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Accommodating Exogenous Variable and Decision Rule Heterogeneity in Discrete Choice Models: Application to Bicyclist Route Choice

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ACCOMMODATING EXOGENOUS VARIABLE AND DECISION RULE HETEROGENEITY IN DISCRETE CHOICE MODELS: APPLICATION TO BICYCLIST ROUTE CHOICE

by

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ABSTRACT

The thesis contributes to our understanding of incorporating heterogeneity in discrete choice models with respect to exogenous variables and decision rules. Specifically, we evaluate latent segmentation based mixed models that allow for segmenting population based on decision rules while also incorporating unobserved heterogeneity within the segment level decision rule models. In our analysis, we choose to consider the random utility framework along with random regret minimization approach. Further, instead of assuming the number of segments (as 2), we conduct an exhaustive exploration with multiple segments across the two decision rules. Within each segment we also allow for unobserved heterogeneity. The model estimation is conducted using a stated preference data from 695 commuter cyclists compiled through a web-based survey. The probabilistic allocation of respondents to different segments indicates that female commuter cyclists are more utility oriented, however the majority of the commuter cyclist's choice pattern is consistent with regret minimization mechanism. Overall, cyclists' route choice decisions are influenced by roadway attributes, cycling infrastructure availability, pollution exposure, and travel time. The analysis approach also allows us to investigate time based trade-offs across cyclists of different classes. Interestingly, we observed that the trade-off values in regret and utility based segments for roadway attributes are similar in magnitude; but the values differ greatly for cycling infrastructure and exposure attributes, particularly for maximum exposure levels.

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CHAPTER ONE: INTRODUCTION

1.1 Population Homogeneity

Discrete choice models and their variants are employed extensively for analyzing decision processes in various fields including transportation, marketing, social science, bio-statistics, and epidemiology. In discrete choice models, decision maker's choice behavior is examined as a response to several exogenous variables that include attributes of the choice alternative or characteristics of the decision maker. The widely employed traditional discrete choice models restrict the impact of exogenous variables to be the same across the entire sample of records. The assumption is referred to as population homogeneity and is often highlighted as a limitation.

Several approaches have been employed to address population homogeneity restriction in discrete choice models. Segmenting the population based on exogenous variables and estimating separate models for each segment is a common approach. However, because there may be many variables to consider in the segmentation scheme, the number of segments (formed by the combination of the potential segmentation variables) can explode rapidly. To address the potential explosion of segments, clustering methods have been employed where target groups are divided into different clusters based on a multivariate set of factors and separate models are estimated for each cluster. However, both methods require allocating data records exclusively to a particular cluster, and do not consider the possible effects of unobserved factors that may moderate the impact of observed exogenous variables. Additionally, these approaches might result in very few records in some clusters resulting in loss of estimation efficiency.

A second approach to allow heterogeneity effects (variations in the effects of variables across the sample population) is to specify random coefficients (rather than imposing fixed coefficients) (for example, see (Eluru and Bhat, 2007, Kim et al., 2013, Morgan and Mannering, 2011, Paleti et al., 2010, Srinivasan, 2002)). But, while the mean of the random coefficients can be allowed to vary across decision makers based on observed exogenous variables, the random coefficients approach usually restricts the variance and the distributional form to be the same across all decision makers. A third approach to accommodate heterogeneity is to undertake an endogenous (or sometimes also referred to as latent) segmentation approach (see, for example (Bhat, 1997, Eluru et al., 2012, Xie et al., 2012, Xiong and Mannering, 2013, Yasmin and Eluru, 2016, Yasmin et al., 2014b)). In this approach, decision makers are allocated probabilistically to different segments, and segment-specific choice models are estimated. At the same time, each segment is identified based on a multivariate set of exogenous variables. The approach limits the number of segments to a manageable number (relative to the combinatorial scheme realized in the first approach).

A further extension of this approach would be accommodating unobserved heterogeneity in segment specific choice models (Hess and Stathopoulos, 2013) thus subsuming the choice models from the second approach. Overall, the endogenous segmentation with segment level unobserved heterogeneity, offers an elegant alternative to address heterogeneity (observed and unobserved). In recent years, several studies have employed endogenous segmentation approaches (with or without unobserved heterogeneity) across different areas in transportation (for example, see (Eluru et al., 2012, Xie et al., 2012, Xiong and Mannering, 2013, Yasmin et al., 2014b) in safety and see (Anowar et al., 2014, Bhat, 1997, Drabas and Wu, 2013, Walker and Li, 2007) in travel behavior).

1.2 Decision Rule Homogeneity

The exact formulation of discrete choice models are a function of the decision rule employed. In traditional discrete choice models, the analyst generally assumes the same decision rule across the sample population. The predominantly adopted decision rule for developing discrete choice models is the random utility maximization (RUM) that hypothesizes that decision makers, when faced with multiple alternatives with varying attributes, choose the alternative that provides them with the highest utility or satisfaction (Ben-Akiva and Lerman, 1985, McFadden, 1974, Train, 2009). While random utility model formulations have served as the predominant decision rule for discrete choice models, there is growing recognition of their limitations. The implicit compensatory nature of the formulation allows for a poor performance on an attribute (such as travel time) to be compensated by a positive performance on another attribute (such as travel cost) (Chorus et al., 2008). In some choice occasions, such behavior is not realistic. In recent years, motivated by research in behavioral economics, there has been considerable interest in alternative decision rules for discrete choice models such as relative advantage maximization (Leong and Hensher, 2015), contextual concavity model (Kivetz et al., 2004), fully-compensatory decision making (Arentze and Timmermans, 2007, Swait, 2001), prospect theory (PT) (Kahneman and Tversky, 1979, Tversky and Kahneman, 1992) and random regret minimization (RRM) (Chorus, 2010, Chorus et al., 2008).

1.3 Current Study in Context

Based on the aforementioned discussion, it is evident that homogeneity in both exogenous variable impact and decision rule restrict the flexibility offered by discrete choice models. While several research studies have focused on exogenous variable homogeneity, the decision rule homogeneity assumption has received less attention (for example see (Hess et al., 2012, Boeri et al., 2014)). The proposed research contributes to our understanding of incorporating heterogeneity in discrete choice models with respect to exogenous variables and decision rules. Specifically, we evaluate latent segmentation based mixed models that allow for segmenting population based on decision rules while also incorporating unobserved heterogeneity within the segment level decision rule models. In our analysis, we choose to consider the random utility framework along with random regret minimization approach. The random regret minimization approach has received wide application because of its mathematical similarity to the random utility approach and its intuitive appeal (Boeri et al., 2012, Boeri et al., 2013, Chorus, 2010, Chorus and Bierlaire, 2013, Chorus and de Jong, 2011, Hensher et al., 2013, Thiene et al., 2012). The proposed approach extends in such way where a latent segmentation model with one segment represented by random utility formulation and the other segment assuming a random regret formulation (Hess et al., 2012). In our approach, instead of assuming the number of segments (as 2), we conduct an exhaustive exploration with multiple segments across the two decision rules. Further, within each segment we also allow for unobserved heterogeneity. The reader would note that the estimation of latent class models become complex with increasing segments and presence of unobserved heterogeneity (see (Sobhani et al., 2013) for some discussion).

The extensive modeling exercise is developed employing a stated preference data compiled to understand influence of air pollution exposure on bicycle route choice. While bicycling offers health benefits, there is growing recognition that these potential health benefits might be offset by increasing exposure to air pollutants for bicyclists. Several research efforts have documented the potential increased exposure to air pollution for bicyclists owing to their close proximity to traffic, high respiration rates, and longer journeys (Bigazzi et al., 2016, Broach and Bigazzi, 2017, Int Panis et al., 2010). Furthermore, there is growing evidence from health research studies highlighting the potential consequences of increased air pollution exposure (for example see (Weichenthal et al., 2011)). Thus, there is need to explore the impact of air pollution exposure on bicycling choices. Several research efforts have examined bicycle route choice decision process in literature. Most of these approaches rely on stated preference survey compiled data for route choice analysis. The most commonly employed analytical approaches include ordinary least squares (OLS), binary logit (BL) or multinomial logit (MNL), mixed multinomial logit (MMNL), multinomial probit (MNP) models, and heuristic approaches. Based on earlier research (Abraham et al., 2002, Aultman-Hall et al., 1997, Bigazzi et al., 2016, Broach et al., 2011, Cervero, 1996, Dill and Carr, 2003, Dill and Voros, 2007, Guo et al., 2007, Heinen et al., 2010, Hunt and Abraham, 2006, Larsen and El-Geneidy, 2011, Martens, 2007, Menghini et al., 2010, Moudon et al., 2005, Noland and Kunreuther, 1995, Parkin et al., 2007, Pucher and Buehler, 2006, Pucher et al., 1999, Rondinella et al., 2012, Segadilha and Sanches, 2014, Sener et al., 2009, Stinson and Bhat, 2004, Stinson and Bhat, 2003, Stinson and Bhat, 2005, Timperio et al., 2006, Anowar et al., 2017, Hatzopoulou et al., 2013), the most important attributes affecting route choice include: travel time, trip distance, gradient, traffic volume, exclusive bicycle paths, traffic control systems (see Table 1.1). The current study builds on the first research effort that studied the impact of air pollution exposure on bicycling route choice (see (Anowar et al., 2017)). In the previous study, the emphasis was on examining if air pollution exposure information affected route choice. The study employed stated preference experiment data from 695 commuter cyclists and evaluated using a random utility approach to examine cyclist's willingness to trade-off air pollution exposure with other attributes such as roadway characteristics, bike facilities, and travel time.

1.4 Thesis Structure

The remainder of the thesis is organized as follows. Chapter 2 provides a discussion of the econometric methodology applied. In Chapter 3, data source and variables considered are presented in detail. Model estimation results are presented and discussed in Chapter 4. The results from the trade-off analysis is presented in Chapter 5. Finally, Chapter 6 concludes the thesis with recommendations based on the empirical findings of the study.

Table 1.1 Factors Affecting Bicycling and Bicyclist's Route Choice Decision

	Demographics	**Route Characteristics**	**Traffic Characteristics**	**Environment Characteristics**	**Facilities**	**Trip Characteristics**
Pre-Cycling	Gender, Age, Education, Employment Status, Income	Exclusive Bicycle Paths, Grade/Slopes	Traffic Volume	Season, Climate/Weather	–	Trip Distance/Length, Travel Time, Transportation Costs
During Cycling	–	Parking Along Road, Continuity, Exclusive Bicycle Paths, Traffic-controlling Systems, Surface Quality, Grade/Slopes, Physical Barriers	Traffic Volume, Motor Vehicle Speed	Security, Attraction	–	Trip Distance/Length, Travel Time
Post Cycling	–	–	–	–	Presence of Showers, Changing Facilities and Lockers, Parking Facilities	–

CHAPTER TWO: METHODOLOGY

In this chapter, the econometric framework of the latent segmentation model with random utility based Multinomial Logit Model and regret based Multinomial Logit model is presented.

2.1 Econometric Modeling Framework

In this section, we describe the mathematical formulation of the model used in the current study. Let c $(c = 1,2, \dots, C)$ be the index for cyclists, i $(1, 2, \dots, I)$ be the index for route alternatives characterized by m $(m = 1,2, \dots, M)$ attributes, and k $(1, 2, \dots, K)$ be the index for choice occasions for each cyclist. In our case, $I = 3$ and $K = 5$ for all c. Let us also consider S possible number of segments where the cyclists would be probabilistically assigned. According to conventional utility based MNL model, the probability that cyclist c belongs to segment s $(s = 1,2, \dots, S)$ is given as:

$$P_{cs} = \frac{\exp(\gamma_s' z_c)}{\sum_{s=1}^{S} \exp(\gamma_s' z_c)} \tag{1}$$

z_c is a (M x 1) column vector of cyclist attributes that influences the propensity of belonging to segment s, γ_s' is a corresponding (M x 1) column vector of estimable coefficients. Within the latent class approach, the unconditional probability of a cyclist c choosing a commuting route i is given as:

$$P_c(i) = \sum_{s=1}^{S} (P_c(i) \mid s)(P_{cs}) \tag{2}$$

where $P_c(i)|s$ represents the probability of cyclist c choosing route i within the segment s. Note that the decision paradigm used to obtain the conditional probability $P_c(i)|s$ may follow either utility or regret based unordered choice (traditionally multinomial logit) mechanism.

If a random utility based multinomial logit model is assumed to evaluate the route choice decision accommodating unobserved heterogeneity, the conditional probability would take the following form:

$$P_c(i) \mid s = \int \left(\prod_{k=1}^{K} \frac{\exp(\alpha_s' x_{cik})}{\sum_{r=1}^{R} \exp(\alpha_s' x_{cik}))} \right) f(\alpha) d\alpha \tag{3}$$

Here, α_s' is a (L x 1)-column vector of coefficients, and x_{cik} is (L x 1) column vector of route attributes, where $f(\alpha)$ is a density function specified to be normally distributed with mean 0 and variance σ^2. On the other hand, if a random regret based multinomial logit model is assumed to evaluate the route choice decision, the conditional probability would be given as:

$$P_c(i) \mid s = \int \left(\prod_{k=1}^{K} \frac{\exp(-R_{cik})}{\sum_{r=1}^{R} \exp(-R_{cik})} \right) f(\delta) d\delta \tag{4}$$

Here, $R_{cik} = \sum_{j \neq i} \sum_{m=1}^{M} \ln\left[1 + \exp\left\{\delta_m\left(x_{cjmk} - x_{cimk}\right)\right\}\right]$; δ_m is (Lx1) column vector of estimable coefficients associated with attribute x_m; x_{im} and x_{jm} are (Lx1) column vector of route attributes for the considered alternative i and another alternative j, respectively, where $f(\delta)$ is a density function specified to be normally distributed with mean 0 and variance ρ^2. The log-likelihood function for the entire dataset with appropriate $P_c(i)|s$ is as follows:

$$LL = \sum_{c=1}^{C} \log(P_c(i)) \tag{5}$$

Contrary to the traditional endogenous segmentation approaches, capturing decision rule heterogeneity involves a more computationally intensive estimation approach. The estimation approach begins with single segment models from each regime. Then, a new segment from one of the two approaches is added. The process is continued until there is no further improvement in data fit. The approach allows for multiple segments originating from the same decision rule i.e. the segmentation model can have multiple RUM and RRM segments thus offering enhanced flexibility. Finally, given the complexity of adding multiple segments from both regimes, we also consider overall sample shares of the segments in arriving at the final model as opposed to only data fit.

2.2 Summary

The current chapter presented the econometric framework employed for latent segmentation. The empirical context is presented in the subsequent chapter.

CHAPTER THREE: DATA COLLECTION AND COMPILATION

In this chapter, we present details of how the Stated Preference data on bicycle route choice was collected. We also discuss data preparation steps for the research effort.

3.1 Data Source and Experimental Design

The survey design was coded on a Survey Monkey platform (www.surveymonkey.net) for web dissemination which was approved by the Health Sciences Research Ethics Board (HSREB) of the University of Toronto, Canada. Cyclists who are 18 years of age or older from the cities of Toronto, Montreal, Calgary, New York, and Orlando are the main focus of our dissemination. The definition of commuter (utilitarian) and non-commuter (non-utilitarian) cycling was provided at the beginning of the survey.

In this survey, responses from bicyclists were collected along four dimensions. (1) Respondent's personal and household characteristics (such as gender, age, education level, employment type and schedule, nearest intersections at the place of residence and work, household income, number of persons in the household, level of automobile and bicycle ownership, and commute time in minutes); (2) Cycling habits (frequency of cycling, if accompanied by children while making the trip, regular bicycling experience in years, primary reasons for cycling, seasons of cycling, and how often they switch their usual biking route); (3) Hypothetical choice scenarios with three route options per scenario; and (4) Cyclist's perception about the characteristics of his/her usual commuting route.

The experimental design for identifying the hypothetical choice scenarios for the SP game was developed considering the following attributes: <u>roadway characteristics</u>: grade, traffic volume, and roadway type; <u>bike route characteristics</u>: cycling infrastructure continuity and segregation and landmarks along the route; and <u>air pollution</u>: mean exposure level (in ppb) and maximum exposure level (in ppb). A detailed description of the considered attributes and the corresponding attribute levels are presented in Table3.1. Considering and comparing all of these attributes would burden the respondents significantly and complicate their route choice process. Hence, an innovative partitioning technique where only five attributes were used to characterize the alternative routes in each of the SP scenarios was used. Of these five attributes, the air pollution attributes (mean and maximum exposure[1]) were always retained. These air pollution exposures were measured as a concentration of Nitrogen dioxide[2] (NO_2) in units of parts per billion (ppb). In addition, one attribute from roadway characteristics and one from bike route characteristics were randomly chosen for each individual through carefully designed rotating and overlapping approach to capture all variable effects when the responses from the different SP choice scenarios across different individuals are compiled together. Route choice alternatives were developed by experimental design routines in SAS in such a way that every individual gets three choice experiments in the survey. The SP scenarios were preceded by clear definitions of the attributes – pictorial representations were provided to give respondents a clearer idea about exclusive/shared and continuous/discontinuous cycling infrastructure.

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[1] Typical bicyclists are most likely unaware of the analytical measurement units of air pollutant concentrations (for example, parts per billion or ppb) or the potential amount of pollution they are exposed to while on the road. In this survey, two measures were identified that represent the amount of traffic-related air pollution the cyclists are exposed. The first measure is the mean exposure that refers to the average air pollution level over the length of the route. The second measure is the maximum exposure i.e. the maximum level of air pollution that cyclists would encounter for a short part of their trip (for example, when biking behind a bus/truck). While participants might not completely evaluate the exact levels, the research is also interested in how the bicyclists consider the information provided.

[2] NO_2 concentrations in cities like Toronto and Montréal in Canada typically range between 5 ppb and 50 ppb. We chose NO_2 for representing air pollution because NO_2 is a marker of traffic-related air pollution and is highly associated with air pollution from traffic in urban areas (see Hatzopoulou et al., 2013). Other pollutants such as CO, SO_2 are also generated from other sources and it becomes a lot more difficult for participants to understand. NO_2 is routinely monitored in urban areas and the vast majority of the epidemiology literature on air pollution and health effects is based on exposure to NO_2.

An “information provision” experiment was also conducted to understand two issues. First, to identify if receiving information on the potential health effects resulting from exposure to traffic-related air pollution has any impact on a cyclist’s route choice decision and second, to study the sensitivity towards the nature of information provided. For this purpose, three types of informational messages were devised. One (or none) of these messages was presented to the respondent in a window preceding the scenarios and following the description of attributes. The survey was designed so that information display was randomized to ensure that a quarter of the respondents received no information while the rest of them received at least one of the three messages. The details of the experimental design, attribute selection process, and survey dissemination strategies with demographic profile of commuters are described in (Anowar et al., 2017) . The sample characteristics of commuter cyclists found from the survey is presented in the Appendix A.

3.2 Variables Considered

In our study, we considered household and individual socio-demographic characteristics for latent segmentation component and bicycle route choice attributes for segmentation based choice model part. The socio-demographic characteristics considered are: gender, age category, education, employment status, experience of bicycling, bicycling frequency, companionship with children and actual commute time needed reported by respondents, number of household members, number of automobiles and bicycles owned by household. The variables considered for the route choice part are: (1) roadway characteristics: grade (flat, moderate, and steep), traffic volume (low, medium, and heavy), and roadway type (residential/local street, minor arterial, and major arterial), (2) bike route characteristics: cycling infrastructure continuity and cycling infrastructure segregation (exclusive and shared), and (3) air pollution (mean exposure level and maximum exposure level), and (4) trip characteristics: travel time.

Note that residential/local streets are those with light traffic with speeds < 40 km/h or 25 mph, minor arterials are those with moderate traffic with speeds 40-60 km/h or 25-40 mph and major arterials are those with heavy traffic with speeds > 60 km/h or 40 mph. A bicycle route is labeled continuous if the whole route has a bicycle facility (a bike lane or a shared-use path). In contrast, a bicycle route is considered to be discontinuous if on some portions of the route bicyclists must share a lane with automobiles. Finally, exposure to traffic-generated pollution was expressed in two ways. First, mean exposure ranging from 5-15 ppb and maximum exposure ranging from 20-60 ppb. We used discretized travel time attribute ranging from 20-40 minutes.

3.3 Summary

The chapter presented an overview of the data source, SP survey design and dissemination and an overview of the variables compiled for analysis.

Table 3.1 Attribute Levels for the SP Experiments

Attribute Category	Attribute	Definition of Attribute	Attribute Levels
Roadway characteristics	Grade	Nature of terrain	1. Flat 2. Moderate 3. Steep
	Traffic volume	Amount of traffic on the roadway	1. Light 2. Moderate 3. Heavy
	Roadway type	Functional classification of roadway	1. Residential /Local roads 2. Minor arterial 3. Major arterial
Bike route characteristics	Cycling infrastructure continuity	Continuous bike route – if the whole route has a bicycle facility (a bike lane or shared-use path) Discontinuous - otherwise	1. Continuous 2. Discontinuous
	Cycling infrastructure segregation	Exclusive/Segregated– if physically separated from motor vehicle traffic Shared – otherwise	1. Exclusive 2. Shared
Environmental condition	Amount of traffic-related air pollution subjected to while cycling	Mean exposure levels to pollutants	1. 5 ppb 2. 10 ppb 3. 15 ppb
		Maximum exposure levels to pollutants	1. 20 ppb 2. 40 ppb 3. 60 ppb
Trip characteristics	Duration of trip	Travel time to destination (for commuting bicyclists only)	1. 20 minutes 2. 25 minutes 3. 30 minutes 4. 35 minutes 5. 40 minutes

CHAPTER FOUR: EMPIRICAL ANALYSIS

Employing the data described in the preceding chapter, we estimated several models including random utility based multinomial logit model, random utility based mixed multinomial logit model, random regret based multinomial logit model, random regret based mixed multinomial logit model and several latent segmentation based models from utility and regret regimes. The current chapter identifies the various model frameworks estimated and presents the results for these models. The presentation of results includes model estimates and segmentation characteristics for the model segments (as appropriate).

4.1 Model Specification and Performance Evaluation

The empirical analysis in this research effort involves the estimation of several models. More specifically, we estimated four traditional models and nine latent class models. Four traditional models include: (1) random utility based multinomial logit model, (2) random utility based mixed multinomial logit model, (3) random regret based multinomial logit model, (4) random regret based mixed multinomial logit model. The estimated latent class models are: (1) random utility based latent multinomial logit model with two segments, (2) random regret based latent multinomial logit model with two segments, (3) random regret based latent multinomial logit model with three segments, (4) latent class multinomial logit model with hybrid segments (LCMHS). In the LCMHS category, we tested different combinations of decision rules with different number of classes. These are: (1) LCMHS with two segments (1 random utility based segment, 1 random regret based segment), (2) LCMHS with three segments (2 random regret based segment – 1 random utility based segment), (3) LCMHS with three segments (1 random regret based segment – 2 random utility based segment), (4) LCMHS with four segments (2 random regret based segment – 2 random regret based segment), (5) LCMHS with four segments (3 random regret based segment – 1 random utility based segment) and (6) LCMHS with four segments (1 random regret based segment – 3 random utility based segment). Note that we also tested for taste heterogeneity in the segment specific models, but the results were not supportive of the presence of further segment level unobserved heterogeneity.

The performance of the estimated (13) models was compared based on two goodness of fit measures best suited for comparing non-nested models: (1) Akaike information criterion (AIC) and (2) Bayesian Information Criterion (BIC). The AIC for a given empirical model is equal to:

$$AIC = 2k - 2ln(L) \tag{6}$$

where k is the estimated number of parameters and L denotes the maximized value of likelihood function for a given empirical model. The empirical equation of BIC is:

$$BIC = -2ln(L) + K\, ln(Q) \tag{7}$$

where $ln(L)$ denotes the log likelihood value at convergence, K denotes the number of parameters, and Q represents the number of observations. Many of the earlier studies suggested that the BIC is the most consistent information criterion (IC) among all other traditionally used ICs (AIC, AICc, adjusted BIC) for number of segments selection in latent class models (Anowar et al., 2014, Bhat, 1997, Collins et al., 1993, Eluru et al., 2012, Nylund et al., 2007, Yasmin et al., 2014b). The advantage of using BIC is that it imposes substantially higher penalty than other ICs on over-fitting. The model with the lowest AIC and BIC value is the preferred model. The BIC and AIC values for the final specifications of all the models are presented in Table 4.1. Based on these values, LCMHS with four segments (3 random regret based segment – 1 random utility based segment) offers the best data fit.

Table 4.1 Goodness of Fit Measures

Model	Log-likelihood	Number of Parameters (K)	Number of Observations (Q)	BIC	AIC
Traditional Choice Models					
RUM based MNL	-2765.470	23	3475	5718.467	5576.940
RUM based mixed MNL	-2759.650	24	3475	5714.980	5567.300
RRM based MNL	-2709.500	35	3475	5704.367	5489.000
RRM based mixed MNL	-2688.781	32	3475	5638.470	5441.563
Latent Segmentation Models					
RUM based Latent MNL with two segments	-2734.217	20	3475	5631.500	5508.434
RRM based Latent MNL with two segments	-2693.295	23	3475	5574.118	5432.591
RRM based Latent MNL with three segments	-2665.158	26	3475	5542.304	5382.316
LCMS with two segments (1 RUM based segment-1 RRM based segment)	-2729.685	20	3475	5622.438	5499.371
LCMS with three segments (2 RUM based segment-1 RRM based segment)	-2601.792	36	3475	5497.104	5275.583
LCMS with three segments (1 RUM based segment-2 RRM based segment)	-2647.804	29	3475	5532.055	5353.608
LCMS with four segments (2 RUM based segment-2 RRM based segment)	-2559.369	42	3475	5461.178	5202.738
LCMS with four segments (1 RUM based segment-3 RRM based segment)	-2566.263	33	3475	**5401.587**	**5198.526**
LCMS with four segments (3 RUM based segment-1 RRM based segment)	-2624.438	34	3475	5526.090	5316.876

4.2 Population Share Distribution Among Segments

The latent segmentation component determines the probability that a cyclist is assigned to the identified segments. We used the model estimations to generate the population share across the various segments of all the latent class models following the equation (Yasmin et al., 2014a, Bhat, 1997) below:

$$G_S = \frac{\sum_c P_{cs}}{C} \tag{8}$$

where C denotes the total number of respondents in the sample. The shares are presented in Table 4.2. The table offers some interesting insights. In all the latent class models with mixed choice paradigms, cyclists are more likely to be part of the segment(s) with random regret decision rule. For instance, in our best specified model, only 30% of the cyclists are likely to be allocated to the random utility based segment while the rest of them to the three random regret based segment (8%, 43%, and 19%). It is interesting to note that the split of cyclists who make their route choice decision following regret minimization concept is not equal.

Table 4.2 Population Share Distribution

Model	Segment-1	Segment-2	Segment-3	Segment-4
RUM based Latent MNL with two segments	72	28	-	-
RRM based Latent MNL with two segments	47	53	-	-
LCMHS with two segments (1 RUM based segment-1 RRM based segment)	35	65	-	-
RRM based Latent MNL with three segments	16	18	66	-
LCMHS with three segments (2 RUM based segment-1 RRM based segment)	30	34	36	-
LCMHS with three segments (1 RUM based segment-2 RRM based segment)	24	21	55	-
LCMHS with four segments (2 RUM based segment-2 RRM based segment)	19	14	21	46
LCMHS with four segments (1 RUM based segment-3 RRM based segment)	**8**	**30**	**43**	**19**
LCMHS with four segments (3 RUM based segment-1 RRM based segment)	13	25	33	29

4.3 Model Results

In addition to the best model fit, LCMHS with four segments (3 random regret based segment – 1 random utility based segment) provided the most intuitive behavioral interpretation in terms of route choice decision. Hence, in this section we only discuss about the results of this model in detail. Table 4.3 presents the results for the segmentation component (top panel of results) and segment specific route choice models (bottom panel of results). The results for all other models are presented in the Appendix B (Table B.1-B.10). The reader would note that utility based MNL and regret based MNL model results are not presented as they are very similar to utility based mixed MNL and regret based mixed MNL model results respectively.

4.3.1 Latent Segmentation Component

The variables in the segmentation part with positive (negative) coefficient indicate increase (decrease) in the propensity of the cyclists being part of the segment. In our analysis, we considered Segment 1 as the base. The positive sign on the constant term does not have any functional interpretation, but simply reflects the larger likelihood of bicyclists being part of other three segments. The variables influencing segment membership include gender, age, auto ownership, biking frequency, and commute length. Our results indicate that female bicyclists are more likely to be assigned to segment 2 (utility based decision rule segment). Examining the coefficients of Segment 3, we find that bicyclists in this class are more likely to be daily commuters, less than 35 years of age, from a household with less number of automobiles, and have a moderate commute duration. Interestingly, Segment 4 is more likely to be comprised of daily commuters as well (with a slightly higher propensity for Segment 4 membership than Segment 3 membership) but with short commute length.

Table 4.3 Results of LCMS with Four Segments (1 RUM Based Segment-3 RRM Based Segment)

Variables	Segment-1 (RRM)		Segment-2 (RUM)		Segment-3 (RRM)		Segment-4 (RRM)	
	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics
Segmentation Component								
Constant	-	-	0.892	3.225	2.710	6.854	0.710	1.836
Female (Base: Male)	-	-	0.869	3.697	-	-	-	-
Age (Base: 18-34 years)								
35 or more years	-	-	-	-	-1.119	-4.883	-	-
Auto Ownership	-	-	-	-	-0.498	-3.913	-	-
Biking frequency (Base: Rarely)								
Daily	-	-	-	-	0.546	2.023	0.795	2.36
Commute length (Base: Short commute)								
Long Commute	-	-	-	-	-1.013	-2.442	-	-
Moderate to Long Commute	-	-	-	-	-	-	-0.978	-3.448
Route Choice Component								
Roadway Characteristics								
Grade (Base: Flat)								
Steep	-	-	-1.795	-6.221	-2.131	-10.220	-	-
Traffic Volume (Base: Light)								
Medium	-	-	-1.027	-3.492	-	-	-	-
Heavy	-	-	-1.604	-5.906	-1.137	-6.399	-1.906	-5.760
Roadway Type (Base: Residential roads)								
Minor arterial	-	-	-0.904	-5.156	-	-	-	-
Major arterial	-	-	-2.178	-6.356	-1.843	-11.443	-	-
Bike Route Characteristics								
Infrastructure Continuity (Base: Discontinuous)								
Continuous	-	-	1.325	6.071	1.000	5.486	-	-
Infrastructure Segregation (Base: Shared)								
Exclusive	-	-	1.859	8.215	1.029	8.136	-	-
Environmental condition								
Mean Exposure	-0.055	-3.433	-0.058	-3.027	-0.067	-5.776	-0.050	-3.404
Maximum Exposure	-	-	-0.034	-6.957	-0.015	-5.723	-0.027	-6.984
Trip Characteristics								
Travel Time	-	-	-0.050	-4.247	-0.248	-12.122	-0.139	-8.205
Log-likelihood at Convergence	-2566.263							

4.3.2 Segment Specific Route Choice Models

A cursory examination of the results indicates the presence of the higher number of segment specific effects for segment 2 and segment 3. On the other hand, segment 1 route choice behavior is only influenced by one variable. It is also evident that the across the various segments the variable impacts are significantly different manifesting the presence of population heterogeneity. We provide a discussion of model results across the 4 segments in this section by variable characteristics.

4.3.2.1 Roadway Characteristics

Grade, traffic volume and roadway type variables influence route choice behavior in segments 2, 3 and 4. As expected, for commuting purposes, steep roadway grades reduce the likelihood of choosing the route in both utility (segment 2) and regret (segment 3) segments. In segment 2, the coefficient indicates a reduction in utility for routes with steep grade. In segment 3, commuter bicyclists will be predisposed to lower regret toward routes with flat or moderate grades relative to routes with steep grades. Cyclists are inclined to avoid steep grade presumably because of the discomfort from rigorous physical activity while commuting to work (see similar results in (Sener et al., 2009, Anowar et al., 2017)). High vehicular traffic volume (medium and heavy) on roadway deters cyclists from choosing those routes. In segment 2, in particular, there is a larger drop in utility for routes with heavy traffic. The negative coefficients for heavy traffic volume in Segment 3 and Segment 4 suggest that regret reduces if traffic volume on the non-chosen alternatives is higher, thus reducing the likelihood for opting for route with heavy traffic (see (Dill and Voros, 2007)). The presence of increased vehicular traffic will increase the probability of conflict between cyclists with motorized vehicles; so it is expected that that commuter cyclists prefer routes with lower traffic levels. In terms of roadway type, routes on minor and major arterials (relative to routes on residential roads) are less likely to be chosen for commuting purpose. The effect is more pronounced in Segment 2, the utility for a route drops significantly when that route is located on a major arterial. In segment 3, the coefficient for major arterial is negative indicating that the regret associated with not choosing a route with major arterial is lower (relative to other alternatives). The results are quite intuitive and could be attributed to cyclist's perception of higher level of safety on residential streets.

4.3.2.2 Bike Route Characteristics

The effect of bike route characteristics is found significant only in Segment 2 and Segment 3 – these two classes captured respondents who are highly sensitive to cycling infrastructure. The routes with continuous or segregated facilities are associated with higher utility in segment 2 and larger regret in segment 3 increasing the inclination to choose routes with continuous or segregated facilities relative to routes without continuous or segregated facilities. The results indicate that cyclists prefer to ride on a route with continuous cycling facility or on an exclusive route segregated from vehicular traffic with a slightly higher preference for exclusive routes. The result is expected and is reported in earlier research as well (see similar results in (Barnes et al., 2006, Dickinson et al., 2003, Dill and Voros, 2007, Larsen and El-Geneidy, 2011, Pucher and Buehler, 2006, Stinson and Bhat, 2005, Winters et al., 2011)). On the other hand, the bicycle infrastructure variables have no impact on segment 1 and 4.

4.3.2.3 Air Pollution

Of the two air pollution attributes, only mean exposure were found to affect route choice behavior across all segments. This essentially implies that irrespective of the decision rule, cyclists in all segments are strongly sensitive to exposing themselves to air pollution while on road. As expected, increase in mean exposure for a route reduces the likelihood that a bicyclist chooses the alternative. On the other hand, maximum exposure affects route choice behavior in segments 2, 3 and 4. The influence of maximum exposure is also along expected lines – increase in maximum exposure along the route reduces the probability of choosing that route (see (Anowar et al., 2017) for similar results). The reader would note that between mean and maximum exposure, the influence of mean exposure is consistently larger than the influence of maximum exposure on a parts per billion basis. The higher negative coefficient for mean exposure level indicates that cyclists are more sensitive towards a constant level of pollution on a regular basis rather than instantaneous exposure to pollution.

4.3.2.4 Trip Characteristics

For commuters, travel time is an important determinant of route choice. The variable influences route choice decision in segments 2, 3 and 4. An increase in travel time is associated with reduction in utility or reduction in regret for the route with longer travel time. Thus, these routes have a lower probability of being chosen. Several studies have highlighted the impact of travel time along the same lines (see, (Sener et al., 2009, Stinson and Bhat, 2005, Anowar et al., 2017)). It is however, quite interesting that for segment 1, travel time is not a factor. The results highlight the behavior of a small population group that is focused solely on reducing their exposure to air pollution. The discovery of their presence would not have been possible without the 4 segment latent segmentation model developed in our study.

4.4 Summary

This chapter identified the various model structures considered and estimated in our analysis. Further, we provided the goodness of fit measures for all the model frameworks and provided a discussion of the best fitting model. A trade-off analysis will be discussed in the subsequent chapter.

CHAPTER FIVE: TRADE-OFF ANALYSIS

While the model results were generally intuitive, the model results themselves do not provide an easy mechanism to understand the magnitude of the various exogenous factors considered in the model. Thus, to illustrated the value of the proposed model, we conduct a detailed trade-off analysis. The current chapter documents the trade-off analysis approach and presents the "Value of Clean Ride (VCR)" – a very useful measure for policy makers.

5.1 Trade-off Value

Using the outputs from the model, we computed the time-based trade-offs, i.e. how much (in minutes) bicyclists are willing to travel extra for using routes with better facilities or less traffic-generated pollution. This analysis gives us an insight on how the trade-off values are varying across different segments of cyclists. For segment 2, the calculation is straightforward – dividing the coefficient value of each attribute by the coefficient value of travel time. However, Segment 1, Segment 3 and Segment 4 are random regret based classes. When all attributes in a model are evaluated using random regret decision rule, the calculation of trade-offs is done using the following equation:

$$\frac{\sum_{j \neq i} -\beta_t / \left(1 + 1/exp\left[\beta_t\left(t_j - t_i\right)\right]\right)}{\sum_{j \neq i} -\beta_r / \left(1 + 1/exp\left[\beta_r\left(r_j - r_i\right)\right]\right)} \tag{9}$$

where β_t and β_r are the estimated coefficients for the two attributes for which we are calculating the trade-off. In our case, the r^{th} attribute is travel time and the t^{th} attribute represents the attribute for which the "willingness to travel extra" for a one-unit increase/decrease is being investigated. The results from the trade-off exercise (for main effects only) are presented in Table 5.1.

The results of the trade-off analysis provide some interesting insights. For the utility oriented segment, as expected, cyclists are willing to travel 15-45 minutes extra to avoid steep grade, medium/heavy traffic volume, and riding on minor/major arterial. Moreover, they are also willing to travel in excess of 25 minutes to ride on a continuous or exclusive bike facility. "Value of Clean Ride (VCR)" for mean exposure, was estimated at 1.16 min/ppb and for maximum exposure, was estimated at 0.68 min/ppb suggesting that commuter cyclists are more sensitive to mean exposure than maximum exposure. The value obtained in our current analysis is double the value obtained in a previous analysis using the same data (see (Anowar et al., 2017)). This signifies that segment 2 commuter cyclists who more likely to be females are strongly sensitive to air pollution and are willing to travel 5-40 minutes extra to avoid them.

Trade-off values from random utility paradigm is insensitive to the changes in the attribute values. However, we can see from Table 5.1 that random regret formulation based trade-offs calculated for Segment 3 and 4 are alternative and choice set dependent and monotonically decrease with increase in travel time.[3] For example, from trade-off values we can see that when a chosen alternative does poorly in terms of roadway attribute (has steep grade, or has heavy vehicular traffic or is located on a major arterial), but has a faster commuting time, an increase in travel time leads to a small increase in regret while improvement in terms of road grade leads to a relatively large decrease in regret. Hence, cyclists are willing to travel more than 40, 20, and 35 minutes, respectively for travelling on a route with better grades (medium or flat), better traffic situation (medium or low), and convenient roadway type (minor or residential). Cyclists in Segment 4 are willing to travel longer than cyclists in Segment 3 to avoid heavy traffic. Interestingly, the trade-off values in

[3] Trade-off values for travel time cannot be estimated for Segment 1 as the 'Travel Time' attribute was insignificant.

regret and utility based segments for roadway attributes are similar in magnitude; but values differ greatly for cycling infrastructure and exposure attributes, particularly for maximum exposure levels.

5.2 Summary

This chapter provided a summary of the results of a trade-off analysis conducted for the LCMHS model with four segments (3 random regret based segment – 1 random utility based segment). The results included “Value of Clean Ride (VCR)” for all of the segments accommodating both utility and regret based MNL.

Table 5.1 Time Based Trade-offs

Attribute	Attribute Levels	Travel Times (minutes)										
		Segment-2 (RUM)	Segment-3 (RRM)					Segment-4 (RRM)				
		20-40	20	25	30	35	40	20	25	30	35	40
Grade	Steep	35.90	46.22	13.95	7.68	5.30	4.19	-	-	-	-	-
Traffic Volume	Medium	20.54	-	-	-	-	-	-	-	-	-	-
	Heavy	32.08	20.89	6.31	3.47	2.39	1.89	34.04	18.23	11.94	8.88	7.24
Roadway type	Minor Arterial	18.08	-	-	-	-	-	-	-	-	-	-
	Major Arterial	43.56	38.61	11.65	6.42	4.43	3.50	-	-	-	-	-
Infrastructure Continuity	Continuous	26.50	3.26	0.99	0.54	0.37	0.30	-	-	-	-	-
Infrastructure Segregation	Exclusive	37.18	3.29	0.99	0.55	0.38	0.30	-	-	-	-	-
Environmental Condition	Mean Exposure (5 ppb)	5.80	3.07	0.93	0.51	0.35	0.28	2.09	1.12	0.73	0.55	0.44
	Mean Exposure (10 ppb)	11.60	8.13	2.45	1.35	0.93	0.74	5.13	2.75	1.80	1.34	1.09
	Mean Exposure (15 ppb)	17.40	15.17	4.58	2.52	1.74	1.38	9.11	4.88	3.20	2.38	1.94
	Maximum Exposure (20 ppb)	13.60	2.84	0.86	0.47	0.33	0.26	3.44	1.84	1.21	0.90	0.73
	Maximum Exposure (40 ppb)	27.20	7.28	2.20	1.21	0.83	0.66	11.08	5.93	3.88	2.89	2.36
	Maximum Exposure (60 ppb)	40.80	13.32	4.02	2.21	1.53	1.21	22.91	12.26	8.03	5.97	4.87

CHAPTER SIX: CONCLUSIONS

In the extant literature, several approaches have been employed to address population homogeneity restriction in discrete choice models, latent class model is one of the elegant and intuitive approaches. While several of these studies have focused on exogenous variable homogeneity, the decision rule homogeneity assumption has received less attention. Our study aims to bridge the gap in the literature in this context by analyzing population and decision rule heterogeneity drawing on a novel empirical context – impact of air pollution on bicycle route choice. In our analysis, we choose to consider the random utility framework along with random regret minimization approach. Further, instead of assuming the number of segments (as 2), we conduct an detailed exploration with multiple segments across the two decision rules. Within each segment we also allow for unobserved heterogeneity. The model estimation is conducted using a stated preference data from 695 commuter cyclists compiled through a web-based survey. Model fit measures revealed that latent class models with four segments (3 random regret based segment – 1 random utility based segment) provided the best data fit. The probabilistic allocation of respondents to different segments was achieved based on multivariate set of cyclist demographics and cycling habits. The results indicate that female commuter cyclists are more utility prone, however the majority of the commuter cyclist's choice pattern is consistent with regret minimization mechanism.

Overall, cyclists' route choice decisions are influenced by roadway attributes, cycling infrastructure availability, pollution exposure, and travel time. Although travel time is the most important attribute for commuter cyclists in their route choice decision, it is however, quite interesting that for one of the segments, travel time is not a factor. The results highlight the behavior of a small population group that is focused solely on reducing their exposure to air pollution. The discovery of their presence would not have been possible without the 4 segment latent segmentation model developed in our study. This observation has interesting policy implications – it suggests that bicyclists' exposure to air pollution should be incorporated in bicycle route planning. In addition, we find that between mean and maximum exposure, the influence of mean exposure is consistently larger than the influence of maximum exposure on a parts per billion basis. The higher negative coefficient for mean exposure level indicates that cyclists are more sensitive towards a constant level of pollution on a regular basis rather than instantaneous exposure to pollution. The analysis approach also allows us to investigate time based trade-offs across cyclists of different classes. Interestingly, we observed that the trade-off values in regret and utility based segments for roadway attributes are similar in magnitude; but the values differ greatly for cycling infrastructure and exposure attributes, particularly for maximum exposure levels.

APPENDIX A:

DEMOGRAPHIC PROFILE OF COMMUTER BICYCLISTS

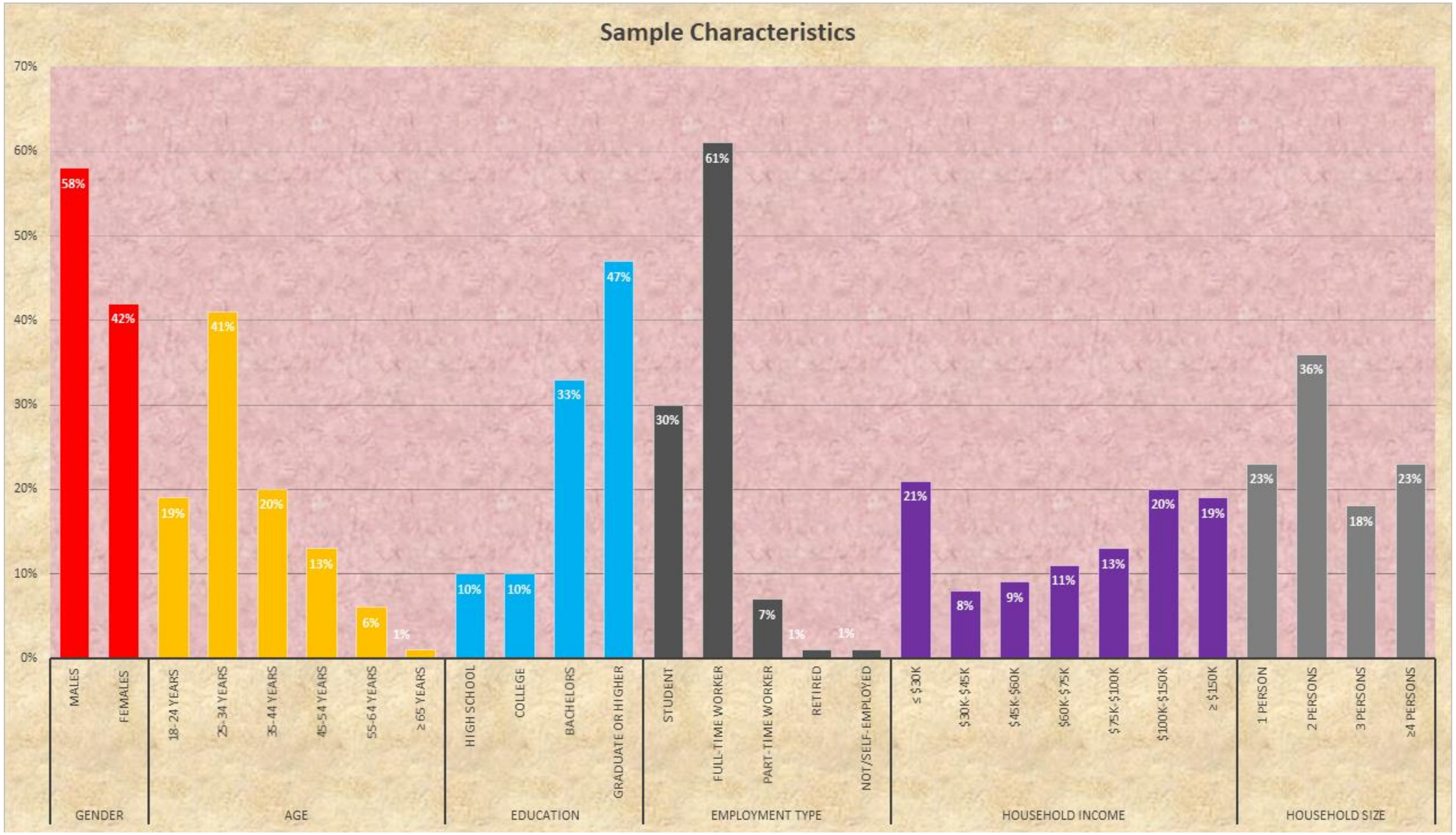

Figure A.1 Demographic Profile of Commuter Bicyclists

APPENDIX B:

RESULTS OF RUM BASED MIXED MNL, RRM BASED MIXED MNL AND OTHER LATENT SEGEMNTATION MODELS

Table B.1 Results of RUM Based Mixed MNL

Attribute Category	**Attribute**	**Attribute Levels**	**Coefficient**	***t*-statistics**
Roadway Characteristics	Grade (Base: Flat)	Steep	-0.982	-10.579
		Female	-0.804	-5.601
	Traffic Volume (Base: Light)	Moderate	-0.657	-7.729
		Heavy	-1.508	-16.662
	Roadway Type (Base: Residential Roads)	Minor arterial	-0.398	-4.776
		Major arterial	-1.290	-15.025
		Female	-0.345	-2.576
Bike Route Characteristics	Infrastructure Continuity (Base: Discontinuous)	Continuous	0.879	13.485
	Infrastructure Segregation (Base: Shared)	Exclusive	0.939	10.353
		Female	0.306	2.561
Environmental Condition	Mean Exposure	Mean exposure	-0.054	-8.791
		Biking experience (Base: 2 or more years)		
		Less than 2 years	-0.021	-1.961
	Maximum Exposure	Maximum exposure	-0.019	-10.271
		Standard deviation	0.016	6.480

		Exposure impact information (Base: No information)		
		Short-term	-0.007	-2.148
Trip Characteristics	Travel Time	Travel time	-0.075	-4.551
		Female	0.018	2.942
		Age (Base: 18-24 years)		
		25-34 years	-0.043	-6.740
		55-64 years	0.027	2.656
		65 years or more	0.056	2.762
		Biking frequency (Base: Rarely)		
		Once or several times a month	-0.049	-2.988
		Daily	-0.080	-4.982
		Commute length (Base: Short commute)		
		Moderate	0.030	4.831
		Long	0.072	7.997
Log-likelihood at convergence (N = 3475): -2759.650				

Table B.2 Results of RRM Based Mixed MNL

Attribute Category	Attribute	Attribute Levels	Coefficient	*t*-statistics
Roadway Characteristics	Grade (Base: Flat)	Steep	-1.803	-3.897
		Female	-0.403	-3.916
		Age Range (Base: 18-24 Years)		
		25-34 Years	-0.596	-5.974
		Bicycling Experience (Base: More than 5 Years)		
		Less than 5 Years	-0.412	-3.910
		Accompanied (Base: With Children)		
		Without Children	1.033	2.653
	Traffic Volume (Base: Light)	Medium	-0.585	-5.607
		Age Range (Base: 18-24 Years)		
		45-54 Years	-0.395	-2.653
		Frequency of Bicycling (Base: Rarely)		
		Daily	0.301	2.197
		Heavy	-1.095	-18.011
	Roadway Type (Base: Residential Roads)	Minor Arterial	-0.245	-4.258
		Major Arterial	-0.667	-10.776
		Female	-0.221	-2.359
		Age Range (Base: 18-24 Years)		
		25-34 Years	-0.230	-2.408
Bike Route Characteristics	Infrastructure continuity (Base: Discontinuous)	Continuous	0.817	12.920
		Age Range (Base: Less than 35 Years)		
		35 Years or more	-0.242	-3.544
	Infrastructure segregation (Base: Shared)	Exclusive	0.826	8.604
		Female	0.229	2.520
		Frequency of Bicycling (Base: Rarely)		

		Daily	-0.196	-2.028
Environmental Condition	Mean Exposure	Mean Exposure	-0.034	-5.858
		Standard Deviation	0.069	11.331
		Bicycling Experience (Base: 2 or more Years)		
		Less than 2 Years	-0.027	-2.448
	Maximum Exposure	Maximum Exposure	-0.015	-11.136
		Standard Deviation	0.012	6.705
		Exposure impact information (Base: No information)		
		Short-term	-0.005	-2.298
Trip Characteristics	Travel Time	Travel time	-0.106	-16.615
		Female	0.017	3.675
		Age Range (Base: 18-24 Years)		
		25-34 Years	-0.033	-5.251
		35 Years or more	0.022	3.803
		Frequency of Bicycling (Base: Rarely)		
		Daily	-0.027	-5.842
		Bicycling Experience (Base: Less than 5 Years)		
		More than 5 Years	0.011	2.383
		Commute length (Base: Short commute)		
		Moderate	0.021	4.948
		Long	0.049	7.692
Log-likelihood at Convergence (N = 3475): -2688.781				

Table B.3 Results of RUM Based Latent MNL with Two Segments

Variables	Segment-1		Segment-2	
	Estimate	***t*-statistics**	**Estimate**	***t*-statistics**
Segmentation Component				
Constant	-	-	0.1207	0.544
Female (Base: Male)			-1.1213	-4.071
Age (Base: 18-34 years)				
35 or more years	-	-	-0.5829	-2.256
Biking frequency (Base: Rarely)				
Less than once to several times per month	-	-	-0.7634	-2.446
Commute length (Base: Short commute)				
Moderate to Long Commute	-	-	-0.5278	-2.103
Route Choice Component				
Roadway Characteristics				
Grade (Base: Flat)				
Steep	-1.9901	-10.796	-	-
Traffic Volume (Base: Light)				
Medium	-0.5979	-5.052	-	-
Heavy	-1.8195	-11.781	-	-
Roadway Type (Base: Residential roads)				
Minor arterial	-0.5826	-6.036	0.4712	2.619
Major arterial	-2.1185	-12.618	-	-
Bike Route Characteristics				
Infrastructure Continuity (Base: Discontinuous)				
Continuous	1.0168	10.244	-	-
Infrastructure Segregation (Base: Shared)				
Exclusive	1.4147	11.821	0.3814	2.126
Environmental condition				
Mean Exposure	-0.0646	-7.174	-0.0511	-3.118
Maximum Exposure	-0.0169	-8.678	-0.0341	-7.64
Trip Characteristics				
Travel Time	-0.1185	-18.196	-0.1816	-10.278
Log-likelihood at Convergence	-2734.216875			

Table B.4 Results of RRM Based Latent MNL with Two Segments

Variables	Segment-1		Segment-2	
	Estimate	***t*-statistics**	**Estimate**	***t*-statistics**
Segmentation Component				
Constant	-	-	0.5567	1.831
Age (Base: 18-34 years)				
35 or more years	-	-	-1.0154	-4.443
Auto Ownership				
2 or more	-	-	-0.7959	-2.835
Biking frequency (Base: Rarely)				
Daily	-	-	0.5885	2.319
Commute length (Base: Short commute)				
Moderate to Long Commute	-	-	-0.5905	-2.683
Route Choice Component				
Roadway Characteristics				
Grade (Base: Flat)				
Steep	-0.3618	-4.058	-1.7995	-10.907
Traffic Volume (Base: Light)				
Medium	-0.395	-3.653	-	-
Heavy	-0.8146	-7.267	-1.263	-9.178
Roadway Type (Base: Residential roads)				
Minor arterial	-0.4006	-5.628	-	-
Major arterial	-0.9872	-5.95	-0.8877	-5.647
Bike Route Characteristics				
Infrastructure Continuity (Base: Discontinuous)				
Continuous	0.5074	6	0.8509	6.739
Infrastructure Segregation (Base: Shared)				
Exclusive	0.6684	8.75	1.342	4.336
Environmental condition				
Mean Exposure	-0.0425	-6.243	-0.0524	-5.857
Maximum Exposure	-0.0165	-10.23	-0.0156	-7.7
Trip Characteristics				
Travel Time	-0.0354	-6.71	-0.2045	-13.681
Log-likelihood at Convergence	-2693.295275			

Table B.5 Results of LCMHS with Two Segments (1 RUM Based Segment-1 RRM Based Segment)

Variables	Segment-1 (RRM)		Segment-2 (RUM)	
	Estimate	***t*-statistics**	**Estimate**	***t*-statistics**
Segmentation Component				
Constant	-	-	1.0009	3.041
Female (Base: Male)	-	-	0.4835	2.03
Age (Base: 18-34 years)				
35 or more years	-	-	-0.5952	-2.294
Auto Ownership	-	-	-0.3474	-2.777
Income (Base: Low Income)				
High Income	-	-	0.638	2.555
Route Choice Component				
Roadway Characteristics				
Grade (Base: Flat)				
Steep	-0.414	-3.783	-2.3841	-8.804
Traffic Volume (Base: Light)				
Medium	-	-	-1.2563	-7.065
Heavy	-	-	-2.4797	-11.709
Roadway Type (Base: Residential roads)				
Minor arterial	-	-	-0.6397	-5.518
Major arterial	-	-	-2.8088	-12.347
Bike Route Characteristics				
Infrastructure Continuity (Base: Discontinuous)				
Continuous	-	-	1.353	8.485
Infrastructure Segregation (Base: Shared)				
Exclusive	0.4319	3.962	1.484	10.007
Environmental condition				
Mean Exposure	-0.0401	-4.813	-0.0475	-4.069
Maximum Exposure	-0.0187	-8.432	-0.0144	-4.71
Trip Characteristics				
Travel Time	-0.0442	-7.943	-0.2009	-14.887
Log-likelihood at Convergence	-2729.685475			

Table B.6 Results of RRM Based Latent MNL with Three Segments

Variables	Segment-1		Segment-2		Segment-3	
	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics
Segmentation Component						
Constant	-	-	-0.2721	-0.94	2.2434	5.432
Female (Base: Male)	-	-	0.8565	3.026	-	-
Age (Base: 18-34 years)						
35 or more years	-	-	-	-	-0.8104	-3.45
Auto Ownership	-	-	-	-	-0.4917	-3.843
Biking frequency (Base: Rarely)						
Daily	-	-	-	-	0.8847	3.518
Biking experience (Base: Less than 2 years)						
2 to 5 Years	-	-	-	-	0.9802	2.95
Commute length (Base: Short commute)						
Moderate to Long Commute	-	-	-	-	-0.6445	-2.747
Route Choice Component						
Roadway Characteristics						
Grade (Base: Flat)						
Steep	-	-	-1.4436	-4.439	-1.2822	-10.691
Traffic Volume (Base: Light)						
Heavy	-0.788	-3.684	-0.5474	-3.304	-1.0213	-11.128
Roadway Type (Base: Residential roads)						
Minor arterial	-	-	-0.4583	-2.085	-	-
Major arterial	-	-	-	-	-1.2264	-13.715
Bike Route Characteristics						
Infrastructure Continuity (Base: Discontinuous)						
Continuous	-	-	1.5098	4.963	0.6078	7.015
Infrastructure Segregation (Base: Shared)						
Exclusive	-	-	2.1802	4.908	0.7595	9.181
Environmental condition						
Mean Exposure	-0.0407	-3.948	-	-	-0.0505	-7.328
Maximum Exposure	-0.0145	-5.767	-0.0199	-5.77	-0.016	-10.507
Trip Characteristics						
Travel Time	-0.0354	-6.71	-0.0281	-2.853	-0.1706	-17.948

Log-likelihood at Convergence	-2665.1582

Table B.7 Results of LCMHS with Three Segments (1 RUM Based Segment-2 RRM Based Segment)

Variables	Segment-1 (RRM)		Segment-2 (RUM)		Segment-3 (RRM)	
	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics
Segmentation Component						
Constant	-	-	-2.4359	-5.031	-0.0287	-0.107
Female (Base: Male)	-	-	-	-	0.4435	2.019
Age (Base: 18-34 years)						
35 or more years	-	-	1.0596	3.489	-	-
Auto Ownership	-	-	0.4901	3.429	-	-
Biking experience (Base:5 years or more)						
Less than 2 years	-	-	0.9852	2.508	-	-
Less than 5 years	-	-	-	-	0.6805	2.792
Commute length (Base: Short commute)						
Moderate to Long Commute	-	-	1.3112	3.775	0.9811	3.42
Route Choice Component						
Roadway Characteristics						
Grade (Base: Flat)						
Steep	-	-	-	-	-1.8319	-10.961
Traffic Volume (Base: Light)						
Medium	-0.835	-2.548	-	-	-	-
Heavy	-1.802	-5.638	-1.1947	-5.032	-0.7621	-7.02
Roadway Type (Base: Residential roads)						
Major arterial	-0.4642	-2.663	-	-	-1.7609	-10.852
Bike Route Characteristics						
Infrastructure Continuity (Base: Discontinuous)						
Continuous	0.4694	2.587	-	-	0.8338	7.614
Infrastructure Segregation (Base: Shared)						
Exclusive	0.4709	2.507	0.8839	5.572	1.1475	10.312
Environmental condition						
Mean Exposure	-0.0647	-3.689	-0.0457	-3.517	-0.0326	-3.902
Maximum Exposure	-0.0199	-5.884	-0.02	-5.962	-0.0176	-8.508
Trip Characteristics						
Travel Time	-0.1954	-8.568	-	-	-0.1385	-15.047
Log-likelihood at Convergence			-2647.80405			

Table B.8 Results of LCMHS with Three Segments (2 RUM Based Segment-1 RRM Based Segment)

Variables	Segment-1 (RRM)		Segment-2 (RUM)		Segment-3 (RUM)	
	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics
Segmentation Component						
Constant	-	-	0.5664	1.616	-0.3167	-0.583
Female (Base: Male)	-	-	-	-	0.9036	3.871
Age (Base: 18-34 years)						
35 or more years	-	-	-0.855	-3.194	-	-
Employment Status						
Full-time or Part-time Worker	-	-	0.6878	2.417	0.72	2.492
Number of Household Member	-	-	-	-	0.3255	2.746
Bicycle Ownership	-	-	-	-	-0.4846	-3.008
Auto Ownership	-	-	-0.4639	-3.359	-	-
Biking experience (Base:5 years or more)						
Less than 5 years	-	-	0.5126	2.194	-	-
Commute length (Base: Short commute)						
Moderate to Long Commute	-	-	-	-	0.7794	3.375
Route Choice Component						
Roadway Characteristics						
Grade (Base: Flat)						
Steep	-0.3006	-2.325	-4.8934	-6.019	-1.6774	-6.893
Traffic Volume (Base: Light)						
Medium	-0.6115	-3.455	-	-	-0.4568	-2.495
Heavy	-1.1337	-7.485	-2.4846	-5.153	-1.0687	-5.916
Roadway Type (Base: Residential roads)						
Minor arterial	-	-	-0.8284	-3.376	-0.7873	-5.053
Major arterial	-	-	-4.4786	-9.179	-2.2092	-7.949
Bike Route Characteristics						
Infrastructure Continuity (Base: Discontinuous)						
Continuous	-	-	1.9149	4.124	0.9804	6.286
Infrastructure Segregation (Base: Shared)						
Exclusive	0.2954	2.552	1.5321	5.593	1.4442	8.488
Environmental condition						
Mean Exposure	-0.0653	-5.877	-0.0782	-3.535	-0.0365	-2.692

Maximum Exposure	-0.0248	-9.868	-	-	-0.019	-6.29
Trip Characteristics						
Travel Time	-0.0912	-11.681	-0.423	-8.299	-0.0417	-4.39
Log-likelihood at Convergence			-2601.791575			

Table B.9 Results of LCMHS with Four Segments (2 RUM Based Segment-2 RRM Based Segment)

Variables	Segment-1 (RRM)		Segment-2 (RUM)		Segment-3 (RUM)		Segment-4 (RRM)	
	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics
Segmentation Component								
Constant	-	-	-0.3441	-1.554	0.845	1.591	2.0661	5.166
Female (Base: Male)	-	-	-	-	-0.7824	-2.556	-	-
Age (Base: 18-34 years)								
35 or more years	-	-	-	-	-0.6656	-2.02	-1.2007	-4.733
Number of Household Member	-	-	-	-	-0.2769	-2.048	-	-
Auto Ownership	-	-	-	-	-	-	-0.5001	-3.862
Biking frequency (Base: Rarely)								
Daily	-	-	-	-	0.9291	2.46	0.5643	2.024
Commute length (Base: Short commute)								
Long Commute	-	-	-	-	-1.4334	-2.071	-1.1423	-2.723
Route Choice Component								
Roadway Characteristics								
Grade (Base: Flat)								
Steep	-0.9015	-5.908	-	-	-	-	-2.0274	-9.947
Traffic Volume (Base: Light)								
Medium	-0.6841	-3.859	1.0208	2.715	-1.3025	-2.372	-	-
Heavy	-1.0481	-5.383	-	-	-2.656	-3.154	-1.1102	-6.132
Roadway Type (Base: Residential roads)								
Minor arterial	-	-	-1.2814	-3.477	-	-	-0.2789	-2.263
Major arterial	-0.5335	-3.013	-1.8661	-4.236	-	-	-1.8005	-12.094
Bike Route Characteristics								
Infrastructure Continuity (Base: Discontinuous)								
Continuous	-	-	2.0755	6.536	0.6078	2.392	0.9639	5.703
Infrastructure Segregation (Base: Shared)								
Exclusive	0.3327	2.506	2.9195	4.47	0.7444	2.92	0.8961	6.778
Environmental condition								
Mean Exposure	-0.0398	-3.671	-	-	-0.1272	-4.429	-0.0463	-4.149
Maximum Exposure	-0.0228	-8.025	-0.0159	-2.254	-0.0319	-6.427	-0.0155	-6.167
Trip Characteristics								

Travel Time	-	-	-0.0489	-2.858	-0.2252	-8.513	-0.2004	-11.018
Log-likelihood at Convergence				-2559.368775				

Table B.10 Results of LCMHS with Four Segments (3 RUM Based Segment-1 RRM Based Segment)

Variables	Segment-1 (RRM)		Segment-2 (RUM)		Segment-3 (RUM)		Segment-4 (RUM)	
	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics
Segmentation Component								
Constant	-	-	-1.4278	-2.539	3.9151	3.571	0.9716	3.676
Female (Base: Male)	-	-	0.512	2.079	-	-	-	-
Age (Base: 18-34 years)								
35 or more years	-	-	-	-	-	-	-0.6226	-2.475
Employment Status								
Full-time or Part-time Worker	-	-	0.6862	2.301	-	-	-	-
Number of Household Member	-	-	1.2878	3.17	-	-	-	-
Bicycle Ownership (Less than 2)								
2 or more	-	-	-0.7503	-2.254	-	-	-	-
Auto Ownership	-	-	0.3698	2.623	-	-	-	-
Accompany (Base: With Children)								
No Children	-	-	-	-	-1.6005	-2.861	-	-
Commute length (Base: Short commute)								
Long Commute	-	-	1.5101	3.004	1.1199	2.121	-	-
Route Choice Component								
Roadway Characteristics								
Grade (Base: Flat)								
Steep	-	-	-	-	-3.132	-6.531	-5.0334	-7.418
Traffic Volume (Base: Light)								
Medium	-	-	-	-	-1.2787	-4.867	2.0723	2.057
Heavy	-	-	-0.7466	-3.913	-2.3774	-8.497		
Roadway Type (Base: Residential roads)								
Minor arterial	-	-	-0.754	-4.215	-	-	-1.0871	-3.113
Major arterial	-	-	-2.0681	-7.849	-	-	-6.8506	-8.125
Bike Route Characteristics								
Infrastructure Continuity (Base: Discontinuous)								
Continuous	-	-	0.9905	5.115	0.7945	3.588	-	-
Infrastructure Segregation (Base: Shared)								
Exclusive	-	-	1.4949	7.655	0.8669	4.293	1.8778	5.281

Environmental condition								
Mean Exposure	-	-	-	-	-0.121	-6.649	-	-
Maximum Exposure	-0.0393	-3.911	-	-	-0.0341	-6.655	-	-
Trip Characteristics								
Travel Time	-0.1386	-4.621	-0.0237	-2.229	-0.1401	-7.423	-0.4295	-9.089

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