.000	0.000	0.000
5590019.02	0.954	0.022	0.024	0.958	0.042	0.000
5590020	0.903	0.050	0.046	1.000	0.000	0.000
5590021	0.878	0.040	0.082	1.000	0.000	0.000
5590022	0.860	0.030	0.111	0.895	0.000	0.105
5590023	0.844	0.053	0.102	0.750	0.000	0.250
5590024	0.847	0.069	0.084	1.000	0.000	0.000
5590025	0.788	0.074	0.138	1.000	0.000	0.000
5590026	0.751	0.089	0.160	1.000	0.000	0.000
5590028	0.815	0.068	0.117	0.909	0.000	0.091
5590029	0.681	0.127	0.192	0.750	0.083	0.167
5590030	0.823	0.043	0.134	0.882	0.000	0.118
5590031	0.642	0.108	0.250	1.000	0.000	0.000
5590032	0.640	0.092	0.268	0.750	0.000	0.250
5590033	0.663	0.109	0.228	0.222	0.000	0.778
5590034	0.805	0.105	0.090	0.833	0.083	0.083
5590035	0.635	0.120	0.244	0.400	0.000	0.600
5590036	0.879	0.037	0.084	0.875	0.000	0.125
5590037	0.845	0.062	0.093	0.909	0.091	0.000

Table B-1 -Continued

	Stats Canada 1996			WALTS 1997		
CTUID	Auto(%)	Transit(%)	W/B(%)	Auto(%)	Transit(%)	W/B(%)
5590038	0.771	0.135	0.094	0.750	0.000	0.250
5590039	0.860	0.081	0.059	1.000	0.000	0.000
5590040	0.897	0.058	0.045	0.917	0.000	0.083
5590041	0.920	0.031	0.049	0.913	0.043	0.043
5590042	0.927	0.028	0.045	0.933	0.000	0.067
5590043	0.941	0.031	0.028	0.964	0.000	0.036
5590100	0.981	0.000	0.019	0.923	0.000	0.077
5590101	0.989	0.000	0.011	0.950	0.050	0.000
5590102	0.975	0.000	0.025	1.000	0.000	0.000
5590110	0.958	0.003	0.039	1.000	0.000	0.000
5590120.01	0.981	0.000	0.019	0.967	0.000	0.033
5590120.02	0.971	0.000	0.029	1.000	0.000	0.000
5590120.03	0.970	0.004	0.026	0.969	0.031	0.000
5590130	0.992	0.000	0.008	0.975	0.025	0.000
5590140	0.992	0.000	0.008	1.000	0.000	0.000
5590150	0.934	0.000	0.066	1.000	0.000	0.000
5590160	0.936	0.004	0.060	1.000	0.000	0.000
5590170	0.984	0.000	0.016	1.000	0.000	0.000

Note: W/B means Walk/Bicycle

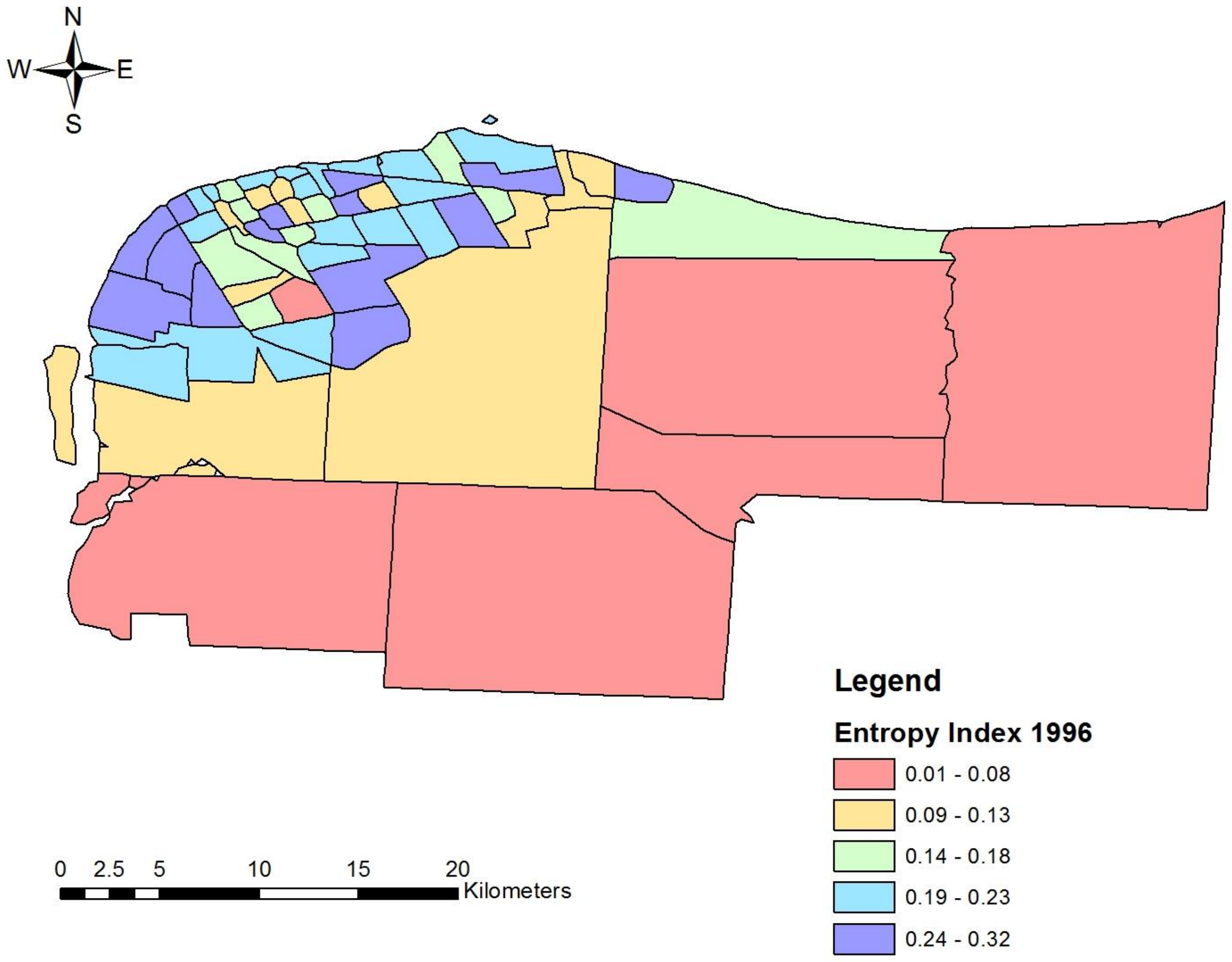

Figure B-4 Land Use Entropy Index of Windsor-Essex Area

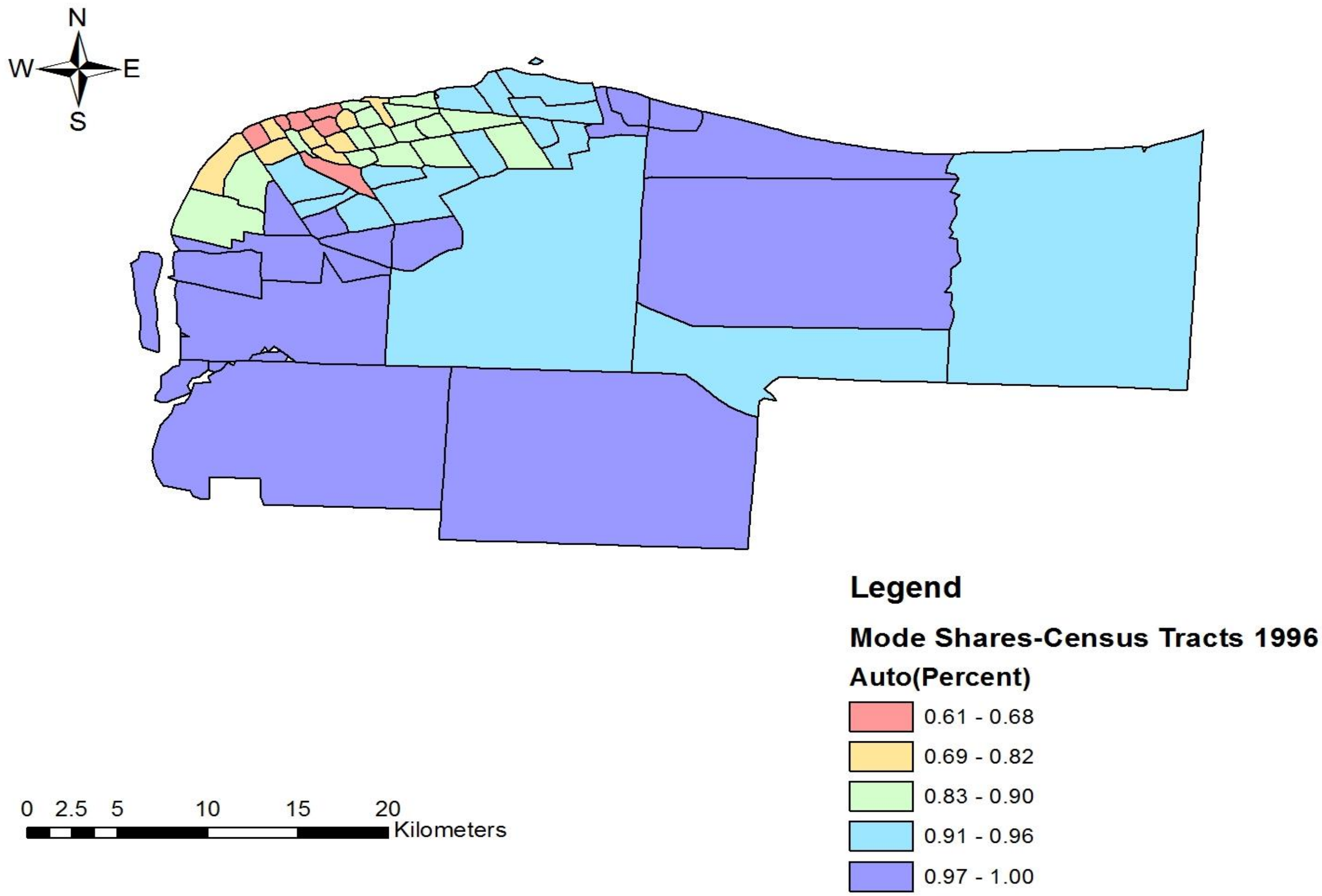

Figure B-5 Auto Mode Shares – Census Tracts 1996

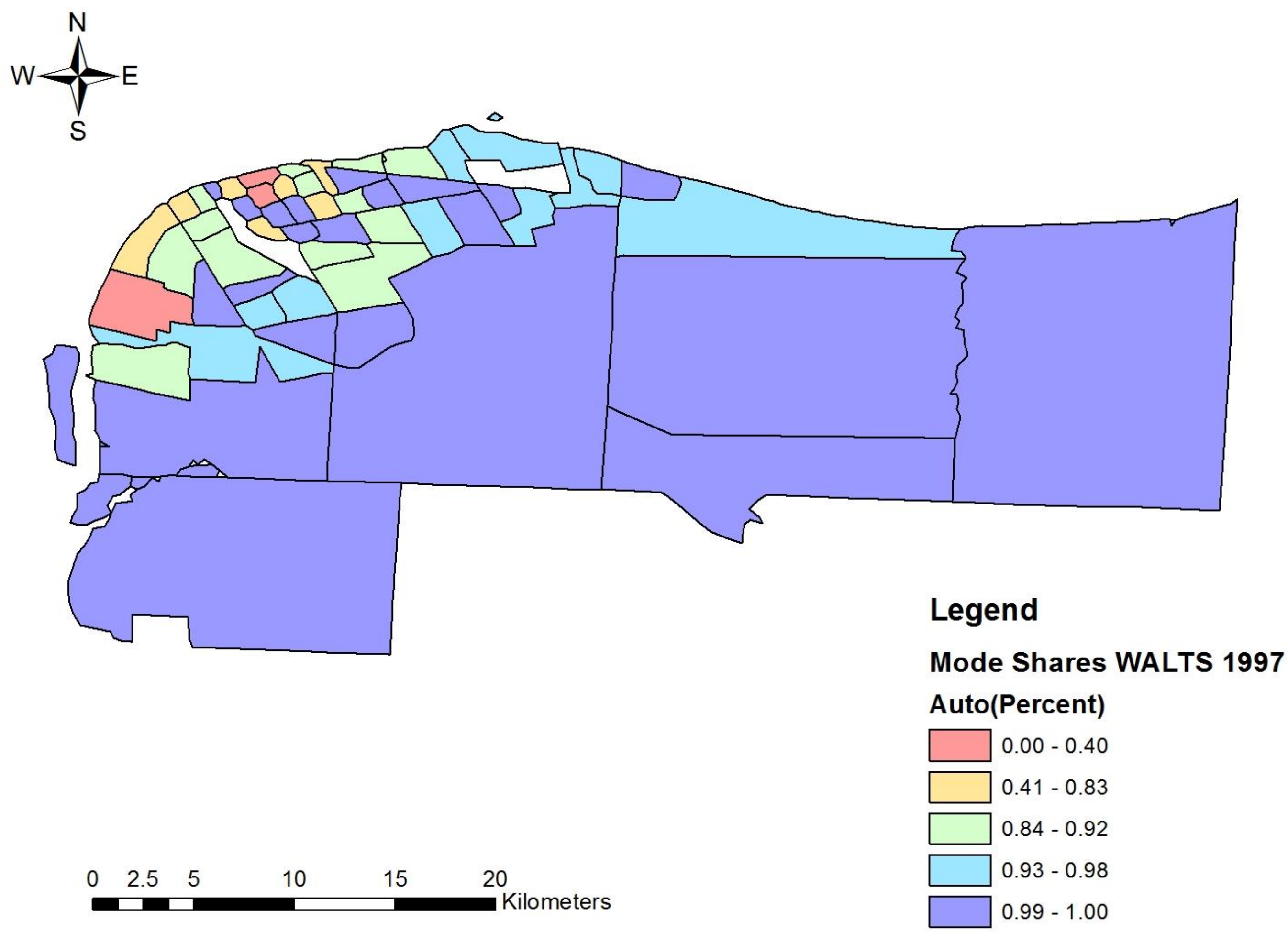

Figure B-6 Auto Mode Shares – WLATS 1997

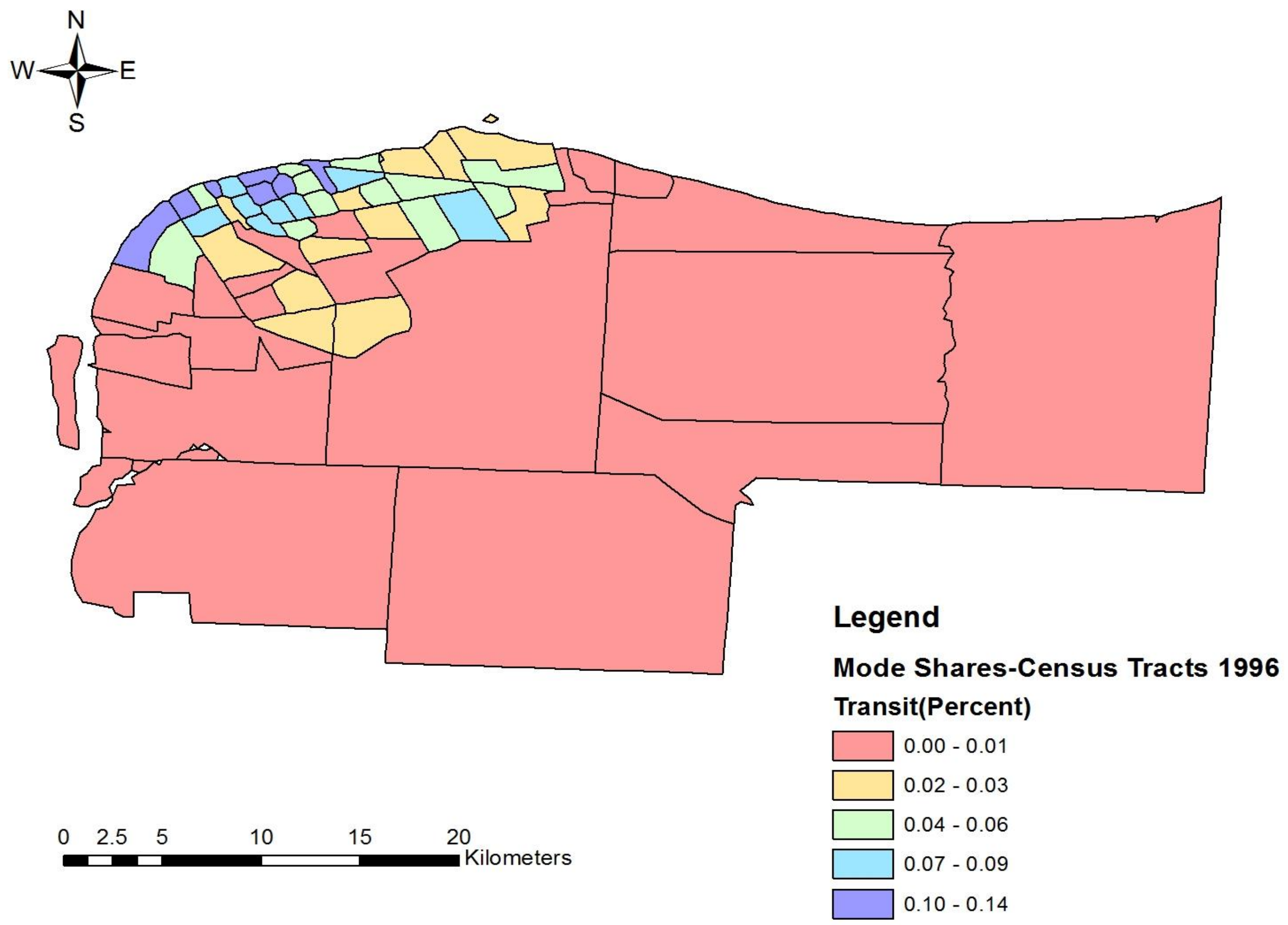

Figure B-7 Transit Mode Shares – Census Tracts 1996

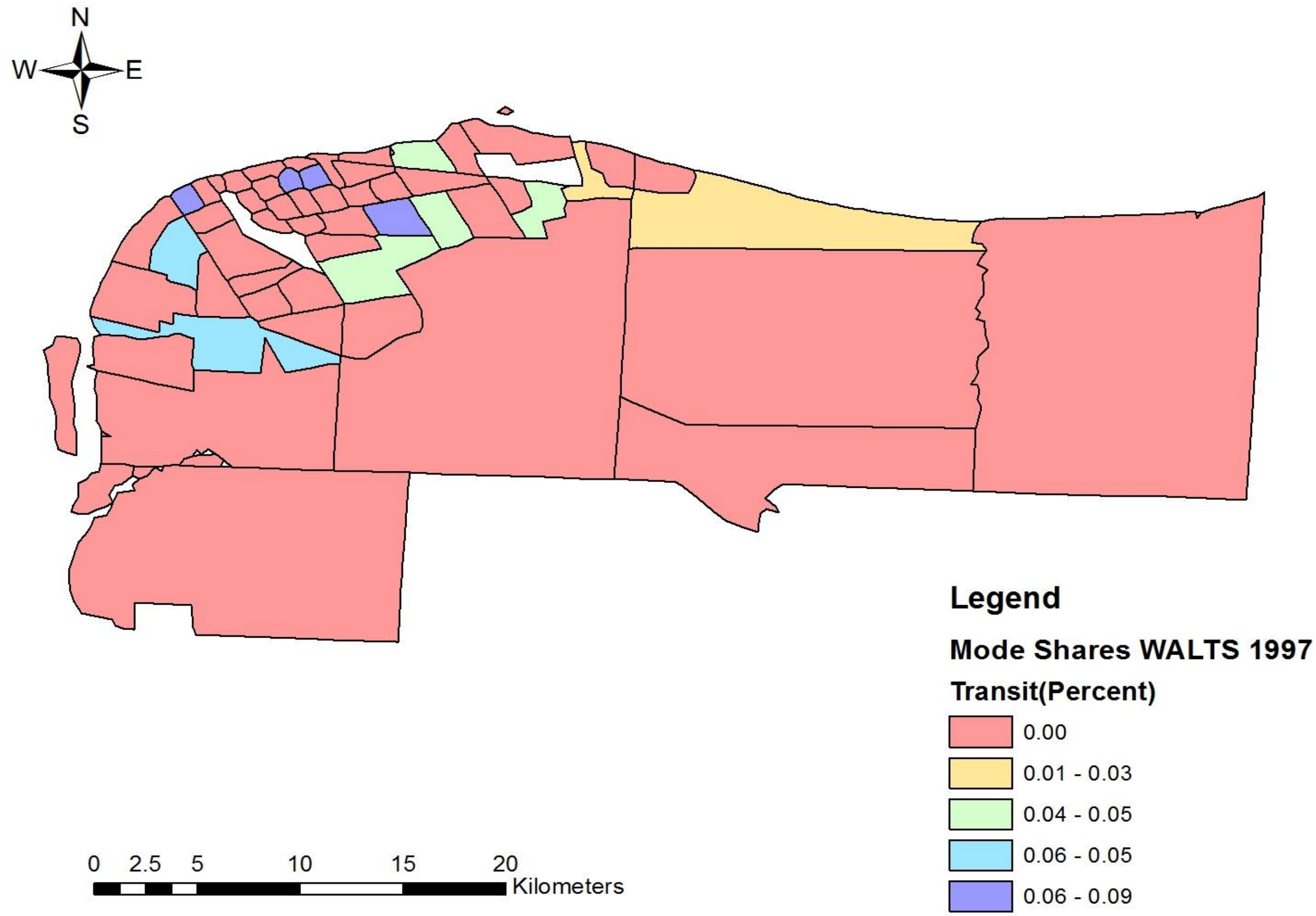

Figure B-8 Transit Mode Shares – WLATS 1997

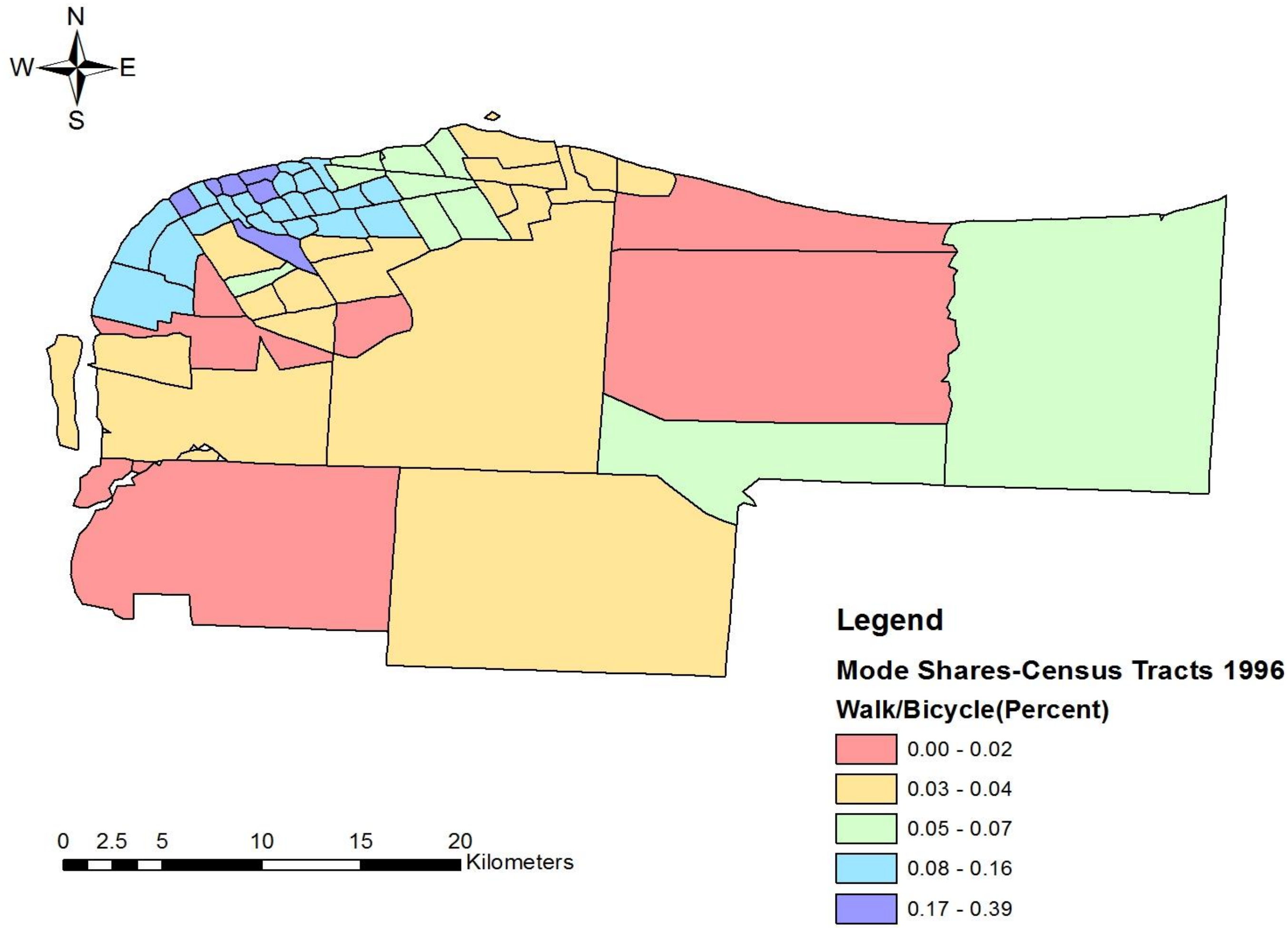

Figure B-9 Walk/Bicycle Mode Shares – Census Tracts 1996

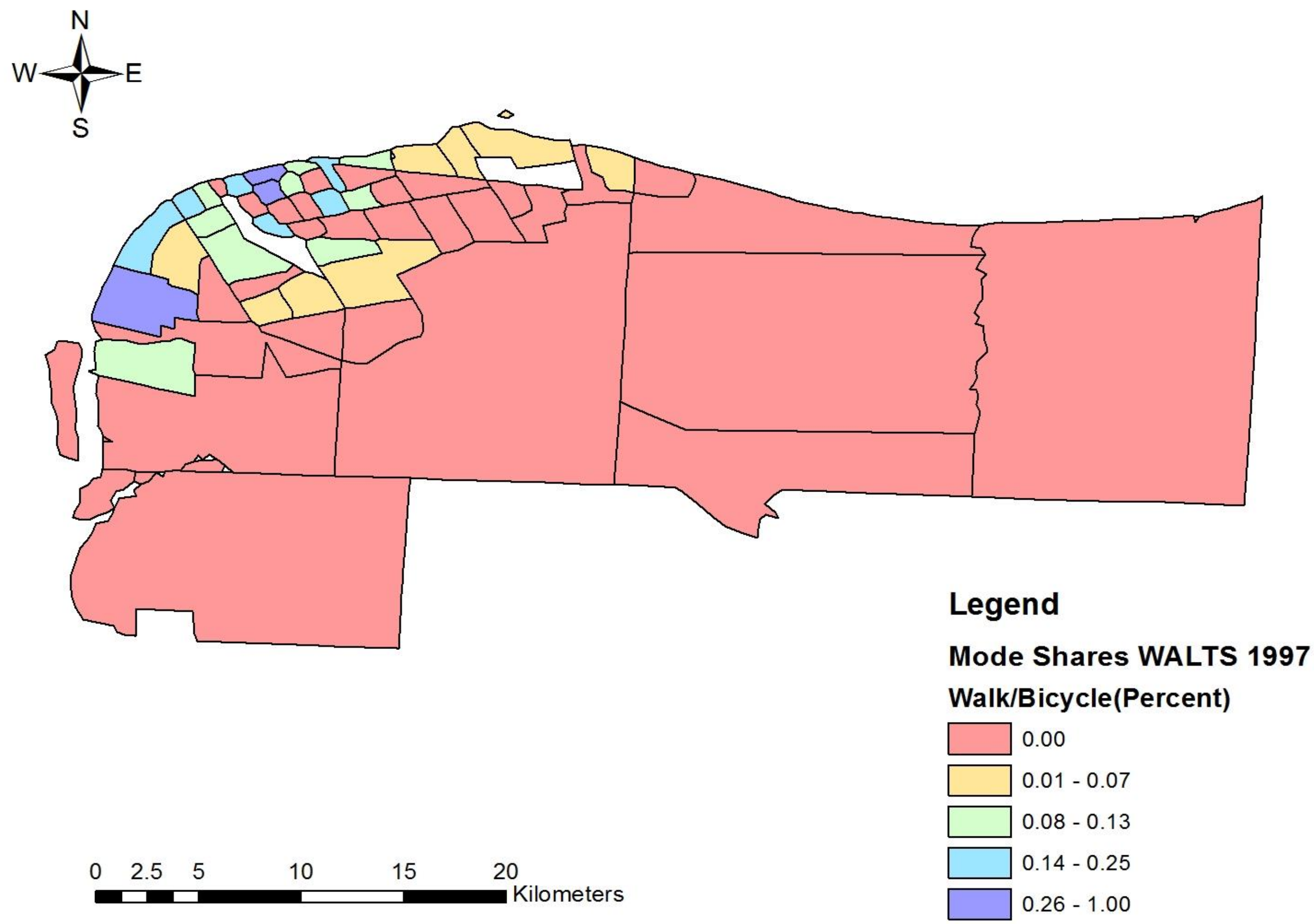

Figure B-10 Walk/Bicycle Mode Shares – WLATS 1997

APPENDIX C

Specifications and Utility Functions for the MNL and MXL Models

Work Trips Dataset

MNL Model Specifications for Work Trips: (Modes: Auto, Transit, Walk Bicycle)

NLOGIT ;
Lhs = mode;
Choices = *auto, transit, walk/bicycle;*
Model:
U(auto) = β_{ttm} * ttime + β_{nveh} * nveh + β_{fltemp} * fltemp + β_{trc} * trc + β_{sfam_A} * sfam /

U(transit) = β_{ttm} * ttime + β_{trc} *trc + β_{studnt_T} * studnt + β_{sfam_T} * sfam /

U(walk/bicycle) = $ASC_{walk/bic}$ + β_{ttnm} * ttime + β_{nbic} * nbic + β_{studn_O} * studnt $

MXL Model Specifications for Work Trips: (Modes: Auto, Transit, Walk Bicycle)

Calc;ran(10000)$
NLOGIT ;
Lhs = mode;
Choices = *auto, transit, walk/bicycle;*
Halton;
Rpl=*age1,femsfam*;
Fcn = *ttnm*(n|#11)
Pts=20;
Model:
U(auto) = β_{ttm} * ttime + β_{nveh} * nveh + β_{fltemp} * fltemp + β_{trc} * trc + β_{sfam_A} * sfam /

U(transit) = β_{ttm} * ttime + β_{trc} * trc + β_{studnt_T} * studnt + β_{sfam_T} * sfam /

U(walk/bicycle) = $ASC_{walk/bic}$ + β_{ttnm} * ttime + β_{nbic} * nbic + β_{studn_O} * studnt $

Prob = Probs ;
Utility = u1;
Crosstab;
Describe $

Non Work Trips Dataset

MNL Model Specifications for Non Work Trips: (Modes: Auto, Transit, Walk Bicycle)

NLOGIT ;
Lhs = mode;
Choices = *auto, transit, walk/bicycle;*
Model:

U(auto) = β_{ttm} * ttime + β_{nveh} * nveh + β_{fltemp} * fltemp + β_{trc} * trc + β_{tpshop} * shopp /

U(transit) = β_{ttm} * ttime + β_{trc} * trc + β_{dwlapt} * dwlapt + β_{studn} * studnt /

U(walk/bicycle) = $ASC_{walk/bic}$ + β_{ttnm} * ttime + β_{hmkr} * hmkr $

MXL Model Specifications for Non Work Trips: (Modes: Auto, Transit, Walk Bicycle)

Calc;ran(10000)$
NLOGIT ;
Lhs = mode;
Choices = *auto, transit, walk/bicycle;*
Halton;
Rpl= *unemp, studnt_ag12*
Fcn = *ttnm*(n)
Pts=15;
Model:

U(auto) = β_{ttm} * ttime + β_{nveh} * nveh + β_{fltemp} * fltemp + β_{trc} * trc + β_{tpshop} * shopp /

U(transit) = β_{ttm} * ttime + β_{trc} *trc + β_{dwlapt} * dwlapt + β_{studn} * studnt /

U(walk/bicycle) = $ASC_{walk/bic}$ + β_{ttnm} * ttime + β_{hmkr} * hmkr $

Prob = Probs ;
Utility = u1;
Crosstab;
Describe $

Shopping Trips Dataset

MXL Model Specifications for Shopping Trips: (Modes: Auto, Transit, Walk Bicycle)

Calc;ran(10000)$
NLOGIT ;
Lhs = mode;
Choices = *auto, transit, walk/bicycle*;
Halton;
Rpl= *age4sfam , fltemp*
Fcn = *ttnm*(n)
Pts=10;
Model:

$U(auto) = \beta_{ttm}$ * ttime + β_{nveh} * nveh + β_{trc} * trc + $\beta_{fspouse}$ * femhmkr /

$U(transit) = \beta_{ttm}$ * ttime + β_{trc} * trc + β_{dwlapt} * dwlapt + β_{hsize_T} * hhsize /

$U(walk/bicycle) = ASC_{walk/bic}$ + β_{ttnm} * ttime + β_{studnt} * studnt +
β_{hsize_O} * hhsize $

Prob = Probs ;
Utility = u1;
Crosstab;
Effects;
Describe $

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