

**Development of Integrated Urban System Models: Population
Life-transitions, Household location, and Vehicle Transaction
Decisions**

by

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To My Father, Late Md. Wajiur Rahman

&

My Mother, Fatema Rahman

Table of Contents

List of Tables	viii
List of Figures	x
Abstract	xiv
List of Abbreviations Used	xv
Acknowledgements	xvi
Chapter 1 Introduction	1
1.1 Background and Motivation.....	1
1.2 Objectives.....	4
1.3 Significance	4
1.4 Thesis Outline.....	5
Chapter 2 Literature Review	7
2.1 Introduction	7
2.2 Typology of Integrated Urban Models	8
2.2.1 Economic Activity-based Models	9
2.2.2 Market Principle Models	10
2.2.3 Quasi Market-based Models.....	13
2.2.4 Hybrid Models of Heuristic, Utility, and Market Principles	15
2.2.5 Emerging Complex System Models	18
2.3 Modelling Location Choice, Mode Transition, and Vehicle Transaction Decisions.....	21
2.3.1 Modelling Residential Location.....	21
2.3.2 Modelling Commute Mode Transitions.....	23

2.3.3	Modelling Vehicle Transactions	26
2.4	Issues in the Existing Integrated Urban Models	28
2.5	Research Questions and Concluding Remarks	31
Chapter 3	Conceptual Framework and Data	33
3.1	Theoretical Context	33
3.2	Modelling Framework of the Proposed Integrated Urban Model	35
3.2.1	Baseline Synthesis.....	37
3.2.2	Population Life-stage Transition	37
3.2.3	Residential Location Transition.....	37
3.2.4	Vehicle Ownership Transition	38
3.2.5	Activity-based Travel.....	39
3.2.6	Population and Urban Form Representation	39
3.3	Data Sources and Description.....	40
3.3.1	Retrospective Survey Data	40
3.3.2	Secondary Data Sources	43
3.4	Derived Independent Variables	46
3.4.1	Life-cycle Events	46
3.4.2	Accessibility Measures	47
3.4.3	Land Use and Neighbourhood Characteristics	47
3.4.4	Socio-demographic and Dwelling Characteristics	48
3.5	Conclusions	48
Chapter 4	Modelling Residential Location Processes.....	50
4.1	Introduction	50
4.2	Residential Mobility	53

4.2.1	Methodology	53
4.2.2	Discussion of Model Results	57
4.3	Residential Location Choice	61
4.3.1	Methodology	62
4.3.2	Goodness-of-fit Measures	75
4.3.3	Discussion of Model Results	79
4.4	Modelling Mode Transitions	85
4.4.1	Modelling Methods	85
4.4.2	Model Results.....	89
4.5	Conclusions and Summary of Contributions.....	103
Chapter 5	Modelling Vehicle Transactions	109
5.1	Introduction	109
5.2	Modelling Methods	110
5.3	Model Results	112
5.3.1	Results of the Segment Allocation Model	116
5.3.2	Discussion of the Latent Segmentation-based Logit (LSL) Model Results	117
5.4	Conclusions and Summary of Contributions.....	123
Chapter 6	Baseline Synthesis and Microsimulation of Life-stage Transitions	126
6.1	Introduction	126
6.2	Implementation of the iTLE Proto-type Model	127
6.3	Population Synthesis.....	128
6.3.1	Synthesis Process.....	128
6.3.2	Synthesis Results.....	130

6.4	Vehicle Ownership Level Synthesis.....	134
6.4.1	Model Estimation.....	134
6.4.2	Vehicle Ownership Level Synthesis Results	136
6.5	Population Life-stage Transition Module.....	137
6.5.1	Microsimulation Process	137
6.5.2	Validation Results	139
6.5.3	Microsimulation Results.....	144
6.6	Conclusions and Summary of Contributions.....	145
Chapter 7	Microsimulation of Residential Location Processes.....	148
7.1	Introduction	148
7.2	Microsimulation Processes	149
7.2.1	Residential Mobility	149
7.2.2	Residential Location Choice	150
7.3	Validation Results	151
7.4	Predicted Evolution of the Halifax Population Behaviour	152
7.4.1	Predicted Evolution of Duration of Stay.....	152
7.4.2	Predicted Evolution of the Spatial Distribution of the Halifax Population.....	157
7.4.3	Predicted Demographic Composition of the High Density Neighbourhoods in Halifax.....	159
7.5	Conclusions and Summary of Contributions.....	166
Chapter 8	Microsimulation of Vehicle Transactions	169
8.1	Introduction	169
8.2	Microsimulation Processes	170
8.2.1	Vehicle Ownership State.....	170

8.2.2	First Time Vehicle Purchase	172
8.2.3	Vehicle Transaction or Do Nothing.....	172
8.2.4	Vehicle Transaction Type	172
8.3	Validation Results	173
8.4	Predicted Evolution of Vehicle Ownership in Halifax	174
8.4.1	Predicted Spatial Distribution of the Household Vehicle Ownership Level	174
8.4.2	Predicted Vehicle Transactions by Population Demographics	179
8.4.3	Predicted Vehicle Ownership per Household Member	182
8.4.4	Predicted Vehicle Ownership Composition of the Neighbourhoods	183
8.5	Conclusion.....	185
Chapter 9	Conclusions.....	188
9.1	Summary.....	188
9.2	Contributions of this Research.....	197
9.3	Future Directions	199
9.4	Concluding Remarks	201
References	202
Appendix A: Historical Rates	223
Appendix B: Parameter Estimation Results of the Reduced Version of the Micro-behavioural Models	228
Appendix C: Predicted Spatial Distribution of the Halifax Population	234
Appendix D: Predicted Evolution of the Vehicle Ownership of Halifax Population	242

List of Tables

Table 2-1	Longer-term Decision Components of the Most Notable Existing Integrated Urban Models	20
Table 3-1	List of Secondary Data Sources Utilized to Develop the Components of the Proposed Integrated Urban Model.....	44
Table 4-1	Parametric Estimation Results of Single-episode and Multiple-episode Hazard-based Duration Models for Residential Mobility.....	58
Table 4-2	“IF-Then” Logic Statements of the Fuzzy Logic Model for Location Search.....	71
Table 4-3	Number of Segment Determination of the Residential Location Choice Model	75
Table 4-4	Goodness-of-fit Measures of the Proposed and Traditional Residential Location Choice Models.....	76
Table 4-5	Summary Statistics of Explanatory Variables used in the Estimation of Residential Location Choice Model.....	77
Table 4-6	Results of the Latent Segment Allocation Component of the Residential Location Choice Model.....	79
Table 4-7	Parameter Estimation Results of the Fuzzy Logic-based LSL Model for Residential Location Choice	80
Table 4-8	Distribution Matrix of the Mode Loyalty and Mode Transition Associated with Residential Relocation.....	87
Table 4-9	Summary Statistics of Explanatory Variables used in the Estimation of Commute Mode Transition Model.....	91
Table 4-10	Parameter Estimation Results of the RPL Model for Commute Mode Transition	94
Table 5-1	Descriptive Statistics of Explanatory Variables used in the Estimation of Vehicle Transaction Model	113
Table 5-2	Results for the Latent Segment Allocation Component of the Vehicle Transaction Model	117

Table 5-3	Parameter Estimation Results of the LSL model for Vehicle Transaction.....	119
Table 6-1	List of Categories of the Household-level and Individual-level Control Variables for Population Synthesis.....	129
Table 6-2	Parameter Estimation Results of the Base Year Logit-link Model for the Population Synthesis Procedure.....	129
Table 6-3	Comparison of the Synthetic and Observed Population Characteristics for the Base Year 2006	132
Table 6-4	Parameter Estimation Results of the Vehicle Ownership Level Synthesis Model.....	135
Table 6-5	Comparison of Simulated and Observed Population Characteristics for the Year 2011	140

List of Figures

Figure 3-1	Conceptual Framework of the Proposed Life-oriented Integrated Urban Model	34
Figure 3-2	The Conceptual iTLE Modelling Framework.....	36
Figure 4-1	Residential Location Transition Process.....	51
Figure 4-2	Conceptual Framework of the Fuzzy Logic-based Location Choice Model	64
Figure 4-3	Fuzzy Membership Functions for the Constraint Sets Considered in the Location Search Model	67
Figure 4-4	Fuzzy Membership Functions for the Opportunity Sets Considered in the Location Search Model	69
Figure 6-1	APE measures of the Synthetic Population for the Base Year 2006	131
Figure 6-2	Vehicle Ownership Level Synthesis Results for the Year 2006	137
Figure 6-3	Process Diagram for the Birth Component of the Life-stage Transition Module	138
Figure 6-4	Age Distribution of Female and Male of Simulated and Observed Population for the Year 2011	142
Figure 6-5	Age and Marital Status Distribution of Female of Simulated and Observed Population for the Year 2011	143
Figure 6-6	Age and Marital Status Distribution of Male of Simulated and Observed Population for the Year.....	143
Figure 6-7	Household Income and Dwelling Type Distribution of Simulated and Observed Population for the Year 2011.....	144
Figure 6-8	Predicted Life-stage Transition Rates for the Years 2007-2021	145
Figure 7-1	APE measures of the Simulated Households for the Year 2011	151
Figure 7-2	Difference between the Simulated and Observed Number of Households in the DAs for the Year 2011	152
Figure 7-3	Predicted Duration of Stay of Population Aged < 40 Years for the Years 2007-2021	153

Figure 7-4	Predicted Duration of Stay of Population Aged 40-54 Years for the Years 2007-2021	154
Figure 7-5	Predicted Duration of Stay of Population Aged 55-64 Years for the Years 2007-2021	154
Figure 7-6	Predicted Duration of Stay of Population Aged > 64 Years for the Years 2007-2021	155
Figure 7-7	Predicted Duration of Stay of Population by Age and Location of the Residence for the Years 2007-2021	156
Figure 7-8	Predicted Duration of Stay of Population by Household Income and Location of Residence for the Years 2007-2021	156
Figure 7-9	Predicted Household Density Change from 2006 to 2021	157
Figure 7-10	Predicted Spatial Distribution of the Halifax Population for the Year 2021	158
Figure 7-11	Predicted Yearly Avg. Household Density of the High Density DAs in Halifax for the Years 2007-2021	159
Figure 7-12	Predicted Yearly Avg. HH Income in Low Income High Density DAs in Halifax for the Years 2007-2021	160
Figure 7-13	Predicted Yearly Avg. HH Income in High Income High Density DAs in Halifax for the Years 2007-2021	161
Figure 7-14	Predicted Yearly Avg. Age of HH Head in Low Income High Density DAs in Halifax for the Years 2007-2021	162
Figure 7-15	Predicted Yearly Avg. Age of HH Head in High Income High Density DAs in Halifax for the Years 2007-2021	162
Figure 7-16	Predicted Distribution of Single Person HH in the High Density Neighbourhoods of Halifax for the Year 2021	164
Figure 7-17	Predicted Distribution of Couple without Child HH in the High Density Neighbourhoods of Halifax for the Year 2021	164
Figure 7-18	Predicted Distribution of Couple with One Child HH in the High Density Neighbourhoods of Halifax for the Year 2021	165
Figure 7-19	Predicted Distribution of Couple with Two Child HH in the High Density Neighbourhoods of Halifax for the Year 2021	165

Figure 7-20	Predicted Distribution of Couple with more than Two Child HH in the High Density Neighbourhoods of Halifax for the Year 2021	166
Figure 8-1	Operational Framework of the Vehicle Transaction Component of iTLE	171
Figure 8-2	Vehicle Ownership Level Comparison of the Predicted and Observed Halifax Population for the Year 2016.....	174
Figure 8-3	Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2007	175
Figure 8-4	Predicted Spatial Distribution of Zero Vehicle Ownership Households in the DA for the Year 2021	177
Figure 8-5	Predicted Spatial Distribution of One Vehicle Ownership Households in the DA for the Year 2021	177
Figure 8-6	Predicted Spatial Distribution of Two Vehicle Ownership Households in the DA for the Year 2021	178
Figure 8-7	Predicted Spatial Distribution of Three or More Vehicle Ownership Households in the DA for the Year 2021.....	178
Figure 8-8	Predicted Distribution of Age and Income of Households Purchasing First Vehicle for the Year 2021	180
Figure 8-9	Predicted Distribution of Age and Income of Households Acquiring Vehicles for the Year 2021	180
Figure 8-10	Predicted Distribution of Age and Income of Households Disposing Vehicles for the Year 2021	181
Figure 8-11	Predicted Distribution of Age and Income of Households Trading Vehicles for the Year 2021	181
Figure 8-12	Predicted Spatial Distribution of Vehicle Ownership per Household Member by Income for the Year 2021.....	182
Figure 8-13	Predicted Spatial Distribution of Vehicle Ownership per Household Member by Age for the Year 2021	183
Figure 8-14	Predicted 15 Year Evolution of Average Vehicle Ownership per Household in the DA for the Years 2007-2021	184

Figure 8-15 Predicted Spatial Distribution of the Avg. Vehicle Ownership per Household in the DA by Avg. Household Income in the DA for the Year 2021 185

Abstract

This research presents the development of a life-oriented, agent-based integrated transport land use and energy (iTLE) model. A life-oriented theory and perspective is adopted to accommodate life-trajectory dynamics of key longer-term household-level decisions within the integrated urban modelling system. This study develops the following components of the proposed integrated urban model: population synthesis, vehicle ownership level synthesis, life-stage transition, residential location, vehicle transaction, and mode transition. The modelling and computation procedure of the integrated model addresses evolution of location choice and vehicle transaction over the life-course of the households in response or anticipation to decisions and changes at different life-domains. One of the mechanisms adopted to accommodate the temporal dimension of such multi-way decision interactions is through introducing lead and lag events. Advanced econometric models are developed to accommodate the effects of repeated choices during the life-course of the households, as well as capture unobserved heterogeneity. For example, a dynamic vehicle transaction model is developed utilizing a latent segmentation-based logit (LSL) modelling technique. Moreover, residential location and vehicle transaction are assumed to have an underlying process orientation. For instance, residential location is conceptualized as a two-stage process of: 1) mobility, and 2) location choice. Methodologically, the second stage of location choice is modelled as a two-tier process of location search and choice, by utilizing a fuzzy logic-based modelling method and LSL modelling technique. Vehicle transaction is modelled as a process of first time purchase, acquisition, disposal, and trade. Finally, this research implements a proto-type version of the iTLE model for Halifax, Canada. The proto-type generates a synthesis-based population and vehicle ownership level information for the base year 2006. The model microsimulates life-stage transition, residential location, and vehicle transaction for a 15-year period of 2007-2021. This research also presents validation of the iTLE proto-type model results, and predicts the evolution of life-stage, mobility, location, and vehicle transaction for the Halifax population. This simulation modelling system would be useful for analyzing complex, integrated land use and transport policy scenarios.

List of Abbreviations Used

APE	Absolute Percent Error
BIC	Bayesian Information Criteria
CBD	Central Business District
DA	Dissemination Area
DMTI	Desktop Mapping Technologies Inc.
HMTS	Household Mobility and Travel Survey
HRM	Halifax Regional Municipality
IPU	Iterative Proportional Updating
iTLE	integrated Transport Land Use and Energy Model
IUM	Integrated Urban Model
LSL	Latent Segmentation-based Logit
NovaTRAC	Nova Scotia Travel Activity Survey
PUMF	Public Use Microdata File
RPL	Random-parameters Logit
SRMSE	Standard Root Mean Square Error

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Chapter 1

Introduction

1.1 Background and Motivation

The increasing urban sprawl and dependence on private vehicles posit challenges for planning healthy communities, and promote equitable and sustainable travel opportunities for people. Since location and travel choices are inter-dependent decisions, effective integrated transport and land use policies are required to trigger a shift towards balanced urban growth and sustainable travel choices for the current population and generations to come. Integrated urban models facilitate a modelling platform to effectively evaluate complex land use and transport policies, since large-scale urban models simulate the essential decision processes of the individuals/households to represent the evolution of urban form and transport. Therefore, the development of integrated urban models have emerged from the need to mimic such two-way interactions between land use and transport.

In addition to the two-way inter-dependency, there exists a multi-way decision interactions as travel behaviour and location choice evolve in response or anticipation to decisions and changes at different life-domains. For example, the decisions of where to live, where to work, how many vehicles to own, and what mode to choose, interacts with each other. Although the interaction between land use and transport is well recognized within the existing models, such as UrbanSim, ILUTE, and PUMA (Waddell 2002, Salvini and Miller 2005, Ettema et al. 2007); the evolving life-oriented interactions among the multi-domain decisions have not been well addressed within the integrated urban modelling literature. Life-history, its evolution, and influence on different

essential decision processes need to be addressed within the integrated urban models as these models simulate individuals' decisions over a long multi-year time frame. During this period, individuals' demographic career evolves, such as a single person become married, have children, get divorced, and finally decease. A change in the demographic status influences individuals' decisions at different life-domains. For example, birth of a child influences residential location choices (Strom 2010), as well as vehicle transactions (Oakil et al. 2014). To adequately address the decision dynamics, population life-course and associated changes are required to evolve within the simulation environment of the integrated models. Hence, it is imperative for integrated models to respond to the changes across the agents' life-stages, starting with the long-term and medium-term decisions, and life-stage transitions.

Among the several components of an integrated urban model, location choice, vehicle ownership, and mode choice, are critical elements. Residential location is a long-term decision (Habib 2009), which predicts the spatial distribution of an urban region. Location choice decisions have an inherent process orientation. For instance, residential location is a process of decision to move (i.e. mobility) and location choice. Following the decision to move, households chooses a location to move in, which itself can be characterized as a two-tier process of home search and location choice. In this process, first households undertake a search process to identify a pool of potential location alternatives and finally choose a location from the pool. However, the process orientation of the decisions are rarely accommodated within the operational integrated urban models. In addition, an important dimension is to examine how a change in the long-term state such as residential location influences travel activities such as commute mode choice.

Another critical component of integrated models is medium-term decisions such as vehicle ownership that directly influences short-term decisions of travel activity. Vehicles are a major source of greenhouse gas (GHG) emission.

In Canada, a quarter of the total GHG emission is from the transportation sector (Environment Canada 2014). The forecasting of vehicle ownership offers the opportunity to test the impacts of strategies targeting the promotion of sustainable travel choices, such as use of fuel efficient vehicles, and use of alternative/clean fuel vehicles, among others. However, limited of the existing urban models include vehicle ownership component. Furthermore, vehicle ownership decisions have an underlying process orientation, since households add, dispose, and trade vehicles. Hence, it is not only necessary to microsimulate vehicle ownership within the integrated urban modelling platform, but also required to address the process orientation of the phenomenon.

The motivation of this research is to mimic the multi-domain interactions and process orientation of the household-level decisions within an integrated urban modelling system. This study presents the development of a proto-type, life-oriented integrated Transport Land Use and Energy (iTLE) model. The iTLE is an agent-based model that follows life-course perspectives and theories (Chatterjee and Scheiner 2015). Life-course perspectives focus on how transitions along the life-time and interactions among decisions taken at different domains along the life-course influence individuals' choices and behaviour (Chatterjee and Scheiner 2015, Zhang 2017, Zhang 2015). The iTLE simulates agents' decisions longitudinally at each simulation time-step along their life-course. The process orientation and multi-domain interaction among the decisions are addressed within the micro-modelling structures and computational procedures of the iTLE. This research addresses the development of the following core components of iTLE: life-stage transition, residential location, vehicle transaction, and mode transition. In addition, the study generates baseline information including, population synthesis, and vehicle ownership level synthesis. This research also offers predicted spatio-temporal evolution of the urban population for the Halifax Regional

Municipality, in-terms of their demographic distribution, housing pattern, neighbourhood composition, and vehicle ownership and transaction configuration.

1.2 Objectives

The goal of this thesis is to develop a state-of-the-art agent-based integrated urban model that addresses the process orientation and interactions among a number of decisions along the life-course of the agents within the empirical and microsimulation environment. To achieve this goal, the specific objectives of this thesis evolves within the following four dimensions:

1. To develop micro-models of household location processes, including residential mobility, location choice, and commute mode transition associated with relocation.
2. To develop econometric models of vehicle transaction processes, such as first time vehicle purchase, acquisition, disposal, and trade.
3. To generate baseline synthesis, life-stage transition, and proto-type implementation of household decision processes within a life-oriented urban systems model.
4. To predict micro-level spatio-temporal evolution of an urban region by utilizing integrated urban systems model.

1.3 Significance

The contribution of this research encompasses the modelling and microsimulation paradigms of the integrated urban modelling literature. It has theoretical as well as applied implications. From a theoretical perspective, this study adopts a life-oriented approach to investigate how decisions in different life-domains such as location choice, vehicle ownership, and mode choice

interact along the life-course of the individuals/households. The investigation provides important behavioural insights towards understanding of how changes along the life-course shapes individuals/households behaviour. The process orientation of the decisions are addressed within the modelling framework through utilizing innovative modelling techniques. Developing such advanced mathematical models that also warrants improved empirical results significantly contributes to the literature of travel demand modelling techniques.

In terms of the applied implications, this research is one of the first attempts to translate the multi-directional interactions and process orientation of the decisions from the micro-behavioural models to the computational procedure of integrated urban models. Such multi-way feedback mechanisms within the simulation environment of an urban model adds the capacity to test the response of population at different life-stages under alternative land use and transport policy scenarios. Particularly, this research microsimulates individuals/households life-stages, residential location, and vehicle transaction decisions within an agent-based integrated urban modelling system. The microsimulation results offer insights towards the micro-level spatio-temporal evolution of an urban region, including demographic distribution, housing pattern, neighbourhood configuration, and vehicle ownership pattern. Such information will be useful inputs for the development of a state-of-the-art activity-based travel model. The findings have important implications towards making effective integrated land use and transport policies.

1.4 Thesis Outline

This thesis is comprised of nine chapters. Chapter two reviews the relevant literatures, including a typology of the integrated urban models, followed by literature review on modelling residential location, mode transition, and

vehicle transaction decisions. This chapter concludes with a summary of the literature review to identify research gaps, and then poses research questions and concluding remarks.

Chapter three discusses the conceptual framework and data used to develop an integrated urban model for Halifax. This chapter also provides details on the independent variables considered during the model estimation processes of different components of the urban model.

Chapter four describes the methods and results of modelling residential location processes. Discussions on modelling residential mobility, location search, location choice, and mode transition decisions are presented in this chapter.

Chapter five provides the modelling methods and estimation results of the vehicle transaction model.

Chapter six presents the development of a proto-type version of the iTLE model for Halifax, Canada. This chapter focuses on the results of microsimulating life-stages, and generating baseline synthesis information including population and vehicle ownership level synthesis.

Chapter seven provides the details on microsimulating residential location within the iTLE model. This chapter discusses the spatial and temporal evolution of housing pattern and neighbourhood composition of Halifax.

Chapter eight presents the microsimulation results of the vehicle transaction component of the iTLE model.

Finally, chapter nine summarizes the research findings and list of contributions, and offers insights towards future research directions.

Literature Review

2.1 Introduction

This research attempts to fill some gaps in the existing literature of modelling and microsimulating residential location and vehicle transaction decisions within an integrated urban modelling system. Integrated urban models (alternatively termed as IUM in this study) are large-scale modelling systems that simulate population's decisions to predict the evolution of urban form and transport. The potential of IUMs in enhancing the effective evaluation of complex land use and transport policies have resulted in the development of several large-scale models, such as ILUTE, UrbanSim, PUMA, SelfSim, and SimMobility, among others. The components of IUMs can be categorized into long-term decision models (e.g. location choice), medium-term decision models (e.g. vehicle ownership), and short-term decision models (e.g. mode choice). Long-term and medium-term decisions are critical components of an IUM which have a dynamic nature, as these decisions interact with each other. For example, the decision of where to live influences the decision of how many vehicle to own, and vice-versa (Rashidi and Mohammadian 2011). These crucial decisions evolve over the life-course as well as interact with life-stage transitions; for instance, birth of a child influences residential location choices (Strom 2010). Majority of the IUMs do not tackle such multi-domain interactions among decisions taken at different life-stages of the population. Although significant advances is made in developing the short-term models, also known as the transport component of the IUMs; one of the criticisms of most of the IUMs has been the lack of behavioural representation for the long-term and medium-term models. To effectively evaluate land use and transport

policies, integrated urban models need to be responsive to the decision dynamics across the agents' decision making domains and life-stages. The empirical settings as well as the computation procedure of the IUMs are required to accommodate the multi-way feedback mechanism among the decision processes.

This chapter reviews relevant literatures on integrated urban models and modelling of essential decision processes to identify the scope for this research. First, a typology of the existing integrated urban models with a brief description is presented. Then, a review of modelling longer-term decision processes including residential location choice followed by mode transition and vehicle transaction are described. After that a discussion on the modelling issues of the existing integrated urban models is presented. Finally, some research questions are formulated, which pegs the scope for the contributions of this research.

2.2 Typology of Integrated Urban Models

To-date, a number of integrated urban models are developed, starting from the Lowry model (Lowry 1964) in early 1960s to the recent SelfSim (Zhuge et al. 2016) model. A number of review articles on integrated urban models already exist (Huang et al. 2014, Iacono et al. 2008, Hunt et al. 2005, Miller 2009, Wegener 2004, Timmermans 2003). This section reviews the recent developments and updates on the most noteworthy models that are currently available. Based on the operating principles, IUMs can be subdivided into the following five categories: (1) Economic Activity-based Models, (2) Market Principle Models, (3) Quasi Market-based Models, (4) Hybrid Models of Heuristic, Utility, and Market Principles, and (5) Emerging Complex System Models. A brief description of the above mentioned five categories of integrated urban models are presented below.

2.2.1 Economic Activity-based Models

Economic activity-based integrated urban models are developed on the basis of modelling urban spatial economy using input-output modelling methodology. Input-output models assume a constant production function where a fixed proportion of production is allocated for consumption. The model makes an equilibrium production-consumption assumption. These are aggregate level zonal models. Such integrated urban models include PECAS (Hunt and Abraham 2003, 2005), MEPLAN (Echenique et al. 1969, Echenique et al. 1990), and TRANUS (de la Berra et al. 1984).

One of the widely used operational models in North America is the Production, Exchange, Consumption Allocation System (PECAS), which was implemented in different cities all around world including, Sacramento, San Diego, California, Atlanta, Baltimore, and Calgary, among others. PECAS has two core modules: space development, and activity allocation (Hunt and Abraham 2003). Space development module follows a logit modelling technique to represent the aggregate changes of land and floor space. Activity allocation module follows a make (production of commodities) and use (consumption of commodities) input-output table that represents the aggregate allocation of activities within the space and interaction among the activities. The interaction is the movement of commodities, which generates the flow from production zone to exchange zone, and from exchange zone to consumption zone. PECAS operates at a yearly time-step with an equilibrium assumption between production and consumption.

Another well-known model is the MEPLAN, which operates at the zonal-level with an input-output model at the core (Echenique et al. 1969). The land use component of MEPLAN allocates demand into zones based on the random utility concept. The interaction between production and consumption zones generate demand for travel, which is converted into traffic for mode choice and

route choice models. The output from the economic activity model is fed back to the land use model. MEPLAN was implemented in Sacramento, and California, among others. The MEPLAN was also implemented for the following European cities: Bilbao, (Spain), Dortmund (West Germany) and Leeds (England) (Echenique et al. 1990). Similar to MEPLAN is TRANUS, another integrated urban model using input-output matrix for modelling (de la Berra et al. 1984). TRANUS has a supply model for land and floor space developers, where price is endogenously determined using static equilibrium assumption. The supply model was developed using a logit modelling technique. TRANUS was implemented in Sacramento, Baltimore, Maryland, and Oregon, USA.

2.2.2 Market Principle Models

The basic of the market principle models is to conceptualize the urban system as a market/combination of multiple markets where consumers and suppliers interact and negotiate. Among the existing models, ILUTE (Miller et al. 2004, Savini and Miller 2005), MUSSA (Martinez 1996, Maritnez and Donoso 2004), CPHMM (Anas and Arnott 1993, 1994), NYMTC-LUM (Anas 1998), and SelfSim (Zhuge et al. 2016) follow market principle-based assumptions.

Integrated Land Use, Transportation, and Environment (ILUTE) modelling system is one of the most notable state-of-the-art integrated urban models, which is designed to be a fully agent-based microsimulation modelling platform. It is one of the most comprehensive models as it includes the simulation of population demographics, location choice, auto ownership, and travel activities. The decision processes within the system are abstracted as market interaction between buyers and sellers (Savini and Miller 2005). For example, the process of residential location choice is conceptualized to take place in the housing market as a three-stage process of mobility, bid, and

location choice. Once a household is determined to become active in the mobility stage, bid is made on a dwelling, and finally households move to a location through buying a house. The relocation component follows a random utility-based discrete choice modelling technique. The demographic updating component simulates the following demographic processes: birth, death, marriage, divorce, move out, driver's licence, education level, and in- and out-migration. This component follows a rule-based, random utility-based, and hazard-based modelling methods (Chingcuanco and Miller 2012a). The vehicle ownership component is conceptualized as a nested structure (Mohammadian 2002). In the upper-level of the nest, vehicle transaction decisions of purchase, disposal, trade, and do nothing are modelled. In the lower-level, vehicle type choice decisions are modelled, categorizing vehicles by size and vintage. In a recent update of the transaction model of ILUTE, the trade decision is conceptualized to be sensitive to both purchased and disposed vehicle types (Duivestein 2013). Whereas, in the earlier version of the trade component, only the purchased vehicle type influenced the disposed vehicle type (Mohammadian 2002). ILUTE does not assume any system equilibrium for the market clearing process. The system state of ILUTE moves forward at a yearly time-step by operating at the dwelling unit level.

MUSSA is an aggregate level urban model, developed by Martinez (1996). At the core of its framework, there is an auction mechanism based on the theory of willingness to pay to determine the location of households and firms. The auction process is performed with an equilibrium solution algorithm using a bid function. Households bid for multiple dwellings based on the dwelling attribute and finally chooses the one with the highest utility. The demand and supply are generated using a rate-based model in accordance to the national growth.

Another market principle model is the Chicago Proto-type Housing Market Model (CPHMM), which was initially developed as a land use model (Anas and

Arnott 1993, 1994)). Later CPHMM was connected with a travel demand model developed for the New York region, which is known as the New York Metropolitan Transit Corporation Land Use Model (NYMTC-LUM) (Anas 1998). The central idea of the CPHMM is based on equilibrium assumption of labour market, housing market, and commercial space market. The simulation of each market is operated through the following three sub-modules: “asset bid-price” sub-module determines the value of housing and land at the beginning, “stock adjustment” sub-module determines buyers and sellers decision on the basis of utility and profit, and “market clearing” sub-module clears market through allocating households into different housing units by adjusting rent and price to balance demand and supply. The sub-modules were developed using a logit modelling technique and represent aggregate-level behaviour of households, housing units, and land owners. The model operates at the zonal level of traffic analysis zones (TAZ) on a yearly basis.

One of the recent market-based urban model is the SelfSim. It is an agent-based model, which is currently under development. Conceptually, SelfSim has six major models: demographic model, travel demand model, accessibility model, residential location model, activity location model, and transport development model (Zhuge et al. 2016). At the core, residential location and real estate price (RLC-REP) models were developed taking a market-based approach. In the RLC-REP framework, first, active households are identified heuristically based on their affordability and inducement (i.e. marriage). Then, a negotiation between households and owners is conducted, where active households temporarily choose a house on the basis of its utility (i.e. price and accessibility attributes). The utility function was developed using utility maximization and prospect theory. Finally, the negotiation is completed as owners update price and households move to a house. SelfSim simulates at the aggregate level of road node (where all the houses and activity facilities along a road are assumed to be a community, and centered at the node of the road)

at a yearly time-step. A proto-type of SelfSim, basically the RLC-REP model was calibrated for the city of Baoding, China. The activity location model and transport development model are under development (Zhuge et al. 2016).

2.2.3 Quasi Market-based Models

Quasi market-based models partially follow market principle where the interaction between buyers and sellers takes place in the market; however, finally the market is cleared heuristically. Such models include: UrbanSim (Waddell et al. 2003, Waddell 2002, 2010), SimTRAVEL (Pendyala et al. 2012), UrbanSim and Metropolis integration in Paris (De Palma et al. 2007), Integrated Land Use and Transport Model of Brussels (Efthymiou et al. 2013), and ILUMASS (Wagner and Wegener 2007, Moeckel et al 2002).

UrbanSim is one of the most widely implemented integrated urban models (Waddell 1998, 2002). It has six major components: economic and demographic transition, mobility, location choice, real estate development, land price, and travel demand model. The transition and mobility components are heuristic models, location choice follows multinomial logit modelling technique, real estate is a semi-log linear regression model, land price is a hedonic price model, and travel demand follows conventional four-stage modelling technique. UrbanSim represents the behaviour of households, persons, and firms through a market clearing process. During the initial development of UrbanSim, the market was cleared on the basis of willingness to pay theory with the assumption of market equilibrium. Later, the market clearing process was updated by undertaking a capacity constrained algorithm using a first come first serve technique of allocating dwellings to the households. In this technique, if a house is selected by a household, it is taken out of the market, making it unavailable for other households even if they bid higher. UrbanSim simulates at a yearly basis and can be operated at different spatial levels:

parcel, grid cell (150m X 150m), traffic analysis zone, and/or other spatial units. The proto-type was implemented in Eugene-Springfield, Oregon (Waddell 1998). Later, it was also implemented in the Salt Lake City and Seattle. UrbanSim has recently adopted an open source licensing for the software, which was written in the Python programming language and known as the Open Platform for Urban Simulation (OPUS). UrbanSim takes a modular-based approach in developing the software architecture, which has facilitated advancing the experimentation with new methods to improve the model components, and implement UrbanSim in different cities around the world. As a result, UrbanSim has been adopted as the land use component of a number of existing integrated urban models. SimTRAVEL is one of such initiatives, which integrates UrbanSim with an activity travel demand (OpenAMOS) model and a traffic assignment (MALTA) model. Under the SustainCity project, funded by the European Union, UrbanSim is adopted to develop integrated urban models for Paris (De Palma et al. 2007), Brussels (Efthymiou et al. 2013), and Zurich (Lochl and Axhausen 2010).

Integrated Land-Use Modelling and Transportation System Simulation (ILUMASS) is another notable quasi market-based model. ILUMASS was designed to have three major modules: land use, transport, and environment (Wagner and Wegener 2007). Each component has multiple sub-modules. For instance, the sub-modules of the land use component are: population, firm, residential location, firm location, residential building, and non-residential building. The residential location choice was modelled as a demand and supply function between households and landlord in the housing market. The spatial choice unit in ILUMASS has three-levels of resolutions: micro (100 X 100 meters grid cell), meso (traffic analysis zone), and macro (municipality). The simulation time-scale is at a yearly-level. ILUMASS was tested for the metropolitan area of Dortmund in the Ruhr industrial district in Germany.

2.2.4 Hybrid Models of Heuristic, Utility, and Market Principles

Hybrid models are developed as a combination of the heuristic, utility, and market theories. Such models include: PUMA (Ettema et al. 2007, Ettema 2011), CEMUS (Eluru et al. 2008), SimDELTA (Simmonds et al. 2011, Feldsman et al. 2007), RAMBLAS (Veldhuisen et al. 2000, 2005), SILO (Moeckel 2016), TRESIS (Hensher and Ton 2002), and LUSDR (Gregor 2007).

Predicting Urbanisation with Multi-Agents (PUMA) is an agent-based integrated urban model that conceptually includes a variety of land use and transport components. While operationalizing, a much simpler system was implemented for the northern part of the Dutch Randstad (Ettema et al. 2007). The operational system implemented the longer-term decisions, leaving the travel activity component for future development. The implemented components include, demographic events, residential location, and work location choice models. At the center of the system is the residential location choice component, which was modelled as a three stage process: decision to search, decision to move, and choice of location. The first two stages were modelled using a binary logit modelling technique and location choice was modelled using a multinomial logit modelling approach. Choice of location is made through interaction between buyers and sellers in the market on the basis of maximum lifetime utility. In estimating utility, transaction cost for the movement was incorporated with the utility of the new housing. If derived utility from the new house is higher, households move, otherwise they return to their previous house. Recently, a joint model of residential choice and real estate price was developed based on the perceptions of housing market probabilities; however it was tested as an experiment only (Ettema 2011). The demographic events simulated within PUMA includes: ageing, birth, marriage, divorce, and leave parental home. The temporal resolution of the system is at a yearly basis and the spatial resolution is 500 X 500 meters grid cell.

Comprehensive Econometric Microsimulator for Urban Systems (CEMUS) was developed with the focus to represent greater behaviour of the household- and individual-level decisions using state-of-the-art modelling techniques. It has the following two major components: socio-economic and land use component known as CEMSELTS (Guo et al. 2005), and activity scheduler known as CEMDAP (Pinjari et al. 2006). CEMSELTS has two major modules: the migration module, and the socio-economic evolution module. The migration module comprises of emigration and immigration models for the households and individuals. The socio-economic evolution module has three major components: individual-level demographic update, household formation, and household-level long-term choice models for residential relocation, automobile ownership, information and communication technology adoption, and bicycle ownership. One of the interesting dimensions of CEMUS is to include the automobile ownership component, which simulates households' vehicle ownership level of 0, 1, 2, 3, and 4 or more vehicles. Households' and individuals' behaviour are represented by developing a number of advanced econometric models, such as binary logit models, multinomial logit models, ordered-response probit models, heuristic models, and rate-based probability models. CEMUS operates at the zonal-level at a yearly basis. A proto-type of CEMUS was tested for the Dallas-Fort Worth region, which focuses on the validation of the base year population update component (Eluru et al. 2008).

SimDELTA developed by the David Simmonds Consulting Ltd in UK (Simmonds et al. 2011, Feldsman et al. 2007) is the advanced version of the earlier integrated urban models, DELTA and MASTER (Mackett 1993). SimDELTA has the following sub-models: demographic change, household location, employment location, auto ownership, and transport model. Majority of the components of SimDELTA are rate-based models using monte-carlo simulation. Only in the case of auto ownership, an ordered probit modelling technique is used for probability estimates. A change in the vehicle ownership

level is forecasted using a monte-carlo simulation technique. The model operates at the zonal level with a simulation time-step of one year. SimDELTA was implemented in South and West Yorkshire, UK.

RAMBLAS is a national-level integrated urban model for the Netherlands. RAMBLAS is basically a heuristic and rate-based model using national statistics and housing survey data. It extensively uses monte-carlo simulation technique for modelling majority of the decision processes. For the residential location decisions, a logit model was developed for probability estimation; then monte-carlo simulation is used to match households to available housing (Veldhuisen et al. 2005). The model operates at the spatial levels of postal code, municipality, or any other zonal resolutions. The model is implemented in the North Wing of the Randstad region, which includes Amsterdam and its surroundings.

Another hybrid model is the Simple Integrated Land-use Orchestrator (SILO), which was first developed as a proto-type for the Minneapolis-St. Paul, Minnesota; and currently implemented in Maryland. SILO has four major components: demographic change, real estate development, household relocation, and travel demand model (Moeckel 2017). The spatial choice decisions, such as residential location and housing development are discrete choice models. Residential location was modelled on the basis of three constraints: price of a dwelling, the travel time to work, and the monetary transportation budget. SILO simulates at the zonal-level at a yearly basis. In addition, hybrid models include Transportation and Environment Strategy Impact Simulator (TRESIS) for Sydney (Hensher and Ton 2002), Australia; and Land Use Scenario Developer (LUSDR) for Oregon, USA (Gregor 2007).

2.2.5 Emerging Complex System Models

The emerging complex system models are the new developments in the field of integrated urban modelling. These models are designed to capture the complex behaviour of the individuals/households in the urban system through agent-based microsimulation, and also extend the dimension of integrated urban models towards emission and energy estimation. The emerging complex system models include: SimMobility (Lu et al. 2015, Adnan et al. 2016), SynCity (Keirstead et al. 2010), POLARIS (Auld et al. 2016, Hope et al. 2014), and iTEAM (Ghauche 2010).

SimMobility is a multi-level, modular-based, mobility-sensitive microsimulation platform for urban system. The design of SimMobility comprises of three simulators: (1) long-term simulator representing house and job relocation, car ownership; (2) medium-term simulator (known as DYNAMIT) representing daily activity scheduling, mode, route, destination, and departure time choice; and (3) short-term simulator (known as MITSIM) representing lane changing, braking, and acceleration. SimMobility is an event-based modelling platform; where agents make decisions only after being active, which is triggered by their perception of an event. For instance, the residential relocation module operates in the following four stages: (1) 'awakening' households to begin the search; (2) eligibility, affordability, and screening constraints; (3) market bidding; and (4) developer behaviour to construct built space. In the case of vehicle ownership, the assessment of ownership is triggered if agents change their residential location. SimMobility was implemented at the postal code level for Singapore (Adnan et al. 2016).

One of the emerging models with a focus to extend urban modelling towards urban energy system modelling is SynCity. It utilizes a mathematical modelling technique to optimize urban energy policies. SynCity consists of four major components: (1) layout model (Input) for residential and commercial

buildings, available transportation infrastructures and modes, and average activity profiles of the citizens; (2) agent activity model; (3) network model; and (4) service network model. SynCity was tested at the building-level for a proposed hypothetical eco-town in UK (Keirstead et al. 2010).

Planning and Operation Language for Agent-based Regional Integrated Simulation (POLARIS) is an agent-based modelling (ABM) software. It is an innovative ABM platform, where several separate models can be integrated into a single system and implemented in a computationally efficient manner. Auld et al. (2016) utilized the software tool kit to integrate a travel demand model with a network model. Specifically, a proto-type integration of ADAPTS with a dynamic traffic assignment model was implemented for the Chicago Metropolitan Area. However, integration of long-term and medium-term decisions within the POLARIS platform have not occurred yet.

Another emerging model is the Integrated Transport and Energy Activity-based Model (iTEAM), which is designed to be a decision support tool to inform sustainable policies and investments (Ghauche 2010). It is a multi agent-based microsimulation model with a modular design. iTEAM microsimulates household and firm behaviour by integrating land use, transportation, and energy consumption in an urban area. The models were developed using bid-rent, hedonic price, and random utility-based modelling techniques. The long-term choice is integrated with the short-term activities through the concept of life-style stress. Energy is estimated by converting transportation and equipment usage into resource consumed.

Furthermore, another stream of integrated urban modelling is the cellular automata (CA) models (Ye and Li 2002, Kii and Doi 2005, Ottensmann 2005, Levinson and Chen 2005). CA-based models are simpler urban models that represent an urban region through cells. In such models, cells are the agents, not the households or individuals. The evolution of urban regions was modelled

through the changing states of the cells, which can be dependent on the observed probability or a function of the states in the adjacent cells. Such mechanistic approach of modelling does not represent household or individual behaviour, which is one of the major limitations of the CA models.

As discussed above, longer-term decisions of location choice, and vehicle ownership are the most critical components of an integrated urban model. A comparison among the most notable integrated urban models in-terms of their longer-term decision components is presented in Table 2-1. Although all the models include residential location choice component, few of them contain residential mobility. Limited of the models are consist of life-stage transition, and vehicle ownership components. Particularly, inclusion of vehicle transaction component is even rare.

Table 2-1 Longer-term Decision Components of the Most Notable Existing Integrated Urban Models

Components	Life-stage Transition	Residential Location		Vehicle Ownership	
		<i>Mobility</i>	<i>Location Choice</i>	<i>Ownership Level</i>	<i>Transaction</i>
Models					
<i>CEMUS</i> (Eluru et al. 2008)	✓	✓	✓	✓	×
<i>ILUMASS</i> (Wagner and Wegener 2007)	×	×	✓	×	×
<i>ILUTE</i> (Salvini and Miller 2005)	✓	✓	✓	×	✓
<i>PUMA</i> (Ettema et al. 2007)	✓	✓	✓	×	×
<i>SelfSim</i> (Zhuge et al 2016)	×	×	✓	×	×
<i>SimMobility</i> (Adnan et al. 2016)	×	×	✓	✓	×
<i>UrbanSim</i> (Waddell 2002)	×	✓	✓	×	×

2.3 Modelling Location Choice, Mode Transition, and Vehicle Transaction Decisions

Long-term location choice process is the skeletal component of an integrated urban model, which predicts the spatial configuration of an urban region. Vehicle ownership is another essential component, since it predicts the vehicle ownership information of the population that directly feeds into the transport models to predict the traffic flow as well as test the impacts of strategies targeting the promotion of sustainable travel choices. Although, generally commute mode choice is conceptualized as a short-term decision, it has a longer-term dimension as well. Unless the modelling paradigm of these critical decision components represent the behaviour adequately, reasonable understanding and forecasting of the phenomenon might be challenging. A review of modelling such longer-term decisions is presented in the section below.

2.3.1 Modelling Residential Location

Residential location decisions have an inherent process orientation in relation to mobility and determination of location. In the process of relocation, households first decide to move, then they choose a location. Moreover, the location component itself is a two-tier process of search and choice of a location. In this process, households first undertake a search process to identify potential location alternatives, and finally move to a location. Although a vast amount of literature exists on modelling location choice decisions, limited studies have addressed the mobility (Habib and Miller 2008) and search processes (Rashidi and Mohammadian 2011). Particularly, one of the major challenges in modelling spatial choice decisions such as residential location is to address the search process. One approach is to consider all available location alternatives (e.g., Thill and Horowitz 1991); however, this method is not

behaviourally realistic as households do not evaluate all the alternatives during relocation (Fotheringham 1988). Moreover, the estimation process is computationally burdensome due to a substantial number of location alternatives. The most widely used method for reducing computational burden is to randomly select a subset from the all available alternatives (Ben-Akiva and Lerman 1985, Guevara 2010). Although the random sampling approach provides a consistent estimate (McFadden 1978, Guevara and Ben-Akiva 2013), it is merely a statistical method to reduce the number of location alternatives and ignores behavioural realism of the search process. Another method is the constrained-based sampling technique, where all the alternatives within a certain threshold range of a parameter are considered in the choice set (Zheng and Guo 2008). The underlying deterministic nature of this technique lacks to capture behavioural realism adequately.

A more plausible approach is to develop behaviourally realistic search model, where households formulate a pool of potential location alternatives (Habib and Miller 2007). In this line of research, a number of studies have attempted to address the search process (Rashidi and Mohammadian 2015, Fatmi et al. 2016). One of the limitations of these studies is to develop the search model on the basis of single attribute. For instance, Rashidi and Mohammadian (2015) developed a hazard-based screening model for spatial search based on average commute distance. Fatmi et al. (2015) considered the influence of prior locations in generating the potential choice set for the subsequent location on the basis of distance to the CBD. Advancing the research on residential search, Bhat (2015) developed a search model that probabilistically generates choice set using multidimensional housing attributes. One of the most notable contributions in this paradigm is made by Rashidi et al. (2012), who developed a hazard-based search model to generate household-specific choice set on the basis of commute distance and average land value. However, the location choice model developed using choice set generated from the hazard-based

search model did not improve the model fit compared to the random sampling model (Zolfaghari et al. 2012).

Further, the choice of residential location evolves over the life-time of the households, as they move from one location to another along the life-course. Most of the previous researches ignore such dynamics and are static in nature (Pinjari et al. 2011, Eluru et al. 2010, Gehrke et al. 2014, Lee and Waddell 2010). Few studies have taken a dynamic approach to examine how changes along the life-time influences location choice. For example, Habib and Miller (2009) developed a reference dependent mixed logit model to investigate the role of status quo and response towards gains and losses during location decisions. Chen and Lin (2011) investigated the effects of historical deposition on location decisions and argued that the choice of prior locations has an influence on the choice of the subsequent locations. Strom (2010) tested the effects of life-cycle events and revealed that the birth of the first child is associated with the choice of larger-sized dwelling with a higher number of rooms. Kim et al. (2005) argued that households with young children prefer to reside in locations on the basis of educational opportunities, residential facilities, and open spaces. They also revealed that households start to value job accessibility as children grow older. Recently, some studies have examined the effects of timing of the life-cycle events on vehicle ownership level (Oakil et al. 2014), and mode transition decisions (Oakil et al. 2011). It is critical to address the timing of an event, since households require time to adjust prior to or after an event in the life-course. Further examination on the life-trajectory dynamics of residential location choice decisions is necessary.

2.3.2 Modelling Commute Mode Transitions

As residential relocation is a significant decision in the life-time of the households, a change in location might be directly associated with different

decision processes such as mode choice. Mode choice, particularly for commute, is an important travel decision that has a profound longer-term dimension, as many change their commute mode over the course of life in response to changing life circumstances (Oakil et al. 2011). Commuting is the most frequently made daily trip, as a result individuals become habitual in their choice of commute mode (Gardner 2009). Since habit persistency is a natural phenomenon of human behaviour (Bamberg et al. 2010), individuals are resistant to changes in their commute mode (Kenyon and Lyons 2003). Commute mode changes are more often the result of key long-term change of state such as, residential/work location change (Stanbridge et al. 2004, van der Waerden et al. 2003), change in auto ownership level (Zhang 2006), or occurrence of life-cycle events, such as household formation, birth of a child, or residence members moving in or out (Oakil et al. 2011, Verhoeven et al. 2005).

Among the long-term changes, change in residential location considerably influences a change in commute mode (Dargay and Hanly 2007, Stanbridge et al. 2004). Stanbridge et al. (2004) demonstrated that a change in residential location might trigger a change in commute mode choice. Indeed, over one-quarter (27%) of home movers surveyed changed their commute mode following relocation (Stanbridge and Lyons 2006). Similarly, Dargay and Hanly (2007) found that the occurrence of commute mode changes was associated with residential relocation among the respondents in the British Household Panel Survey. Clark et al. (2003) developed a probability model to investigate how one worker and two worker households evaluate commute distance in choosing their work locations.

The reason for a close association between relocation and mode switch is attributed by the fact that a change in residential location changes the built environment, and accessibility characteristics of the home neighbourhood; which influences the choice of commute mode. For instance, individuals living in urban areas are more likely to commute by transit/walking/biking, whereas

suburban residents tend to be more auto-dependent (Schwanen and Mokhtarian 2005). Locations with higher mixed land use encourages the use of transit and active transportation, and discourages the use of car (Cao et al. 2009). Individuals living in urban areas walk more (Coogan et al. 2007) and choose to take more transit trips (Kitamura et al. 1997). On the other hand, individuals who prefer single-detached dwellings and single occupancy vehicles (SOV), live in sub-urban areas (Mae 1997) and own cars (Wachs and Crawford 1992). Although the relationship between residential location choice and commute mode choice is evident in the literature, limited studies have examined how a change in residential location influences a change in commute mode choice.

Mode transition has been investigated as a longer-term decision by Oakil et al. (2011), Fatmi and Habib (2017), and as a shorter-term decision by Hess et al. (2007), among others. Shorter-term mode changes have been examined in response to temporary incentives (Nurdeen et al. 2007) and acquisition of specific travel information (Athena et al. 2010). Recently, researchers have shown interest in analyzing individuals' mode transition behaviour as a longer-term decision. For instance, Oakil et al. (2011) developed a panel model to investigate how individuals' switch commute mode to and from car. Clark et al. (2015) developed a logistic regression model to analyze the behaviour of car commute and transition to and from car, active transportation commute and transition to and from active transportation. Wang and Chen (2021) developed a structural equation model of mode switching behaviour between single occupancy vehicle driving (SOV) and carpooling using data from the Puget Sound Transportation Panel (PSTP) survey. Idris et al. (2015) used a stated preference survey to investigate the mode shift behaviour of car drivers. They focused on the behaviour of continuing with car and shifting from car to transit and other modes. Although, the importance of understanding mode transition as a longer-term decision has been identified, a gap nonetheless exists in the

literature regarding how mode-specific mode transition occurs along the life-course of the individuals in response to relocation.

2.3.3 Modelling Vehicle Transactions

Modelling vehicle ownership has emerged from the concern for energy security and emission reduction. Vehicle ownership is an important medium-term decision, which interacts with the long-term decisions of where to live, where to work, as well as short-term decisions of what mode to choose, where to travel. It is one of the most explored phenomenon in the field of modelling travel behaviour. A review of literature suggests that a wide-array of dimensions of the phenomenon is investigated, including vehicle ownership level (Anowar et al. 2014), vehicle type choice (Garikapati et al. 2014), vehicle transaction (Mohammadian and Miller 2003), vehicle vintage type (Bhat et al. 2009), and vehicle holding and usage (Bhat and Sen 2006). For example, Anowar et al. (2014) investigated the vehicle ownership level in four categories: zero, one, two, and three or more vehicles. Garikapati et al. (2014) estimated a joint model of vehicle count for the following five vehicle types: car, SUV, van, pickup, and motorbike. Vehicle transaction was investigated as the transaction decisions of purchase, disposal, do nothing, and trade of vehicles by Mohammadian and Miller (2003). Bhat et al. (2009) investigated the choice of vehicles by the following two categories of vintage types: new vehicles (vehicle age less or equal to five years), and old vehicles (vehicle age more than five years). Bhat and Sen (2006) developed a vehicle holding model by examining households' usage (annual miles travelled) of different types of vehicles.

Vehicle transaction is a dynamic decision making process which refers to addition, disposal, and trading of vehicles. Recently, researchers have attempted to extend the dynamics of the model by accommodating the effects of life-cycle events on vehicle transaction decisions (Kitamura 2009, Oakil et

al. 2014). For example, Yamamoto (2008) investigated vehicle transaction decisions using longitudinal data from two surveys conducted in France and Japan. In the case of France, the study developed a competing-risk hazard-based duration model to examine acquisition, disposal, and replacement decisions utilizing data from a nationwide panel survey conducted in France. For Japan, the study developed a multinomial logit model to examine increase, decrease, and no change in the number of household vehicles using data from a retrospective component of the person trip survey conducted in Kofu City, Japan. The study found that life-cycle events, such as residential relocation, and change in the number of adults in the household significantly affect the vehicle transaction decisions. Rashidi and Mohammadian (2011) investigated the interdependencies among residential relocation, employment relocation, and vehicle transaction utilizing panel data from the Puget Sound Transportation Study conducted in the Seattle Metropolitan Area, U.S.A. They formulated a hazard-based system of equations, where residential and employment relocations are included as endogenous variables in the vehicle transaction model to predict the timing of vehicle ownership change. They found that a change in job is more likely to influence a household to make a vehicle transaction; whereas, a residential relocation was found to show a lower likelihood to change the household vehicle fleet size. In this line of research, Oakil et al. (2014) further tested the effects of timing of life-cycle events on vehicle transactions. They developed a mixed logit model to investigate vehicle transaction decisions; particularly, focusing on the vehicle acquisition and disposal decisions. The study revealed that households require adjustment period before and after a life-cycle event. For example, households were found to purchase a vehicle in anticipation of the child birth and dispose of a vehicle after changing a job. However, further investigation is required regarding developing dynamic models for vehicle transaction decisions.

2.4 Issues in the Existing Integrated Urban Models

In summary, long-term, medium-term, and short-term decisions are essential components of IUMs. There is an inherent inter-dependency among these decisions. For example, long-term decision of where to live influences medium-term and short-term decisions of whether or not to own a vehicle, what mode to choose, and vice versa. Integrated urban models need to be responsive to these decision dynamics across the agents' life-stages; starting with residential location, vehicle transaction, and life-stage transitions. However, such multi-way feedback mechanism is not well addressed within the existing urban modelling framework.

It is also required to examine how a change in critical long-term state such as residential location triggers a change in decisions of other life-domains such as commute mode choice. In the existing literature, dynamic modelling of commute mode transition decisions associated with the changes in residential location over the life-time of the individuals have not occurred to any significant extent. Moreover, limited studies have considered mode-specific mode transition among a comprehensive set of modes, such as car, transit, and active transportation (walk/bike).

An important aspect is addressing the process orientation of the essential decisions, which is limited in the existing urban modelling literature. For example, residential location is a two-stage process of mobility and location choice. Majority of the integrated models focuses on the location choice decision. Only a few, such as ILUTE, CEMUS, UrbanSim, and ILUMASS have the mobility component. However, to avoid complexity during implementation, some of the models, for example, UrbanSim and ILUMASS use historical rates in-place of behavioural models for the mobility module. Even the location choice component can be characterized as a two-tier process of home search and location choice. In the modelling paradigm of residential location, some

attempts have been made to address the search process. Such efforts have not warranted improvements in the empirical estimation of location choice models (Zolfaghari et al. 2012). Further examination is necessary on how to address the process orientation of the decisions; particularly, the long-term and medium decisions of residential location and vehicle transaction.

Although vehicle ownership is an important element for both the land use and transport components of the IUMs, few of the existing IUMs such as ILUTE, CEMUS, and SimMobility have this module. Only ILUTE accommodates vehicle transaction simulation, including acquisition, disposal, and trade. However, acquisition of a vehicle has an underlying dimension of whether the household is purchasing the first vehicle in their lifetime or the household is adding a vehicle to the already existing vehicle fleet. It is critical to identify the transaction decision of the first time vehicle purchase, since purchasing the first vehicle is a key event itself in the lifetime of the household which might trigger a mode shift to car. Therefore, in addition to implementing the vehicle transaction, such extension towards first vehicle purchase is necessary.

To address the life-trajectory dynamics of different decision processes within the IUM framework, individuals' life-stages have to be simulated. A large body of literature exists on the population demographic microsimulation (Nelissen 1993, Gribble 2000, Orcutt et al. 1976, King et al. 1999); however, integrated urban models have not sufficiently addressed life-stage transition processes. In addition, one of the major purposes of integrated urban models is to predict the evolution of urban form. Limited of the existing models are operational to report the spatio-temporal evolution of an urban region at the disaggregate-level of individuals as well as at the micro-spatial resolution.

In terms of modelling techniques, innovative methods need to be developed that accommodate the life-trajectory dynamics such as the process orientation of the decisions, and hold the potential to improve the empirical estimation

procedure. Models are also required to capture the multi-way decision dynamics; particularly, interactions among longer-term decisions of residential location, vehicle transaction, and life-stage transitions. These decisions are significant events in the life-time of the households, which require considerable investment of time and money. Hence, households might need adjustment period prior to or after an event/decision in the life-course. It is important to accommodate such time dimension of decisions and life-cycle events within the model estimation technique. Another temporal dimension is the repeated choices made by the same households along their life-course when panel observations are considered. For instance, in the case of residential location, households repeatedly move from one location to another along their housing career. Due to the repeated location choices, there exists a correlated sequence of choices, which demands accommodation within the empirical formulation of the models. Furthermore, models should address the heterogeneity among the households/individuals during the decision making processes.

Although considerable progress has been made in developing integrated urban models based on fundamental theories and approaches, such as economic activity-based models, market principle models, quasi market-based models, hybrid models, and agent-based complex system models; however, life-oriented approach is rarely adopted in developing urban models. A life-oriented perspective and theory is required to address the life-trajectory dynamics of key household-level decision processes, such as residential location and vehicle transaction. Life-oriented approach focuses on how transitions along the life-time and interactions among decisions taken at different life-domains shape individuals' choices and behaviour (Chatterjee Scheiner, 2015, Zhang 2017, Zhang 2015). Life-oriented approach and perspective offers the opportunity to disentangle a wide-ranging modelling issues such as multi-domain decision interactions, evolution of life-stages of individuals and households, evolving

nature of the decisions along the life-course, and process orientation of the decisions, among others.

2.5 Research Questions and Concluding Remarks

From the above discussion, it is evident that a wide-ranging theories, modelling methodologies, and simulation frameworks are developed to address the evolution of urban systems through integrated urban modelling. However, representing greater behaviour of the agents during longer-term decision processes as well as adding the capacity to reasonably predict the spatio-temporal evolution of the urban region demand further investigation. Particularly, the following research questions need to be addressed:

1. How to accommodate life-trajectory dynamics within key household-level longer-term decision models?
2. How to represent process orientation within the micro-modelling structure as well as computational procedure of an integrated urban model?
3. How to advance development of integrated urban systems model taking a life-course perspective and predict the micro-level evolution of the urban region?

This research attempts to address the above mentioned research questions. Specifically, this study adopts a life history-oriented approach to develop an agent-based integrated urban model that encompasses the modelling and simulation of longer-term decision processes, including life-stage transitions, residential location, first time vehicle purchase, and vehicle transaction. Interactions among these decisions are established within the empirical and computational procedures. The process orientation of the agents' decisions are accommodated during developing the modelling methodologies, which is later translated to the simulation framework. Further in the modelling paradigm,

this study investigates how a change in commute mode is associated with a change in residential location. Innovative modelling techniques are developed to accommodate the life-trajectory dynamics of the decision processes. The proto-type integrated urban model developed in this study is capable of predicting the micro-level spatio-temporal evolution of the population in an urban region.

Conceptual Framework and Data

3.1 Theoretical Context

The need to recognize the multi-directional interactions among the household decision processes has motivated this research to develop a life-oriented integrated Transport Land Use and Energy (iTLE) Model. The proposed model is developed on the basis of solid theoretical foundation, and includes a comprehensive set of decision components. To address the multi-way interactions and temporal dimension, the software architecture including the micro-modelling structures and computational procedures consistently adopts the concept of life-oriented approaches and theories. Life-oriented approach focuses on the inter-dependencies among the decisions and changes occurring at different life-domains of people (Zhang 2017, Zhang 2015). Zhang et al. (2011) identified nine major life-domains, such as residence, job, education and learning, health, family life, family budgets, neighbourhood, leisure and recreation, and travel behaviour; and revealed that interactions exist among the decisions taken in different life-domains (Zhang 2014). To develop better empirical and simulation models of household-level decision processes, it is imperative to examine the interactions among changes in multiple life-domains, since choices at any domain are part of the extended inter-connected choices made hierarchically across different domains (Salomono and Ben-Akiva 1983, Lanzendorf 2003).

A life-oriented approach could take a life-course perspective, also known as life history-oriented approach. Life history-oriented approach focuses on the temporal variation of the multi-domain interactions over the life-course.

Particularly, it emphasizes on the effects of changes at different domains along the life-course in shaping individuals' or households' behaviour (Chatterjee and Scheiner 2015). The changes during life-course include life-events and decisions taken at different stages along the life-time (Oakil et al. 2014). Such life-events and decisions include birth of a child, getting a job, job change, and household formation, among others (Habib and Miller 2009). Unlike conventional cross-sectional modelling approaches, which focus on a snapshot of an individual's life-time; the life history-oriented approach considers the whole life-time or a segment of the life-time (Chatterjee and Scheiner 2015). Among the decisions taken at different life-domains, life-stage transitions, residential location choice, and vehicle ownership are the most critical decisions. A schematic representation of how the concept of life-oriented approach is translated into the development of the proposed integrated urban model is presented in Figure 3.1.

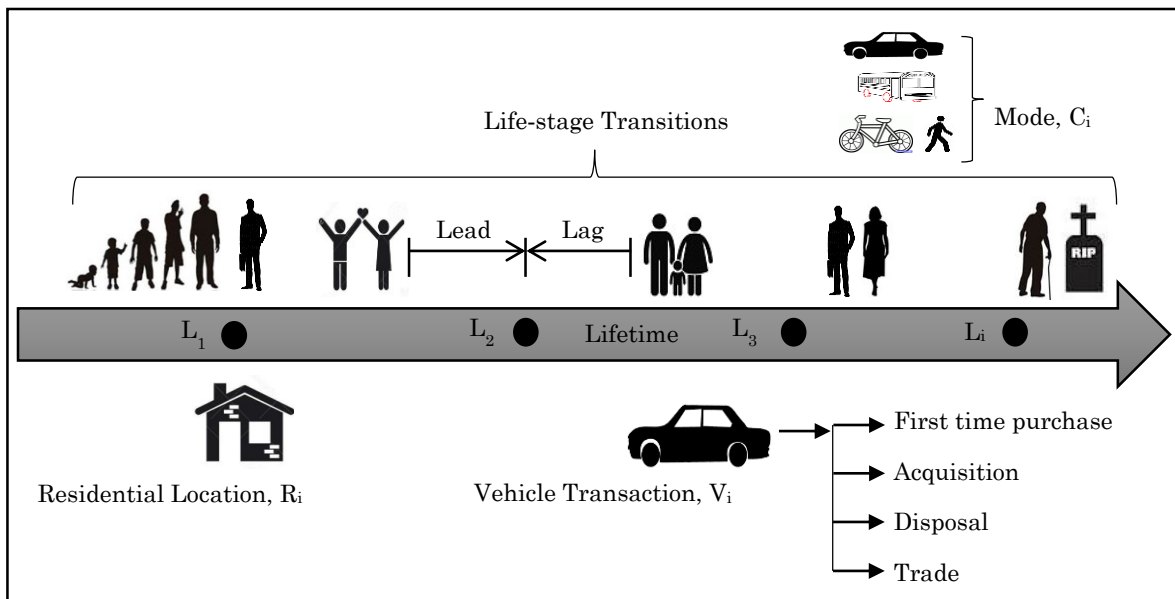


Figure 3-1 Conceptual Framework of the Proposed Life-oriented Integrated Urban Model

The proposed life-oriented integrated urban systems model simulates individuals' decisions longitudinally along their whole life-time or a segment

of the life-time. Figure 3.1 represents that individuals enter the proposed urban system through birth. They grow older within the system, and exit through death. Along their life-course, changes at different life-domains occurs, such as marriage, child birth, job change, residential location change, vehicle transaction, and mode change, among others. These decisions and changes interact with each other. Such multi-way interactions have a temporal dimension. For example, households require an adjustment period to adapt prior or after a change in life-stage, due to the limitations in time and money budget. One of the mechanisms adopted to accommodate the interaction among the multi-domain changes is through introducing lead and lag events. A lead event refers to an event on occurrence, and a lag event refers to an event in anticipation. Based on this concept, the iTLE software architecture is developed. A description of the iTLE framework and modelling components are discussed below.

3.2 Modelling Framework of the Proposed Integrated Urban Model

The proposed integrated Transport Land Use and Energy (iTLE) model is an agent-based microsimulation model for urban systems. It is designed to address the multi-domain interactions and recognize the process orientation of a wide range of decisions. The conceptual iTLE modelling framework is presented in Figure 3.2. The model system consists of five core modules: baseline synthesis, population life-stage transition, residential location transition, vehicle ownership transition, and activity-based travel. To represent the behaviour of the agents within each module, a number of micro-behavioural econometric models are developed accommodating life-trajectory dynamics. A brief description of the main elements within the iTLE are given below:

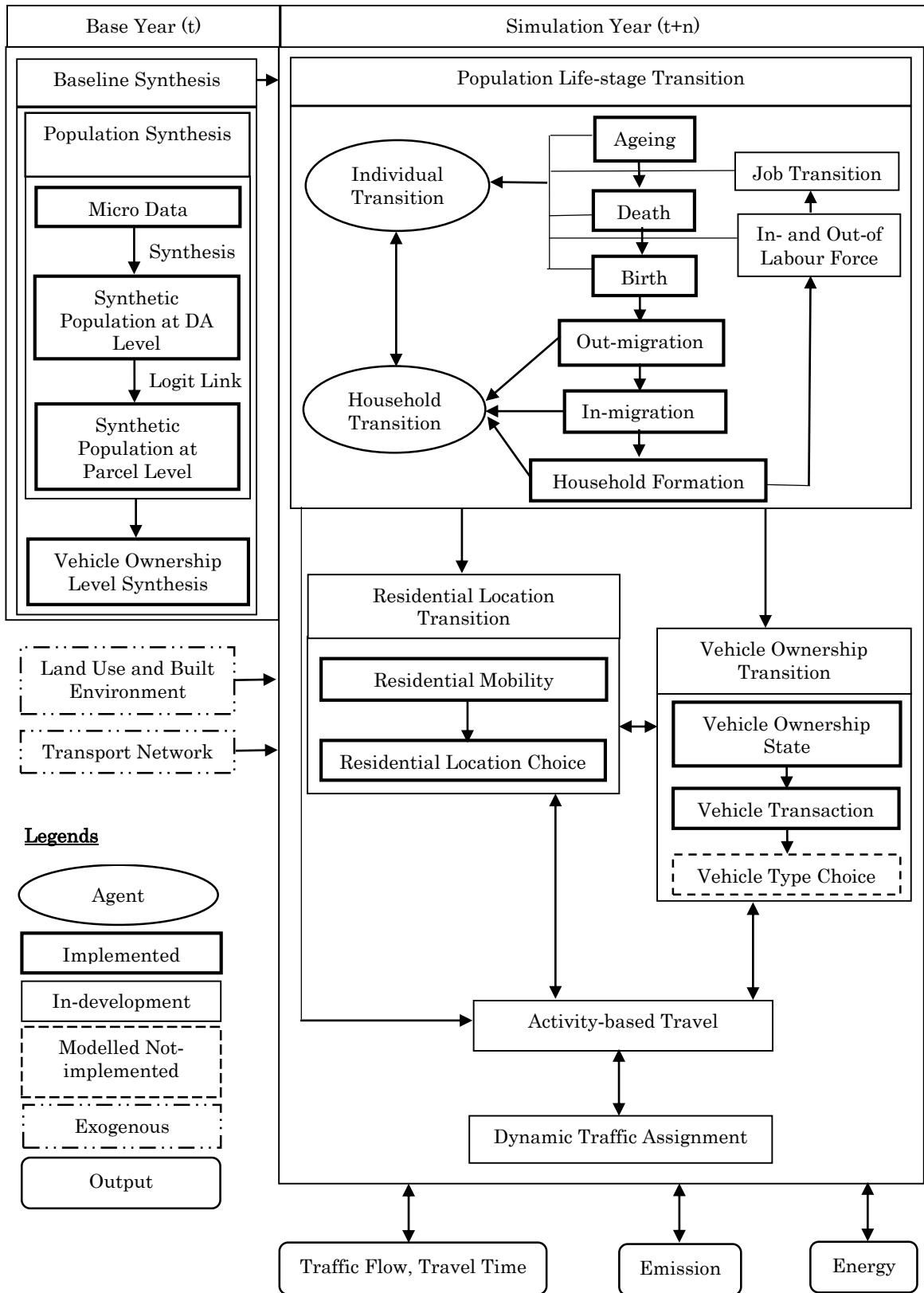


Figure 3-2 The Conceptual iTLE Modelling Framework

3.2.1 Baseline Synthesis

The baseline synthesis component generates micro-level information of the population for an entire urban region, which is used as an input for the microsimulation engine of iTLE. The baseline synthesis involves population synthesis and vehicle ownership level synthesis for the initial time-step. Population synthesis for the iTLE is performed as a two-stage process. First, a synthetic population is generated controlling for both household-level and individual-level characteristics at the smallest zonal level of dissemination area (DA). In the second stage, households are allocated into the micro-spatial unit of parcel. In addition, relevant baseline information, for instance, vehicle ownership level for the synthetic population is generated.

3.2.2 Population Life-stage Transition

Population life-stage transition module focuses on the evolution of the demographic career of the agents. Relevant life-stage transitions along the life-course of the individuals and households are simulated. This process includes simulation of eight transitions: ageing, death, birth, out-migration, in-migration, household formation, in- and out-of labour force, and job transition.

3.2.3 Residential Location Transition

Residential location transition module follows the theory of residential stress (Rossi 1955), which postulates that households decision to move or stay at a location is triggered by the residential stress developed at that location. Stress is generated by the experienced or desired changes in life-stages (Miller 2005), dwelling characteristics (Van Ham *and* Feijten 2008), and neighbourhood attributes (Van Ham and Clark 2009), among others. Such stress arises from

the discrepancies between the desired and current situation of a household. As a result, households' relocate to a new location that minimizes the stress.

Residential location transition is conceptualized as a two-stage process: residential mobility, and residential location choice. In the first stage of mobility, households are assigned to move or stay at a particular location. Households who are assigned to move in this stage, are considered in the second stage. The second stage of location choice is assumed as a two-tier process of location search and choice. In this stage, households first search for locations, and then choose a location. The search process is conceptualized as a stress releasing mechanism, where households generate a pool of location alternatives, which has the potential to minimize the stress. Finally, households are allocated to one of the locations from the pool of alternative locations. In addition, the location transition module includes a commute mode transition component. Following a relocation, individuals are conceptualized to reassess their commute mode. After reassessing, individuals either continue with the same mode, or make a transition to a new mode. A description of the micro-behavioural models and microsimulation results of the residential location transition process are presented in Chapter 4 and Chapter 6 respectively.

3.2.4 Vehicle Ownership Transition

Vehicle ownership transition module is conceptualized as a three stage process: vehicle ownership state, vehicle transaction, and vehicle type choice. The first stage of vehicle ownership state has two components: no vehicle ownership state, and transient ownership state, as conceptualized by Khan and Habib (2016). Households not having a transaction history in their lifetime are assumed to be in the no vehicle ownership state. Households having a transaction history in their lifetime are assumed to be in the transient

ownership state. The second stage of vehicle transaction focuses on the transaction decisions of the households. This component involves the following four transaction elements: first time vehicle purchase, acquisition, disposal, and trade. In the third stage, vehicle type choice behaviour is simulated for the households making the decisions of first vehicle purchase, acquisition, and trade in the earlier stage. In this stage, the simulation determines the choice among six vehicle types: sub-compact, compact, mid-size, luxury, SUV, and van. The micro-behavioural models and microsimulation results for the vehicle transaction component is reported in Chapter 5 and Chapter 7 respectively. The vehicle type choice model is developed by Khan and Habib (2016), and will be implemented later.

3.2.5 Activity-based Travel

This module simulates the travel activities of the individuals, following an activity-based modelling technique. Microsimulation of activity generation, scheduling, and mode choice behaviour are included in this module. Finally, the travel patterns/trips of the individuals are simulated on the transport network using a dynamic traffic assignment method. This module is currently under development, and beyond the scope of this study.

3.2.6 Population and Urban Form Representation

The efficiency and accuracy of an urban systems simulation model largely relies on how closely it replicates individuals' behaviour, and relationships with built environment. In terms of representing individuals' behaviour, agent-based microsimulation modelling is necessary to effectively abstract a complex and dynamic system like an urban region. Therefore, the iTLE represents population at the most disaggregate-level, assuming individuals and households as the agents.

Urban form is represented at the most micro geographic unit of parcel, since residential location component is conceptualized to be modelled considering parcels as the spatial unit of analysis. The micro-scale spatial resolution improves the capability of the model to represent better individual behaviour and effectively analyze micro-scale land use policies. Each parcel acts as a property object, which is characterized by its location (centroid of a parcel), size, type, and accessibility to major activity points and service destinations. The parcel database also maintains the characteristics of more aggregate spatial information, such as dissemination area (DA) based on its location. Maintaining the relationship between parcels and corresponding DAs assists in generating numerous statistics and maps at different aggregation levels for further analysis of the simulation results.

3.3 Data Sources and Description

Development of a life-oriented agent-based microsimulation model for urban system like iTLE requires a tremendous amount of data. Particularly, the focus of iTLE is to address interactions among different decisions along the life-course of the agents as well as process orientation of the decisions. To accommodate such dynamics within the empirical settings, data from conventional cross-sectional surveys are not adequate. Longitudinal survey data are required, which provides information about the life history of respondents. Therefore, this research utilizes retrospective survey data to develop the micro-behavioural components of the iTLE model. A description of the retrospective survey data is presented below.

3.3.1 Retrospective Survey Data

The data source for developing the micro-behavioural models is a retrospective Household Mobility and Travel Survey (HMTS). The HMTS was administered

from September 2012 to April 2013 in Halifax (Peterlin and Habib 2013, Heffernan and Habib 2013). The design of the HMTS was in accordance with previous retrospective surveys, including Residential Mobility Survey I and II (Haroun and Miller 2004), and Residential Search Survey, which were conducted in Toronto, Canada (Habib and Miller 2009). The HMTS collected life-history information across the life-domains of the households, including housing history, vehicle ownership history, compositional change, and employment record, among others. A brief description of these components are given below:

1. **Housing history:** The housing history component collected information regarding the three most recent residential episodes of the respondents. For each residential episode, respondents were asked to provide the following information:
 - Location information including civic address and postal code.
 - Year and month of relocation.
 - Primary reasons for relocation. The reasons are thematically aggregated into the following four major categories: (1) to live in proximity to work or key activity locations, such as school, shopping center, entertainment, and transit stop; (2) to live in desirable neighbourhood or dwelling; (3) due to life-cycle events such as change in household size and formation of a new household; and (4) other reasons.
 - Socio-economic and demographic configuration of the household, including household income, household size, number of children, number of vehicles, number of driver's licence, number of bicycles, and monthly transit pass ownership, among others.
 - Dwelling characteristics, which includes dwelling type, tenure type, number of rooms, and number of bedrooms, among others.

- Choice of primary commute mode, which can be broadly categorized into the following options: car, transit, and active transportation (walk/bike).
2. **Vehicle ownership history:** This component collected information regarding households' vehicle ownership history up to four current and four previous vehicle ownerships. The following information of the vehicles are collected: make, model, manufacturing year, purchase year, new or used, purchased or leased, and purchase price, among others.
 3. **Household compositional change:** Household compositional change refers to the change in size of the household and number of employed household members. This component includes the following information:
 - Year of a change in the household size as a result of birth, death, a member moving out, or a new member moving in.
 - Year of a change in the employment size as a result of addition of a job, loss of a job, retirement, withdrawal from the labour force, or a return to school.
 4. **Employment records:** The employment career component collected information of the three most recent employments, including employment location, employment type, employment starting and ending year and month.
 5. **Attitudinal and other information:** The survey contained 33 statements concerning attitudes. The respondents were asked attitudinal questions on a three point agree-disagree likert scale to specify their level of

agreement or disagreement. In addition, travel time and travel mode of a number of major travel activities are collected.

The HMTS provided a total response from 475 households. The proportion of men and women in the sample is almost equal. In the case of age distribution, 54% of the respondents' age are below 35 years, and 16% of the respondents are above 54 years. 33% respondents earn a household income of above \$100,000 (CAD), and 31% earn a household income of below \$50,000 (CAD). Around 38% of the respondents represent two-person households, and 9% represent five or more person households. Around 50% of the respondents reside within the regional centers, and 38% lives in suburban areas. The HMTS sample was compared with the Statistics Canada Census for Halifax Regional Municipality (HRM) by Salloum and Habib (2015). They found that majority of the stratum of household and individual characteristics are within a 3% variability of the 2011 Census information. Hence, the HMTS can be considered as a representative sample. Further detail of the validation and exploratory analysis of the survey can be found in Salloum and Habib (2015).

3.3.2 Secondary Data Sources

This study utilizes information from a number of secondary data sources during the model estimation and simulation procedures. A list of these secondary data sources are presented in Table 3-1. A brief description of the data is presented below.

Table 3-1 List of Secondary Data Sources Utilized to Develop the Components of the Proposed Integrated Urban Model

Data Items	Data Sources	Data Descriptions	Model Components
Micro sample of the population	PUMF	Individual- and household-level socio-economic characteristics of a random micro sample	Zonal-level Population Synthesis
Target total of the population at the zonal level of DA	Census	Distribution of the population falling under different categories of socio-economic characteristics at the DA-level	Zonal-level Population Synthesis, Validation
Parcel information	Nova Scotia Property Database	Parcel location, size, and type	Logit link, Search, Location Choice
Historical rates	Census	Historical rates of different demographic events	Life-stage Transition
Activity point location	DMTI**	Location of schools, central business district (CBD), business parks, health services, park areas, and shopping centers	MM*
Transport service location	DMTI**	Location of bus stops	MM*
Neighbourhood characteristics	Census	Socio-economic and demographic characteristics at the DA-level	MM*
DA boundaries	Census	DA boundary file in the GIS platform	Zonal-level Population Synthesis and MM*
Road network	HRM***	Road network layer in the GIS platform	MM*
Land use information	HRM***	Polygon file of different land uses at the DA-level in the GIS platform	MM*

*MM refers to all developed micro-models of the iTLE system, which includes residential mobility, search, location choice, mode transition, vehicle transaction, logit link, and vehicle ownership level synthesis.

**DMTI refers to Desktop Mapping Technologies Inc.

***HRM refers to Halifax Regional Municipality

3.3.2.1 Census Data

The data used for generating the population synthesis includes: 2006 Public Use Microdata File (PUMF), and 2006 Census information at the dissemination area (DA) level. The PUMF data is used as the micro sample and the Census data is used as the control total for the population synthesis. The 2006 PUMF data includes micro-level information of the population in Atlantic Canada. The sample size is 20,954 individuals and 8,907 households. The sample size of the 2006 Census data for Halifax is 372,679 individuals and 155,060 households. The spatial resolution of the collected census data is at the smallest zonal-level of dissemination area (DA). The Halifax region includes a total of 572 DAs. For validation purposes of the iTLE, 2011 Census information are collected. The 2011 Census includes 390,325 individuals, 165,155 households, and 594 DAs. This data is also utilized to represent the neighbourhood characteristics at the DA-level.

3.3.2.2 Land Use Data

To represent the urban form, parcel-level data is collected from the Nova Scotia Property Database 2013. This parcel database provides information regarding parcel attributes, including location, size, and type, among others, of all the parcels in the Province of Nova Scotia. Following the cleaning process, a total of 110,995 parcels for Halifax are derived. Additional data sources include location of different activity points, such as location of schools, central business district (CBD), business parks, health services, park areas, and shopping centers; which are collected from the Desktop Mapping Technologies Inc. (DMTI). Location of transportation services such as transit stop locations are collected from the DMTI. Land use data referring to the percentage of different land uses at the DA level are collected from the Halifax Regional Municipality (HRM). Road network is collected from the HRM as well.

3.4 Derived Independent Variables

The micro-behavioural models for residential location, vehicle transaction, and mode transition, developed in this study, accommodate the effects of a wide range of independent variables, such as, life-cycle events, socio-demographics, dwelling characteristics, parcel characteristics, accessibility measures, and neighbourhood characteristics, among others. A brief description of the variables derived from the above discussed data sources are presented below.

3.4.1 Life-cycle Events

One of the unique features of this study is to develop micro-models that are capable of exploring the *priori* hypotheses regarding the interactions among multi-domain longer-term changes. These longer-term changes along the life-course of the individuals and households are termed as life-cycle events. Life-cycle events include, birth of a child, death of a member, move-in of a member, move-out of a member, household formation, residential relocation, addition of a job, loss of a job, job change, retirement, and vehicle transaction, among others. Vehicle transaction decision includes the decision of vehicle acquisition and purchase of the first vehicle. “Vehicle acquisition” refers to the addition of a vehicle to the existing vehicle fleet of the household. “Purchase of the first vehicle” refers to the purchase of the first vehicle in the life-time of the household. “Job change” is defined as getting a job following the loss of a job within the same month of the same year. “Addition of a job” refers to getting the first job or getting a new job after one month of losing the previous job. “Loss of a job” refers to losing a job and failing to secure another job within the same month. Households require adjustment period before/after a life-cycle event. The adjustment period is accommodated within the models by considering the events as lead and lag events. Lead events refer to the effects of an event on occurrence, and lag events refer to the effects of an event in

anticipation. Hence, a lead event indicates to a lagged effect, and a lag event indicates to a lead effect. The micro-models consider lead and lag events for the following periods: same year, one-year lead, two-year lead, three-year lead, one-year lag, two-year lag, and three-year lag. “Same-year” refers that two events occurred in the same calendar year. “1 year lead” refers that an event occurred one to two calendar years before another event. Two-year lead and three-year lead can be described similarly. “One-year lag” indicates that an event occurred one to two calendar years after another event. Similarly, two-year lag and three-year lag can be described. The variables representing life-cycle events are derived from the HMTS data.

3.4.2 Accessibility Measures

Accessibility characteristics refer to the distance from home location to different activity points. The location of activity points and transportation services are utilized to determine the accessibility measures. The accessibility measures are generated on the basis of the road network distances using the Network Analyst tool in ArcGIS. The accessibility measures include commute distance, distance to the CBD, and closest distance to the following locations: transit stop, business center, school, health service, park area, and shopping center, among others.

3.4.3 Land Use and Neighbourhood Characteristics

Land use information refers percentages of different land uses measured using the ArcGIS platform at the DA-level. The data includes land use measures in the following categories: residential, commercial, open space, park, industrial, government, and water body. The land-use information is utilized to determine land-use mix index, which follows the measures proposed in Bhat and Gossen

(2004)¹. The index value ranges from 0 to 1, where a value of 0 indicates perfect homogeneity and 1 indicates perfect heterogeneity. Micro-level land use characteristics, such as parcel size information is derived for estimating the location choice model. In addition, neighbourhood characteristics are derived at the DA-level, which include population density, dwelling density, percentage of owned dwellings, percentage of rented dwellings, percentage of single-detached dwellings, average property value, labour force participation rate, employment rate, percentage of household share of shelter cost to income less than 30%, and percentage of non-movers, among others.

3.4.4 Socio-demographic and Dwelling Characteristics

The models test a number of socio-demographic characteristics, such as gender, age, and education level of the head of the household, household size, household income, presence of children, and number of vehicle ownership. Dwelling characteristics include, number of rooms in the dwelling unit, dwelling type, and tenure type, among others.

3.5 Conclusions

This chapter proposes the development of a life-oriented agent-based integrated urban modelling system, and discusses the conceptual framework and data utilized to address the multi-dimensional interactions among different decision processes within the proposed urban systems model. The theoretical context of the proposed model is discussed in this chapter. Particular emphasis is given on how life-oriented theory and perspective is

¹ Land – use mix index = $1 - \left\{ \frac{\left| \frac{R}{T} - \frac{1}{3} \right| + \left| \frac{C}{T} - \frac{1}{3} \right| + \left| \frac{O}{T} - \frac{1}{3} \right|}{\frac{4}{3}} \right\}$, where, R = residential land use, C = commercial or industrial land use, O = other land use, and T = total land use. All land use measures are in acres.

mapped within an integrated modelling framework. Conceptualizing on this approach, the essential components of an urban model are identified, which includes: baseline synthesis, population life-stage transition, residential location transition, and vehicle ownership transition. To develop a comprehensive multi-domain feedback-based microsimulation model, the requirement for a tremendous amount of data is discussed. Data is collected from a number of sources and through undertaking specialized surveys. The primary data source to develop the micro-behavioural models for different core components of the iTLE is a retrospective survey, known as the HMTS. To develop the population synthesis module, PUMF and Census data are used. Description of these data are provided in this chapter. Finally, *priori* hypotheses are presented by discussing the independent variables considered to develop the micro-models. The mechanism to test multi-way interaction through lead and lag effects of a number of life-cycle events are described. The next two chapters (Chapter 4 and 5) presents the empirical estimation results of residential location transition, mode transition, and vehicle transaction components. The results of baseline synthesis and population life-stage transition module are presented in Chapter 6. The microsimulation results of residential location and vehicle transaction are reported in Chapter 7 and 8, respectively.

Modelling Residential Location Processes

4.1 Introduction

This chapter focuses on modelling the residential location transition processes of the iTLE model. This study also investigates how a change in residential location influences a change in commute mode choice. This research disentangles the following key issues in modelling location choice: 1) accommodating the process orientation of the phenomenon by modelling location decision as a two-stage process of mobility and location choice, 2) addressing the location search process during modelling location choice and examining whether the incorporation of search process improves the empirical estimation of the location choice, 3) investigating the effects of multi-domain decision interactions through introducing life-cycle events as lead and lag events, and 4) testing how a long-term change such as residential relocation influences individuals to reassess their commute mode.

As discussed earlier, the residential location process adopts the theory of residential stress (Rossi 1955). Households' are conceptualized to relocate due to the continual generation of residential stress along their life-time.

This chapter is largely derived from the following journal papers:

- Fatmi, M.R., Chowdhury, S., and Habib, M.A. (2017). Life History-Oriented Residential Location Choice Model: A Stress-Based Two-Tier Panel Modelling Approach. *Transportation Research Part A: Policy and Practice*, 104, 293-307.
- Fatmi, M.R., and Habib, M.A. (2015). Spatial Transferability of a Micro Residential Mobility Model in the Integrated Land Use, Transportation and Environment Modelling System. *Transportation Research Record: Journal of Transportation Research Board*, 2494(2), 29-36.

Residential stress is induced by the experienced or desired changes in different life-domains, such as change in life-stages, dwelling characteristics, and neighbourhood attributes, among others. Moreover, residential relocation evolves over the life-time of the households, as they move from one location to another along the life-course. Ignoring such temporal dimension of the households' housing career might produce biased and inconsistent parameter estimates. Furthermore, heterogeneity exists across the households/individuals, which needs to be addressed within the model formulation technique. To tackle the notion of addressing life-trajectory dynamics and capture unobserved heterogeneity within the modelling framework, this research develops innovative methods for modelling residential location processes. The study conceptualizes that residential location transition process involves mobility, search, location choice, and mode transition decisions. Figure 4-1 shows the location transition process and modelling methods developed for each component of the process.

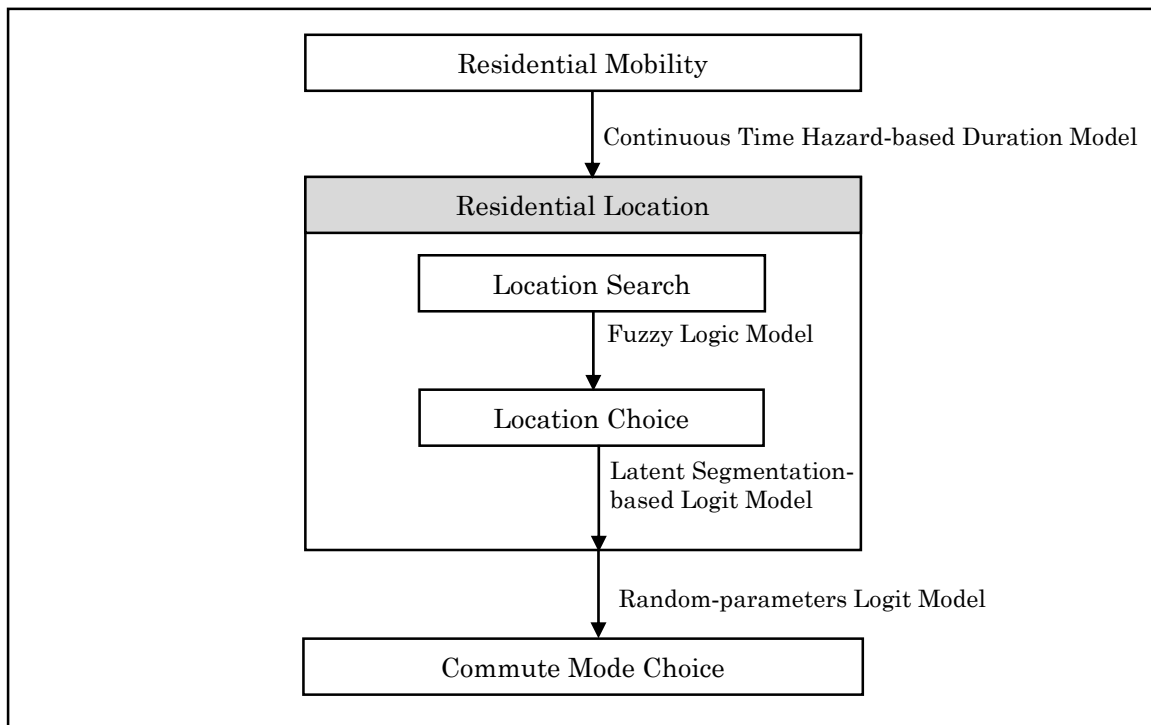


Figure 4-1 Residential Location Transition Process

Residential mobility decision is modelled utilizing a continuous time hazard-based duration modelling technique. Duration refers to the length of stay at a particular location. Traditional single-episode duration model is extended to a multiple episode shared frailty framework to accommodate the effects of repeated durations along the housing career of the households. Both sets of models are estimated for a number of distributions including lognormal, log logistic, and Weibull. In the case of residential search, the model is developed using a fuzzy logic-based modelling method. The model conceptualizes on the theory of residential stress, and accommodates the inter-dependencies between push and pull factors. Constraints regarding households' affordability are imposed by introducing household income and property value within the fuzzy framework. The location choice model is developed utilizing a latent segmentation-based logit (LSL) modelling technique. The LSL model accommodates correlated sequence of repeated choices through introducing joint probability of choice sequence. Unobserved heterogeneity in the decision making process is captured by formulating a flexible latent segment allocation model within the LSL framework. Finally, the commute mode transition model adopts a random-parameters logit (RPL) modelling technique. Similar to the LSL framework, the RPL model formulation accommodates the joint probability of choice sequence. The model captures unobserved heterogeneity by allowing parameters to vary across the individuals.

The organization of the rest of the chapter is as follows: section 4.2 discusses the modelling of residential mobility, particularly, the mathematical formulation of the model and discussion of the parameter estimation results. Section 4.3 describes the methods and results of the location search and location choice model. Section 4.4 presents discussion on the mode transition behaviour, including the mathematical model formulation and estimation results. Finally, section 4.5 concludes with a summary of contributions.

4.2 Residential Mobility

The first stage of residential location decision is mobility, which refers to the decision to move or stay at a particular location. The mobility model is developed utilizing a continuous time hazard-based duration modelling technique. Duration modelling is widely used in medical sciences, economics and urban economics (Haurin and Gill 2002, Jenkins and García-Serrano 2004); for example, analyzing the duration of unemployment (Jenkins and García-Serrano 2004). However, in the residential mobility literature, few studies have adopted this approach (Decoster et al. 2005, Habib and Miller 2008). This method offers the opportunity to test the influence of life-stages, dwelling characteristics, land use, accessibility, and neighbourhood characteristics on the length of stay at a particular location. To address the life-trajectory dynamics, a household's housing career is characterized as the sequence of duration (i.e. episodes/spells) in different dwellings during their lifetime. The conventional duration model is extended to a multiple episode shared frailty model. This research also examines whether the multiple episode shared frailty extension of the model improves the model fit or not.

4.2.1 Methodology

The residential mobility model is developed utilizing a continuous time hazard-based duration modelling technique. In the formulation of the hazard-based duration model, duration is specified as the period that a household will remain in a specific residence and the failure (termination) event is a move to a different location. Hence, the hazard model considers duration at a particular residential location as the dependent variable. The data for the model is extracted from the HMTS survey that contains 475 households with 762 episodes representing duration at a particular residential location, including censored spells. The data is right censored in April, 2013. The average duration

is 2170.924 days (5.96 years) with a minimum of 23 days and a maximum of 15462 days (42.45 years). The duration spells are considered to be continuous time-periods. This model examines time constant covariates only, meaning covariates that are constant or can be assumed to be time-independent for the entire duration of the episode. Examples of these covariates include: birth year of the head of the household, gender of the head of the household, and land use and accessibility measures, among others.

In developing the hazard-based duration model, assume T is the duration at a particular location, which is a non-negative random covariate. The probability density function $f(t)$, considered as an unconditional distribution of durations T can be expressed as:

$$f(t) = \lim_{\Delta t \rightarrow 0} \frac{P(T \leq t + \Delta t) - P(T \leq t)}{\Delta t} \quad (1)$$

Here, Δt represents a short interval, within which a household decides to move at or after a particular time t while the household is still passive until time t . Therefore, the cumulative probability of a household's mobility decision before time t is:

$$F(t) = P(T < t) = \int_0^t f(t) dt \quad (2)$$

Now, $f(t)$ can be explained as the first derivative of $F(t)$ with respect to time. The probability of a household being passive until time t can be expressed as the survivor function $S(t)$.

$$S(t) = 1 - F(t) = P(T \geq t) = \int_t^{-\infty} f(t) dt \quad (3)$$

Essentially, the hazard function $h(t)$ can be written as:

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t} = \frac{f(t)}{s(t)} \quad (4)$$

The hazard function can take different forms, such as: monotonically increasing, monotonically decreasing, constant, or U-shaped (Kalbfleisch and Prentice 2002, Lawless 1982), which depends on the distribution assumptions of the probability density function $f(t)$. This study employs Weibull, log logistic, and lognormal distributions, which are given below:

$$\text{Weibull distribution: } h(t) = \omega\gamma(\gamma t)^{\omega-1} \quad \omega, \gamma > 0 \quad (5)$$

$$\text{Log logistic distribution: } h(t) = \frac{\omega\gamma(\gamma t)^{\omega-1}}{1+(\gamma t)^\omega} \quad (6)$$

$$\text{Lognormal distribution: } h(t) = \frac{\frac{1}{(2\pi)^{1/2}\sigma t} \exp[0.5 \left(\frac{\log t - \mu}{\sigma}\right)^2]}{1 - \int_{-\infty}^t \frac{1}{(2\pi)^{1/2}} e^{-\frac{\mu^2}{2}} du \left(\frac{\log t - \mu}{\sigma}\right)} \quad (7)$$

Where, γ is a scale parameter and ω is a shape parameter.

This research employs a parametric hazard modelling approach instead of non-parametric or semi-parametric models since clear identification of the baseline hazard is necessary for predicting timing of residential moves in the micro simulation-based urban modelling system. It considers the effects of different types of covariates (such as life-cycle events, socio-demographics, dwelling, neighbourhood, land use and accessibility measures) in addition to the effects of duration in the model estimation process. Hence, the underlying hazard model can be expressed as:

$$h(t, x) = h_0(t) \exp(x(t)) \quad (8)$$

Here, $x(t)$ is the observed vector covariates, and $h_0(t)$ is the baseline hazard. For the purpose of ease in interpretation, the model follows an accelerated failure time assumption, which can be expressed as the following log-linear form:

$$\ln(T) = \beta_i x + \alpha \epsilon \quad (9)$$

Here, β_i is the coefficient of the time independent covariate x and ϵ is a stochastic error term with type-I extreme value distribution scaled by α . Finally, the hazard function of the accelerated failure time model can be expressed as:

$$h(t, x) = h_0(t \exp(-\beta x))^{\exp(-\beta x)} \quad (10)$$

At first, parameters are estimated for the single spell duration of a household using the full information maximum likelihood estimation method (Kalbfleisch and Prentice 2002), which can be expressed as:

$$L = \prod_j^n [h(t_j, x_j)]^{\delta_j} [S(t_j, x_j)] \quad (11)$$

Here, δ_j is the censoring parameter, taking the value “zero” if duration of case j is not terminated (censored). It takes the value of “one” if duration of case j is terminated (not censored).

However, as explained earlier, a single spell model assumes the independence of spells even if multiple episodes are reported for the same household. Failure to account for this repeatability might violate the independence assumption on the occurrence of events taken in single-spell models. Since repeated events are evident in the retrospective HMTS survey, this study proposes shared frailty models of multiple episodes that accounts for the group heterogeneity across households due to repeated choices. In effect, the shared frailty models assume a stochastic variation across the parameters that are common among households. The hazard rate for shared frailty model is given below:

$$h(t_{ji}) = h_0(t) \exp(\beta' x_{ji}) \tau_j \quad (12)$$

Here, j represents a household that has multiple episodes i , τ_j represents group specific heterogeneity. τ_j is distributed across households with repeated

episodes according to the distribution function $G(\tau_j)$. The likelihood function for the shared frailty model can be written as:

$$L = \prod_{j=1}^k \int_0^\infty \left(\prod_{i=1}^{n_j} [h(t_{ji}, x_{ji})]^{\delta_{ji}} [S(t_{ji}, x_{ji})] \right) dG(\tau_j) \quad (13)$$

This likelihood function is maximized using expectation-maximization (EM) algorithm to estimate the parameters and the likelihood ratio test is used to assess the requirement of the frailty component τ_j . The goodness-of-fit of the models are compared on the basis of adjusted pseudo r-squared² and Bayesian Information Criteria (BIC)³.

4.2.2 Discussion of Model Results

The first set of the residential mobility models are estimated as single episode models, considering each spell as a separate observation. These models consider lognormal, log logistic, and Weibull distributions for the baseline hazard. In addition, multiple episode shared frailty models are estimated. The multiple episode models assume a gamma frailty distribution. The parameter estimation results of the models are reported in Table 4-1.

The goodness-of-fit measures suggest that the Weibull shared frailty model with gamma distribution provides a higher adjusted pseudo r-squared and lower BIC values than that of other models. Therefore, it is considered as the final model. The model considers an accelerated failure time assumption, so a positive coefficient means an increase in the duration with the increase in the parametric value.

² Adjusted Pseudo R – squared = $1 - \frac{LL_{convergence}}{LL_{constant}}$

³ BIC = $(-2(LL_{convergence}) + K * \ln(N))$, where, n= sample size, and k = number of parameters to be estimated.

Table 4-1 Parametric Estimation Results of Single-episode and Multiple-episode Hazard-based Duration Models for Residential Mobility

Covariates	Single episode model (without frailty)			Multiple episode model (Gamma Shared frailty)		
	Log normal	Log logistic	Weibull	Log normal	Log logistic	Weibull
	Co-eff.	Co-eff.	Co-eff.	Co-eff.	Co-eff.	Co-eff.
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
<i>Socio-demographics and Life-cycle Events</i>						
Male HH head	-0.199 (-2.19)	-0.188 (-2.14)	-0.265 (-3.22)	-0.199 (-2.19)	-0.188 (-2.14)	-0.225 (-2.32)
Year of birth of the head of the HH	0.000001 (0.02)	-0.00001 (-0.20)	0.00004 (0.70)	0.000001 (0.02)	-0.008 (0.20)	0.00002 (0.38)
First spell after HH formation	-0.467 (-5.37)	-0.454 (-5.50)	-0.500 (-6.33)	-0.467 (-5.37)	-0.454 (-5.50)	-0.619 (-6.00)
<i>Dwelling Characteristics</i>						
Number of rooms in the dwelling unit	0.047 (2.68)	0.051 (2.87)	0.066 (4.05)	0.048 (2.68)	0.051 (2.87)	0.056 (3.19)
Dwelling type - rowhouse	-0.315 (-1.96)	-0.351 (-2.19)	-0.258 (-1.77)	-0.315 (-1.96)	-0.351 (-2.19)	-0.326 (-2.03)
Tenure type - rented	-1.351 (-12.71)	-1.321 (-12.72)	-1.224 (-12.44)	-1.351 (-12.71)	-1.32 (-12.72)	-1.354 (-12.62)
<i>Land Use and Neighbourhood Characteristics</i>						
Land-use mix index	0.250 (0.76)	0.074 (0.23)	0.303 (0.94)	0.250 (0.76)	0.074 (0.23)	0.291 (0.94)
Dwelling density	0.00002 (1.24)	0.00001 (1.13)	0.000008 (0.71)	0.00002 (1.24)	0.00001 (1.13)	0.00001 (1.16)
Ratio of non- movers	0.004 (1.34)	0.003 (1.18)	0.002 (0.88)	0.004 (1.34)	0.003 (1.18)	0.002 (0.80)
Labour force participation rate	-0.007 (-2.19)	-0.006 (-1.77)	-0.005 (-1.83)	-0.007 (-2.19)	-0.005 (-1.77)	-0.005 (-1.64)

*HH refers to Household

Table 4-1 Parametric Estimation Results of Single-episode and Multiple-episode Hazard-based Duration Models for Residential Mobility (Continued)

Covariates	Single episode model (without frailty)			Multiple episode model (Gamma Shared frailty)		
	Log normal	Log logistic	Weibull	Log normal	Log logistic	Weibull
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
<i>Accessibility Measures</i>						
Distance from home to work place	0.004 (1.77)	0.004 (1.80)	0.004 (1.55)	0.005 (1.77)	0.005 (1.80)	0.004 (1.58)
Distance from home to CBD	0.166 (1.45)	0.193 (1.76)	0.068 (0.64)	0.166 (1.45)	0.193 (1.76)	0.124 (1.14)
Constant	8.229 (40.96)	8.189 (41.87)	8.450 (44.47)	8.229 (40.97)	8.19 (41.87)	8.393 (40.25)
<i>Model Information Criteria</i>						
<i>BIC</i>	1569.318	1555.393	1571.181	1569.318	1555.393	1548.632
<i>Adjusted Pseudo R-squared</i>	0.18985	0.20309	0.20316	0.18985	0.20309	0.21526

The model results reveal that socio-demographic characteristics, dwelling characteristics, neighbourhood characteristics, and land use and accessibility measures are significant factors in explaining residential mobility decisions. Among the socio-demographic characteristics, households with male head are found to show a shorter duration than their female counterpart. Households with older head demonstrate shorter durations. Interestingly, life-cycle event represented by first spell after household formation shows a shorter duration. This implies that households have shorter duration in their first spell than in subsequent spells, which is expected.

In the case of dwelling characteristics, households living in dwellings with a greater number of rooms remain for longer durations in their residences.

Arguably, this suggests that households with larger residences might stay for longer duration in owned properties. Individuals living in row houses exhibit a shorter duration. Perhaps, row houses cater to low income student groups, who might change residential location more frequently. As anticipated, renters are found to be more active than home owners. As renters have lower locational capital and lesser cost of moving than owners, they are likely to move more frequently.

Among the land use and neighbourhood characteristics, households living in neighbourhoods with higher land-use mix index exhibit longer duration, since neighbourhoods with greater land-use mix offer nearby services and facilities that encourage residents to stay for a longer duration. Households living in higher dwelling density neighbourhoods exhibit longer durations. This may be explained by the fact that neighbourhoods with higher dwelling density have better facilities for inhabitants, which encourage them to live there for longer periods. Households living in stable neighbourhoods with high ratios of non-movers stay for longer durations, as expected. Interestingly, households exhibit shorter duration in neighbourhoods with a high labour force participation rate.

In the case of the accessibility measures, commute distance is found to be a significant factor for the mobility decisions. Households residing farther from their workplace, possibly in suburban areas, demonstrate longer durations as they generally own the property in a stable neighbourhood. Distance from home to the CBD reveals a positive relationship. This implies that households living nearby to the CBD are likely to relocate more frequently than households residing in suburban areas. Thus, suburban inhabitants tend to be more stable at a particular location after purchasing their dwellings.

In addition, a number of variables are tested during the model estimation process. For instance, distance from home to the closest school, shopping

center, and transit stop, average household income in the neighbourhood, and percentage of immigrant in the neighbourhood, among others. These variables did not confirm *priori* hypotheses, as well as did not yield reasonable statistical significance. As a result, these variables are not retained in the final model.

4.3 Residential Location Choice

Following the decision to move in the mobility stage, the next step is the location choice. The choice of location itself has an underlying process orientation in relation to location search and determination of location. In this process, households first undertake a search process to identify potential location alternatives and finally move to a location. Therefore, residential location choice is modelled as a two-tier process of location search and location choice. The search model assumes that households search for locations on the basis of the residential stress. The residential stress acts as a push factor and the characteristics of the location that holds the potential to minimize the stress acts as a pull factor. The search model assumes that households' search process is constrained by their affordability. Hence, constraints regarding household income and property value are imposed in the search model. The proposed search model follows a fuzzy logic-based modelling method, which offers a mechanism to recognize the release of stress by minimizing discrepancies between the current and aspiration level. The modelling process of fuzzy logic accommodates the stress-driven theoretical framework by addressing the inter-dependencies between push and pull factors. The push and pull factors continuously evolve with the changing stress of households over their life-course.

In the final stage of location choice, households choose a location from the pool of alternatives generated in the search process. The model follows a random utility-based discrete choice modelling technique. To address the repeated

choices made by the same households during their housing career, the conventional logit modelling methods are extended to more advanced latent segmentation-based logit (LSL) modelling technique. The LSL model assumes that repeated choices made by the households along their life-course are correlated. The model captures unobserved heterogeneity by implicitly allocating the households into discrete latent segments using a flexible segment allocation model within the LSL framework. The inter-dependencies between location choice and life-cycle events are explored by testing a number of hypotheses. For example, how the plan to buy a car influences residential location choice? does the acquisition of a car in the existing vehicle fleet and the first time vehicle purchase have the same influence? how a change in job affects residential location choice? and does a change in job and addition of a job have the same influence? To explore the influence of timing of critical events, the effect of adjustment period required to adapt prior or after an event is tested as the lead and lagged effects. The major hypotheses regarding the effects of adjustment period includes, how the effects of an event in anticipation and an event on occurrence differs? and how the adjustment period varies for different events? In addition, the study examines whether the influence of life-cycle events varies by population segments or not? Such influence of life-history is tested in interaction with the attributes of the location, including parcel, accessibility, and neighbourhood characteristics. The unit of analysis for the location model is at the parcel-level.

4.3.1 Methodology

Figure 4-2 presents a conceptual framework of the fuzzy logic-based location search model developed in this study. The first step in the stress-based fuzzy logic model is fuzzification that generates constraint sets for the push factors and opportunity sets for the pull factors. The constraint sets represent input

sets and the opportunity sets represent output sets in the fuzzy logic modelling framework.

Four major reasons for relocation derived from the HMTS data are considered the push factors: to live in proximity to work/key activity locations (14.29%), to live in desirable neighbourhood/dwelling (46.75%), due to life-cycle events (21.56%), and other reasons (17.40%). Since households' choices of residential locations are strongly influenced by their affordability, such as income (Guo and Bhat 2007) and average value of the property (Rashidi et al. 2012), this study makes *a priori* assumption that each push factor is constrained by these two parameters. Therefore, in the fuzzification stage, constraint sets in relation to household income and average value of the property for each push factor are generated.

The pull factors are the characteristics of locations that attract households to consider a location to relocate. This study conceptualizes that an inter-dependent relationship exists between the push and pull factors. For example, households relocating to live closer to work locations are expected to search for locations that are closer to their work place on the basis of their income and average value of the property. Hence, the push factor "to live in proximity to work/key activity locations" is assumed to correspond to the pull factor "distance to work location". In the case of households relocating to live in a desirable neighbourhood/dwelling, households are assumed to search for locations that have a higher percentage of non-movers in the neighbourhood. Generally, desirable neighbourhoods refer to the neighbourhoods with reputed schools and open spaces (i.e. park areas) in close proximity, and lower crime rates, among others (Latkin and Curry 2003, Guo and Bhat 2002). Population residing in such quality neighbourhoods are expected to move less frequently. Hence, the push factor "to live in desirable neighbourhood/dwelling" is assumed to correspond to the pull factor "percentages of non-movers in the neighbourhood".

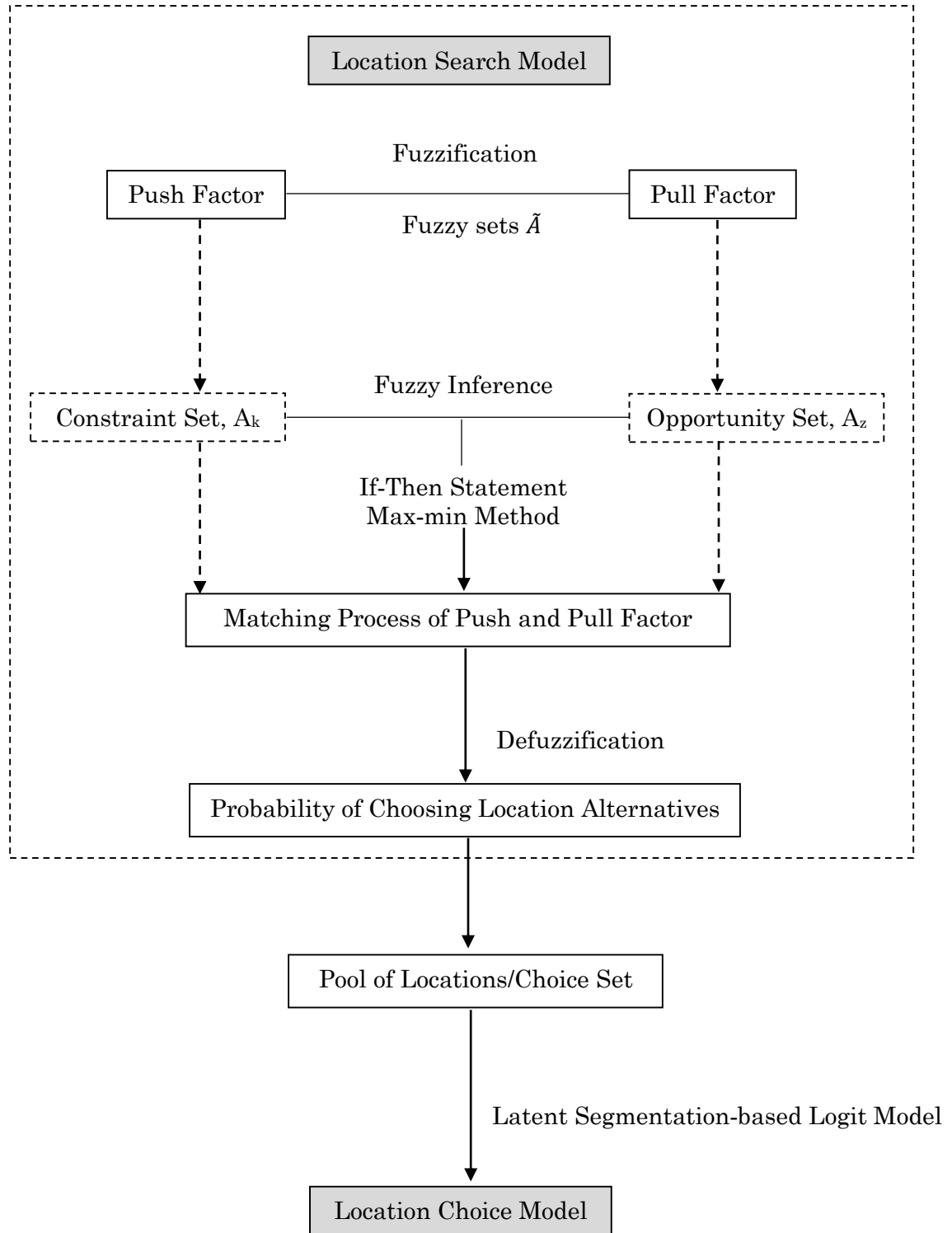


Figure 4-2 Conceptual Framework of the Fuzzy Logic-based Location Choice Model

Households relocating due to the life-cycle events are assumed to search for locations based on the distance from CBD. Life-cycle events such as household formation (due to marriage/living common-law) and change in household size (due to birth of a child/death of a member/move-in or -out of members) influence households' decisions to live in urban or suburban/rural neighbourhoods. For example, households with children prefer suburban areas, since they value accessing open space, cleaner air and water (Cummins and Jackson 2001). On the other hand, households without children prefer urban areas, as they prioritize commuting and convenient access to different amenities (Van Ommeren et al. 1999). In general, one of the most common proxies used to represent urban and suburban/rural neighbourhoods is distance to the CBD (Habib and Miller 2008). Therefore, the push factor "due to life-cycle events" is assumed to correspond to the pull factor "distance to CBD". In the case of households with "other reasons", behavioural information regarding their reason for relocation is not available. Hence, their location alternatives are generated using traditional method of random sampling. Since pull factors are the attractors of a location, the fuzzy sets generated for each of the three pull factors are termed as the opportunity sets in this study.

In the second stage, fuzzy inference, a matching process of the push and pull factors is performed on the basis of "If-Then" statements. The most commonly used methods to conduct fuzzy inferences are max-min and sugeno methods (Guney and Sarikaya 2009). Sugeno method is popular in optimization problems. In contrast, max-min is widely used for decision support modelling due to its intuitive and interpretable nature. Moreover, max-min method offers the flexibility of validating the scales of fuzzy membership functions using known fuzzy rules (Teodorovic 1999, Verkuilen 2005). Therefore, this study uses max-min method for fuzzy inferences. The third stage is defuzzification, where household-specific probability of choosing a parcel is determined by using the center of gravity method. The next step is to generate a pool of

alternative locations for each household. Below is a brief description of the fuzzy logic-based search model developed in this study.

Let's assume, P to be the universe of discourse and \tilde{A} is the fuzzy set of P , where $\mu_A(x)$ is the membership function of the fuzzy set \tilde{A} and $\mu_A \in [0,1]$. Fuzzy sets are represented by intervals and the crisp input is denoted as x . Fuzzy set \tilde{A} representing both constraint sets (input sets) and opportunity sets (output sets) are classified into fuzzy groups. The expression below represents the membership function for the constraint sets, which gives the association between the crisp input and the fuzzy groups in correspondence to the membership value:

$$\mu_{A_k}(x) = \begin{cases} low & x \leq x_1 \\ low/medium & x_1 \leq x \leq x_2 \\ medium/high & x_2 \leq x \leq x_3 \\ high & x \geq x_3 \end{cases} \quad (14)$$

Here, A_k denotes constraint sets, where K can take values of 1 and 2 representing household income and average property value respectively. Figure 4-3 illustrates the two constraint sets developed for each push factor. A triangular shape is adopted for the membership functions following Postorino and Versaci (2008). Both the constraint sets are classified into three fuzzy groups: low, medium, and high. For the constraint set regarding households' income, the threshold for low income is assumed to be \leq \$50,000 CAD⁴, and high income threshold is assumed to be \geq \$100,000 CAD⁵. For the constraint set regarding average property value, the lower price threshold is assumed to

⁴Low income threshold is determined on the basis of the low income cut-off for Canada, which is estimated to be \$47,878 CAD before tax (Statistics Canada 2015). Low income cut-off refers to an income threshold where a household is likely to spend a higher proportion of its income on food, shelter, and clothing than the average household, leaving less income available for other expenses.

⁵High income threshold is determined following the assumption in Prouse et al. (2014), which suggests that households with an income greater than 120% of the average household income (\$76,210 CAD) in Halifax are considered as high income households.

be \leq \$300,000 CAD, and higher price threshold is assumed to be \geq \$400,000 CAD⁶.

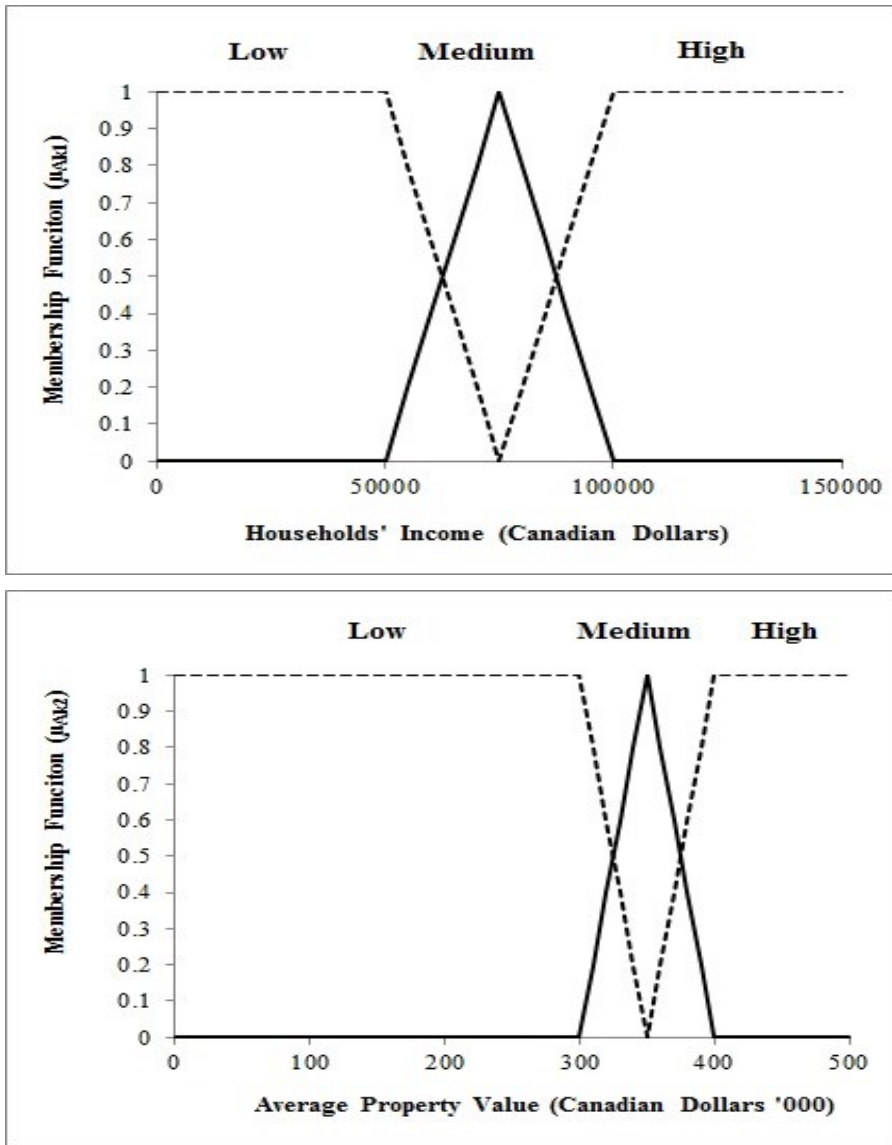


Figure 4-3 Fuzzy Membership Functions for the Constraint Sets Considered in the Location Search Model

⁶ The lower and higher property price threshold is assumed according to the Canada Mortgage and Housing Corporation (2015, 2016). The average and median price of house in Halifax was \$282,951 CAD and \$387,500 CAD respectively. The higher median value compared to the average value reveals a left skewed distribution of the prices, which means majority of the prices are above the average price. Hence, the lower threshold is assumed to be around the average price. On the other hand, the higher threshold is assumed to be around the median price.

Assuming A_z is the opportunity set and $\mu_{A_{kz}}(x)$ is the corresponding membership function. Here, z can take values of 1, 2, and 3; which represent distance to work location, percentages of non-movers in the neighbourhood, and distance to CBD, respectively. The value of z is conditional on the push factor. For the push factor “to live in proximity to work/key activity locations”, an example of the expression for the opportunity set “distance to work” can be given as:

$$\mu_{A_{k1}}(x) = \begin{cases} \textit{good} & x \leq 0.45 \\ \textit{good/poor} & 0.45 \leq x \leq 0.54 \\ \textit{poor} & x \geq 0.54 \end{cases} \quad (15)$$

Similar expressions are constructed for the opportunity sets “distance to CBD”, and “percentages of non-movers in the neighbourhood”. Figure 4-4 shows the opportunity sets of the pull factors. Similar to the constraint sets, a triangular shape is adopted. Each of the opportunity sets are classified into two fuzzy groups. Opportunity set, “distance to work location” is categorized into “good” (< 10km from the work location) and “poor” (\geq 10km from the work location) accessibility to work place⁷. “Percentages of non-movers in the neighbourhood” is classified into “not stable” (< 50% non-movers in the neighbourhood) and “stable” (\geq 50% non-movers in the neighbourhood) neighbourhoods⁸. “Distance to CBD” is categorized into “urban” (< 10km from the CBD) and “suburban and rural” (\geq 10km from the CBD) areas⁹.

⁷ The threshold for the distance between work place and home is assumed to be 10km, since the average commute distance in Halifax is 10.50km (Tang 2011).

⁸ The threshold for the percentage of non-movers in the neighbourhood is considered at the 50% point. This study assumes a neighbourhood to be stable if it has more non-movers than movers’ population. On the other hand, if a neighbourhood has more movers than non-movers, it is considered as a not stable neighbourhood.

⁹ In the context of Halifax, neighbourhoods within 10km (approximately) from the CBD that encompasses peninsula Halifax and Dartmouth, are collectively known as “regional center” in the Regional Planning Strategy (Halifax Regional Municipality, 2014). Hence, 10km distance from the CBD is considered as the threshold to define urban and suburban areas.

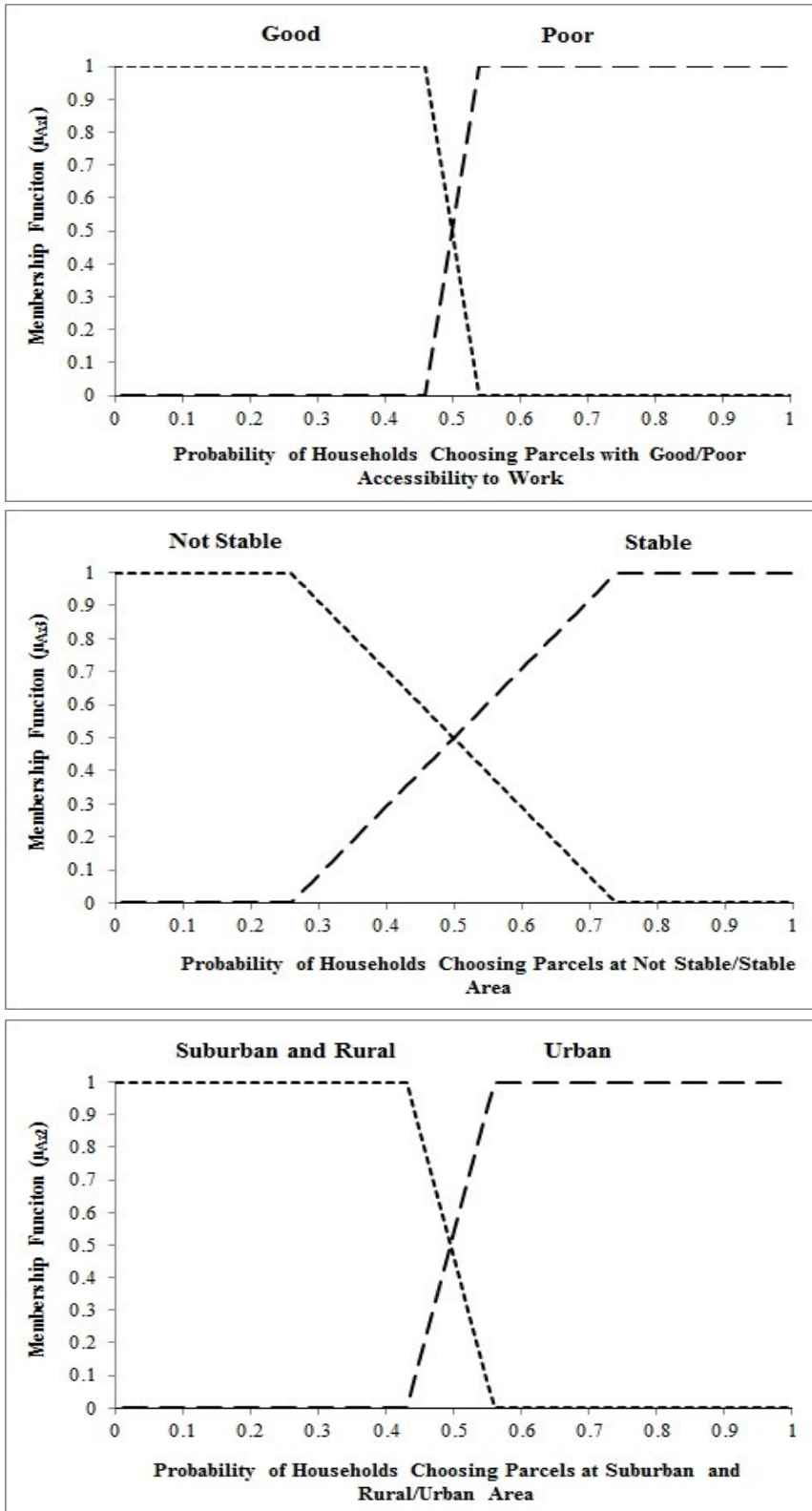


Figure 4-4 Fuzzy Membership Functions for the Opportunity Sets Considered in the Location Search Model

Following the fuzzification stage, the matching process between a push factor and the corresponding pull factor is conducted in the fuzzy inference stage. Particularly, fuzzy inferences handle the degree of match between the constraint set (If) and the opportunity set (Then) by using “If-Then” logic statements (Andrade et al. 2006). The logic statements are derived from observing the general trend of the data. A total of twelve logic statements are developed for the “push-pull” combination of “to live in proximity to work/key activity locations - distance to work location”. A typical format of the logic statements is as follows:

IF household’s income is [HIGH] and average value of the property is [HIGH],
THEN the household chooses residential location with [GOOD] accessibility to work place

A total of twelve and ten logic statements are developed for the “push-pull” combinations of “to live in desirable neighbourhood/dwelling - percentages of non-movers in the neighbourhood” and “due to life-cycle events - distance to CBD” respectively. The logic statements developed for the “push-pull” combinations are presented in Table 4-2.

In the fuzzy inference stage, the constraint set determines the boundaries of the search process which results in the probability of the selection of a parcel in the pool of alternative locations. As indicated earlier, the max-min method is used to conduct the inferences, which can be expressed as the following equation,

$$\mu_A(x) = \max\{\min[\mu_1(x), \mu_2(x), \dots \dots \mu_n(x)]\} \quad (16)$$

Table 4-2 “IF-Then” Logic Statements of the Fuzzy Logic Model for Location Search

IF		THEN	
<i>“Push-Pull” Combination of “To Live in Proximity to Work/Key Activity Locations - Distance to Work Location”</i>			
Rule No.	Household Income	Avg. Value of Property	Accessibility to Work Place
1	Low	Low	Good
2	Low	Medium	Good
3	Medium	High	Good
4	Medium	Medium	Good
5	High	Low	Good
6	High	Medium	Good
7	High	High	Good
8	Low	Low	Poor
9	Medium	Low	Poor
10	Medium	Medium	Poor
11	High	Low	Poor
12	High	Medium	Poor
<i>“Push-Pull” Combination of “To Live in Desirable Neighbourhood/Dwelling - Percentages of Non-movers in the Neighbourhood”</i>			
Rule No.	Household Income	Avg. Value of Property	Neighbourhood Type
1	Low	Low	Not Stable
2	Low	Medium	Not Stable
3	Medium	Low	Not Stable
4	Medium	Medium	Not Stable
5	High	Low	Not Stable
6	High	Medium	Not Stable
7	Low	Medium	Stable
8	Medium	Medium	Stable
9	Medium	High	Stable
10	High	Low	Stable
11	High	Medium	Stable
12	High	High	Stable

Table 4-2 “IF-Then” Logic Statements of the Fuzzy Logic Model for Location Search (Continued)

IF		THEN	
<i>“Push-Pull” Combination of “Due to Life-cycle Events - Distance to CBD”</i>			
Rule No.	Household Income	Avg. Value of Property	Neighbourhood Type
1	Low	Medium	Urban
2	Medium	Medium	Urban
3	Medium	High	Urban
4	High	Medium	Urban
5	High	High	Urban
6	Low	Low	Suburban
7	Medium	Low	Suburban
8	Medium	Medium	Suburban
9	High	Low	Suburban
10	High	Medium	Suburban

For the defuzzification stage, the center of gravity method is adopted to determine a crisp output (Ceder et al. 2013). The center of gravity method is expressed as,

$$y^* = \frac{\int \mu(y)y dy}{\int \mu(y)dy} \quad (17)$$

Here, y^* is the crisp output determined using the center of gravity method, which represents household-specific probability of choosing a parcel. For example, in the case of a household with push factor “to live in proximity to work/key activity locations”, if the crisp output derived from the opportunity set is $y^* < 0.50$, which falls under the area of parcels with good accessibility to the work place (parcels $< 10\text{km}$ from the work location), such household is assumed to consider parcels within 10km from the work location compared to those parcels that are $\geq 10\text{km}$ from the work location. Therefore, the potential location alternatives for that household will include those parcels, which are

within 10km from the work location. For $y^* \geq 0.50$, the potential alternatives include those parcels which are ≥ 10 km from the work location. Similarly, potential location alternatives for the households with the other two push-pull combinations are developed. Note that the number of potential alternative parcels varies for each household, which ranges from approximately 1,500 to 84,000. To reduce the computational complexities of the location choice model in the second tier, a feasible pool of parcel alternatives for each household is developed by randomly selecting a sub-set from the large number of household-specific potential parcels. The pool of alternatives for each household includes a total of ten parcels including the chosen parcel.

In the next step, a location choice model is developed utilizing the pool of alternatives generated in the search model. The location choice model follows a latent segmentation-based logit (LSL) modelling technique. The LSL model captures unobserved heterogeneity by allocating households into discrete latent segments using a segment allocation component. The segment allocation component can be fixed across the segments if the segments are not defined using observed attributes (Fatmi and Habib 2014). This study formulates a flexible segment allocation model within the LSL framework and defines the segments utilizing observed socio-demographic and neighbourhood characteristics (Sobhani et al. 2013, Fatmi et al. 2014). Assuming that household i is allocated to segment s , the segment allocation model can be expressed in the following multinomial logit form:

$$\phi_{is} = \frac{e^{\omega_s + \theta_s Z_i}}{\sum_{s=1}^S e^{\omega_s + \theta_s Z_i}} \quad (18)$$

Here, Z is the observed attributes of the households, ω is the segment membership constant, and θ is the segment membership vector parameter. For the identification purpose of the model, one segment is assumed to be the reference segment, considering ω and θ to be fixed for that segment.

Since, this study utilizes the restrospective HMTS data, correlated sequence of choice exists due to the repeated choices of locations made by the same households during their housing career. To accommodate such correlated sequence of choices, the repeated choice probability is estimated by deriving the joint probability of the choice sequence. Assuming that household i allocated to segment s chooses alternative location j at t choice situation, the joint choice probability can be expressed as:

$$P_{ij}(i \in s) = \prod_{t=1}^T \frac{e^{X_{ic_{it}}t\beta_s}}{\sum_{j=1}^J e^{X_{ijt}\beta_s}} \quad (19)$$

Here, X is the observed vector parameter, β is the segment specific vector parameter, and c is the location chosen by household i at t choice situation from a sequence of location choices $c = c_{i1}, c_{i2}, \dots \dots c_{iT}$. The likelihood of household i choosing an alternative location j can be written as:

$$P_i(j) = \prod_{s=1}^S \phi_{is} P_{ij}(i \in s) \quad (20)$$

The model estimates parameters by maximizing the likelihood function using an expectation-maximization (EM) algorithm. The analytic second derivative matrix of the likelihood function is inverted to calculate the asymptotic covariance matrix for the full set of parameter estimators. The likelihood function can be written as:

$$LL_{max} = \sum_{n=1}^N \ln P_i(j)^{\gamma_{ij}} \quad (21)$$

Here, N is the total number of observations, and γ is a dummy variable. γ takes a value of 1 while household i chooses location j and 0 otherwise. The model estimates segment specific parameter vector β for S segments, and segment membership parameter vector ω and θ for $S - 1$ segments. The model

is evaluated on the basis of the model fit measures of adjusted pseudo r-squared and BIC.

4.3.2 Goodness-of-fit Measures

First, the appropriate number of segments of the LSL model is determined on the basis of the BIC measures, due to the hierarchical nature of the model (Table 4-3). The results suggest that the BIC measure is minimum for the model with two segments. Therefore, the final model is assumed to have two latent segments.

Table 4-3 Number of Segment Determination of the Residential Location Choice Model

Goodness-of-fit Measures	Latent Segmentation-based Logit Model		
	<i>No. of Segments</i>	<i>No. of Segments</i>	<i>No. of Segments</i>
	<i>1</i>	<i>2</i>	<i>3</i>
<i>Log-likelihood (at convergence)</i>	-797.09	-682.57	-651.80
<i>Log-likelihood (at constant)</i>	-886.50	-886.50	-886.50
<i>No. of Parameters</i>	21	43	65
<i>No. of total Observations</i>	385	385	385
<i>BIC</i>	1719.20	1621.13	1690.56

For comparison purposes, in addition to the proposed fuzzy logic-based location choice model, another location choice model is developed using choice set generated from the traditional random sampling method. The models are compared on the basis of the predictive adjusted likelihood ratio index and average probability of correct prediction, which are used by Zolfaghari et al. (2012) to evaluate several choice set generation techniques. To compute the goodness-of-fit measures, 75% of the data are used to estimate the models and the remaining 25% of the data are used for validation purposes. The results suggest that the proposed fuzzy logic-based model improves model fit with a higher predictive adjusted likelihood ratio index and average probability of correct prediction values than that of the traditional model (Table 4-4).

Moreover, the proposed model exhibits a higher adjusted pseudo r-squared value (0.23) than that of the traditional model (0.19). Therefore, it can be concluded that the proposed fuzzy logic-based location choice model outperforms the traditional random sampling-based model in terms of goodness-of-fit measures. This study considers the fuzzy logic-based model as the final model for further discussion on the parameter estimation results. A description of the variables retained in the final model along with their summary statistics is presented in Table 4-5.

Table 4-4 Goodness-of-fit Measures of the Proposed and Traditional Residential Location Choice Models

Goodness-of-fit Measures	Proposed Fuzzy Logic-based Location Choice Model	Traditional Random Sampling-based Location Choice Model
<i>Predicted Log-likelihood (at convergence)*</i>	-464.47	-452.46
<i>Predicted Log-likelihood (at constant)*</i>	-644.72	-591.76
<i>Predictive Adjusted Likelihood Ratio Index**</i>	0.27	0.23
<i>Average Probability of Correct Prediction***</i>	0.29	0.24

*Predicted Log-likelihood is the log-likelihood value of the validation sample, which is computed by maximizing the likelihood function during the estimation of the validation sample

**Predictive Adjusted Likelihood Ratio Index is computed using the predicted log-likelihood values (at convergence and constant)

***Average Probability of Correct Prediction = $(\sum_i \sum_j y_{ij} p_{ij})/N$, where y_{ij} indicates that whether household i actually resides in parcel j , p_{ij} indicates the predictive probability of household i resides in parcel j , and N is the total number of observation in the validation sample

Table 4-5 Summary Statistics of Explanatory Variables used in the Estimation of Residential Location Choice Model

Variables	Description	Mean/ Proportion	Std. Dev.
<i>Socio-demographic Characteristics</i>			
Age	Age of the head of the household	31.77	23.81
Income above 100K (Dummy Variable)	Household income above \$100,000 CAD	48.05%	-
Children (Dummy Variable)	Household with children	53.24%	-
No Vehicle Ownership (Dummy Variable)	Household not owning vehicle in the life- time	3.5%	-
<i>Life-cycle Events</i>			
Birth of a Child_1Year Lag (Dummy Variable)	Birth of a child one year after residential relocation	3.6%	-
New Job_Same Year (Dummy Variable)	Addition of a job occurring in the same year of residential relocation	24.67%	-
Job Change_1 Year Lead (Dummy Variable)	Change of a job occurring one year prior to residential relocation	13.24%	-
First Vehicle_2 Year Lead (Dummy Variable)	Purchase of the first vehicle in the life- time of the household occurring two years prior to residential relocation	1%	-
Vehicle Acquisition_1 Year Lead (Dummy Variable)	Addition of a vehicle to the exiting vehicle fleet of the household occurring one year prior to residential relocation	7.01%	-
Vehicle Acquisition_2 Year Lead (Dummy Variable)	Addition of a vehicle to the exiting vehicle fleet of the household occurring two years prior to residential relocation	5.19%	-

Table 4-5 Summary Statistics of Explanatory Variables used in the Estimation of Residential Location Choice Model (Continued)

Variables	Description	Mean/ Proportion	Std. Dev.
<i>Accessibility Characteristics</i>			
Dist to Work	Distance from home to the work place in km	25.45	28.29
Dist to nearest School	Distance from home to the nearest school in km	2.98	5.45
Dist to nearest Transit Stop	Distance from home to the nearest transit stop in km	11.17	24.75
Dist to nearest Business Center	Distance from home to the nearest regional business center in km	11.56	10.33
Dist to CBD	Distance from home to the Central Business District (CBD) in km	24.40	27.67
Dist to nearest Health Service	Distance from home to the nearest health service in km	4.49	7.62
Dist to nearest Park Area	Distance from home to the nearest park area in km	2.06	4.50
<i>Parcel and Neighbourhood Characteristics</i>			
Lot Size	Parcel lot size in acre	0.64	5.02
Population Density	Population per acre area in the home dissemination area	1530	2258
% of Owned Dwelling	Percentage of owned dwelling in the home dissemination area	80.01%	22.74%
Avg. Property Value	Average property value (CAD X 1000) in the home dissemination area	266.92	102.91
% of HH's Share of Shelter Cost to Income less than 30%	Percentage of households spending less than 30% of their household income on shelter cost in the home dissemination area	80.90%	12.37%
% of Non-movers	Percentage of non-movers in the last five years in the home dissemination area	66.74%	16.82%

4.3.3 Discussion of Model Results

4.3.3.1 Characterization of the Latent Segment Allocation Component

The results of the latent segment allocation component are reported in Table 4-6. The model is estimated considering segment two as the reference segment. The model results suggest a negative sign for the variable representing household income above \$100,000 CAD for segment one, which indicates a lower likelihood of such households to be allocated to segment one. The positive sign of the variable representing age of the head of the household reveals that older head households are more likely to be allocated to segment one. Among the neighbourhood characteristics, the negative sign of the variables representing percentage of owned dwellings in the neighbourhood, and distance from home to the CBD in segment one indicate that urban dwellers have a higher likelihood to be included in segment one. In summary, segment one has a higher propensity to include urban dwellers with lower household income and older head. Presumably, segment one can be identified as a segment for “urbanite households”. On the other hand, segment two can be identified as a segment for “suburbanite households”.

Table 4-6 Results of the Latent Segment Allocation Component of the Residential Location Choice Model

	Latent Segment 1 <i>co-efficient (t-stat)</i>	Latent Segment 2 <i>co-efficient (t-stat)</i>
Segment Membership Probabilities	0.51	0.49
Constant	2.2529 (3.22)	-
<i>Socio-demographic Characteristics</i>		
Income above 100K (Dummy Variable)	-0.8002 (-2.219)	-
Age	0.0124 (1.63)	-
<i>Neighbourhood Characteristics</i>		
% of Owned Dwelling	-0.0259 (-3.16)	-
Dist to CBD	-0.0181 (-1.60)	-

Table 4-7 Parameter Estimation Results of the Fuzzy Logic-based LSL Model for Residential Location Choice

Variables	Latent Segmentation-based Logit Model	
	Latent Segment 1	Latent Segment 2
	<i>co-efficient (t-stat)</i>	<i>co-efficient (t-stat)</i>
<i>Parcel Characteristics and Interaction with Life-cycle Events</i>		
Lot Size	-0.1134 (-1.03)	0.1605 (2.13)
Lot Size × Birth of a Child_1Year Lag	1.2932 (1.00)	1.4578 (1.34)
Lot Size × Job Change_1 Year Lead	-4.6300 (-1.00)	2.3653 (2.49)
Lot Size × New Job_Same Year	0.0979 (0.3)	0.3033 (2.10)
<i>Accessibility Characteristics and Interaction with Life-cycle Events and Socio-demographics</i>		
Dist to Work	-0.0462 (-3.23)	-0.0462 (-3.23)
Dist to Work × Vehicle Acquisition_1 Year Lead	0.0049 (0.20)	0.0263 (0.44)
Dist to Work × First Vehicle_2 Year Lead	0.0953 (1.35)	0.0953 (1.35)
Dist to Work × Children	0.0331 (1.93)	-0.4197 (-8.21)
Dist to nearest School	0.4117 (2.72)	-0.291 (-0.23)
Dist to nearest School × Children	-0.4296 (-2.28)	0.3026 (1.86)
Dist to nearest Transit Stop	-0.0081 (-0.60)	-0.0081 (-0.60)
Dist to nearest Transit Stop × No Car Ownership	-3.8791 (-1.60)	-3.8791 (-1.60)
Dist to nearest Business Center	0.0230 (1.00)	0.0403 (2.08)
Dist to nearest Business Center × Vehicle Acquisition_2 Year Lead	0.0215 (0.23)	0.1221 (1.00)
Dist to nearest Health Service	-0.0485 (-1.00)	-0.4231 (-4.83)
Dist to nearest Park Area	-0.3763 (-2.08)	0.2815 (1.78)
Dist to nearest Park Area × Children	0.3331 (1.40)	-0.6954 (-2.20)
<i>Neighbourhood Characteristics</i>		
Population Density	0.0001 (1.94)	0.0001 (4.77)
Avg. Property Value	0.0022 (2.18)	0.0018 (2.82)
% of HH's Share of Shelter Cost to Income less than 30%	0.0130 (1.32)	0.0219 (3.41)
% of Non-movers	0.1065 (10.41)	-0.0266 (-4.89)

4.3.3.2 Discussion of the Latent Segmentation-based Logit (LSL) Model Results

Parameter estimation results of the fuzzy logic-based LSL model are reported in Table 4-7. A brief discussion of the model results are presented below.

4.3.3.2.1 Parcel Characteristics and Interaction with Life-cycle Events

The model results suggest that location choice is significantly influenced by parcel characteristics. For instance, the variable representing lot size reveals a positive relationship in segment two. Segment two is identified to include suburbanite households who are higher income suburban dwellers. Essentially, suburbanite households prefer larger dwellings (i.e. parcel size), potentially in the suburban areas. In contrast, urbanite households in segment one show a negative relationship. Interestingly, while a life-cycle event represented by birth of a child is interacted with the lot size, a positive relationship is found for urbanite and suburbanite households in both segments. An increase in the household size due to the birth of a child might trigger the requirement of a larger dwelling. Therefore, households prefer larger-sized lots, which is consistent with the findings of Strom (2010). The model confirms a one-year lead effect of this life-cycle event. Life-cycle event represented by job change shows a heterogeneous behaviour as evident in parametric values in the two segments. Households in segment two exhibit a positive relationship. Suburbanite households in segment two belong to the high-income group and arguably a change in job might be associated with further increase in income. Thus, such households reveal preference for larger dwellings following a job change. In the case of addition of a job, urbanite and suburbanite households reveal a higher likelihood for larger-sized lots. Addition of a job refers to increased affordability, which is expected to positively influence the choice of larger dwellings. The model confirms a longer adjustment period for a job change (one-year lagged effect) than that of the

addition of a new job (same year effect). The increased affordability associated with the addition of a job might influence households to relocate to larger-sized lots within a much shorter time from the occurrence of the event.

4.3.3.2.2 Accessibility Characteristics and Interaction with Life-cycle Events and Socio-demographics

In general, households are found to be more likely to reside closer to their work place, which reflect their preferences for shorter commute distance. To examine how vehicle transaction decisions influence location choice, the following two variables are interacted with commute distance: vehicle acquisition, and purchase of the first vehicle. Urbanite and suburbanite households reveal a positive relationship for both the variables. Interestingly, a longer adjustment period is observed for the first time vehicle purchase (two-year lagged effect) compared to a vehicle acquisition (one-year lagged effect). First time vehicle purchase is a key event in the life-time of the household. Due to the limitation in time and money budgets, a longer adjustment period is expected between two large investments of purchasing a house and first car. When the presence of children is interacted with commute distance, a variation in relationship is found in two segments. Suburbanite households (i.e. segment two) who have children show a higher likelihood to reside closer to work place, which might offer them the flexibility of trip chaining to day care centers or schools on the way to and from work. On the other hand, urbanite households with low income (i.e. segment one) show a higher probability to compromise with the longer commute. Locations closer to work place might be expensive and they might be trading off longer commute with the opportunity to reside in proximity to other potential amenities for their children. One such amenity might be the location of school, as argued by Kim et al. (2005). Furthermore, when the presence of children in the household is interacted with distance to

the closest school, urbanite households show a higher likelihood to reside closer to school.

Distance to the closest transit stop reveals a negative relationship. Interestingly, when this variable is interacted with a dummy variable representing households not owning a vehicle in their life-time, the negative effect substantially increases. This reflects the fact that households prefer to live closer to transit stop; however, the propensity to reside closer to transit stop increases for households without vehicle ownership. Distance to the nearest regional business center shows a positive relationship. Since, households prefer locations farther away from regional business centers, which is characterized as big-box retails in the case of Halifax. A similar positive relationship is found while distance to the nearest regional business center is interacted with vehicle acquisition. This result reflects that addition of a vehicle might offer added freedom and convenience for longer trips. Households exhibit a higher probability to choose locations closer to the health care services, since locations closer to health services offer easier access to daily and periodic medical services. Distance to the closest park area exhibits heterogeneous relationship in the two segments. Urbanite households are found to be extremely sensitive to distance to the nearest park area and prefer to live closer to park area. Locations closer to park areas are preferable due to the convenient access to open space, which can serve as a regular recreational place for the household members. In contrast, households in segment two reveal a positive relationship. Interestingly, while distance to the closest park area is interacted with presence of children in the household, suburbanite households exhibit a strong preference for locations closer to park areas. In summary, the model results reflect that the effects of accessibility characteristics in choosing home locations are substantially dictated by life-cycle events.

4.3.3.2.3 Neighbourhood Characteristics

Regarding the neighbourhood characteristics, households have a higher probability to live in neighbourhoods with higher population density. Average property value in the neighbourhood shows a positive relationship, since higher average property value indicates high income neighbourhoods with better housing and access to diversified amenities (Guo and Bhat 2002), which are expected to be desirable. The variable representing percentage of households with a shelter cost to income share of less than 30% reflects high income neighbourhoods with more disposable income after housing related payments. This variable exhibits a strong positive relationship, which extends the fact that locations with more disposable income are more attractive. Interestingly, stable neighbourhoods represented by percentage of non-movers show significant variations between the two segments. Urbanite households prefer stable neighbourhoods and suburbanite households show affinity to evolving neighbourhoods in Halifax. This result is a deviation from an earlier Toronto study (Habib and Miller 2009), in which households generally preferred stable neighbourhoods. This may reflect a unique continual growth of new subdivisions in Halifax, which has become an interesting feature of the city as documented in Brewer and Grant (2015).

In addition to the above discussed variables, the model tests a number of variables such as, death of a member, member move out, loss of a job, distance to the nearest shopping center, average household income, employment rate, percentage of immigrant, and land-use mix index. These variables could not be included in the final model due to discrepancies in the hypothesis confirmation along with reasonable statistical significance. The model also could not confirm statistically significant effects of how neighbourhood characteristics varies by life-cycle events. One of the possible attributing factors might be the unavailability of historical records for changes in urban form.

4.4 Modelling Mode Transitions

This research offers insights towards how a change in one life-domain is associated with a change in another domain. Particularly, this study investigates how residential relocation decisions influence individuals to change their commute mode. The study conceptualizes that individuals reassess their commute mode when they relocate to a new location. Following reappraisal, they either continue using the same mode, which is considered mode loyalty, or make a transition to a new mode, which is considered mode transition. In this study, the mode transition scenario is developed by comparing the choice of commute mode between two distinct temporal points of consecutive residential locations, which offers the opportunity to examine how changes in socio-demographic and accessibility characteristics between these two temporal points affect the decision. These transitional variables are generated by comparing household characteristics between two subsequent residential locations. In addition, the effects of life-cycle events are tested. To account for the correlated sequence of repeated choices of the same individuals over their life-time, a random-parameters logit (RPL) model is developed. The model also captures unobserved heterogeneity.

4.4.1 Modelling Methods

This study utilizes the retrospective HMTS data to generate the mode transition scenarios. A sample of 288 households are utilized from the HMTS data, who have reported at least two consecutive housing records. The dataset yields a total sample of 453 mode loyalty and transition instances. The mode loyalty and transitions are determined by comparing the choice of commute

This section is largely derived from the following journal paper:

- Fatmi, M.R., and Habib, M.A. (2016). Life-Oriented Approach of Modelling of Commute Mode Loyalty and Transition Behaviour. *Transportation Research Record: Journal of Transportation Research Board*, 2565(1), 37-47.

mode in two consecutive residential locations. The results reveal that 67.10% respondents are loyal to the commute mode used at their previous location and continue with the same one at the subsequent location. On the other hand, 32.90% of the respondents make a transition in commute mode when moving to a new location. To understand mode-specific transition and loyalty, this study considers the following nine choice scenarios as the dependent variable:

1. Loyal to Car: respondent's primary commute mode is car in their prior and subsequent location
2. Loyal to Transit: respondent's primary commute mode is transit in their prior and subsequent location
3. Loyal to Active Transportation: respondent's primary commute mode is active transportation (walk/bike) in their prior and subsequent location
4. Transition from Car to Transit: respondent makes a transition in primary commute mode from car in prior location to transit in subsequent location
5. Transition from Car to Active Transportation: respondent makes a transition in primary commute mode from car in prior location to active transportation in subsequent location
6. Transition from Transit to Car: respondent makes a transition in primary commute mode from transit in prior location to car in subsequent location
7. Transition from Transit to Active Transportation: respondent makes a transition in primary commute mode from transit in prior location to active transportation in subsequent location
8. Transition from Active Transportation to Car: respondent makes a transition in primary commute mode from active transportation in prior location to car in subsequent location
9. Transition from Active Transportation to Transit: respondent makes a transition in primary commute mode from active transportation in prior location to transit in subsequent location

Table 4-8 Distribution Matrix of the Mode Loyalty and Mode Transition Associated with Residential Relocation

		To		
		<i>Mode</i>	<i>Car</i>	<i>Transit</i>
From	<i>Car</i>	34%	5.3%	8.39%
	<i>Transit</i>	3.09%	8.17%	4.86%
	<i>Active Transportation</i>	6.4%	4.86%	24.72%

The statistical distribution of the choice scenarios reveals that the highest percentage (34%) of individuals are loyal to car and prefer to continue with car as their primary commute mode in two consecutive locations (Table 4-8). 25% of the individuals are loyal to active transportation (walk/bike) and only 8% are transit loyal. Among the mode transitions, the highest percentage of transition (8%) occurs from car to active transportation, and the lowest percentage of transition (3%) occurs from transit to car.

In the case of developing the random-parameters (RPL) logit model, let's assume that the utility derived by individual i from choosing commute mode transition alternative c at t choice situation can be expressed as:

$$U_{ict} = \beta_i X_{ict} + \varepsilon_{ict} \tag{22}$$

Here, X is the observed attribute, β is the coefficient of the parameter to be estimated, and ε is the random error term, which is independent over individuals, alternatives, and choice situation with independently and identically distributed (iid) extreme value. Since this study accommodates repeated choices from the same individual during their life-time, assuming $j(i,t)$ is the alternative chosen by individual i at t choice situation from a sequence of alternative choices $j_{i1}, j_{i2}, \dots, \dots, j_{iT}$. Now, the conditional probability of making a choice from this sequence of choices can be expressed as:

$$P_i(\beta_i) = \prod_{t=1}^T \frac{e^{\beta_i X_{ij(i,t)t}}}{\sum_m e^{\beta_i X_{ict}}} \quad (23)$$

Here, m is the total number of alternatives. This choice probability is conditional on β . Interestingly, the analyst observes X and does not observe β . Therefore, the choice probability cannot be conditional on β , and the unconditional choice probability is derived by integrating conditional probability over all possible values of β . The unconditional choice probability can be written as following:

$$P_i = \int \prod_{t=1}^T \frac{e^{\beta_i X_{ij(i,t)t}}}{\sum_m e^{\beta_i X_{ict}}} f(\beta_i|\mu, \vartheta) d\beta_i \quad (24)$$

Here, β is distributed over each individual with a density function of $f(\beta_i|\mu, \vartheta)$, where, μ and ϑ are the mean and standard deviation of the function. This study assumes a normal distribution of the density function, following a similar assumption by Revelt and Train (1998). β is an individual specific parameter, representing individual's taste and other associated unobserved factors. Individual's taste and unobserved factors might vary among the sample population, which could be captured by estimating the parameters (μ, ϑ) of the density function. One approach for estimating the choice probability is by maximizing the likelihood function: $LL = \sum_{i=1}^I \ln P_i$. This likelihood function cannot be maximized analytically, since it is a multivariate integral. Therefore, the probabilities are estimated through simulation. In this process, a value of β is drawn from the density function $f(\beta_i|\mu, \vartheta)$ and considered as the first draw. Using this draw, the corresponding choice probability is estimated. Similarly, several draws of β are taken and corresponding choice probabilities are estimated. Finally, the average of the choice probabilities from several draws is estimated in order to approximate the choice probability, which can be expressed as:

$$\bar{P}_i = \frac{1}{R} \sum_{r=1}^R P_i(\beta_i^r) \quad (25)$$

Here, \bar{P}_i is the average of the simulated choice probability, which is an unbiased estimator of the unconditional choice probability P_i , R is the total number of draws, and β_i^r is the r^{th} draw from $f(\beta_i|\mu, \vartheta)$. The variance of \bar{P}_i decreases as R increases. \bar{P}_i is smooth (twice differentiable) and facilitates the numerical search for the maximum likelihood function. The simulated log likelihood function is developed using the average of the simulated probabilities and can be expressed as:

$$SL = \sum_{i=1}^I \ln \bar{P}_i = \sum_{i=1}^I \ln \frac{1}{R} \sum_{r=1}^R P_i(\beta_i^r) \quad (26)$$

Here, I is the total number of observations. This simulated log likelihood is maximized for 500 Halton draws using a Monte-Carlo simulation approach. Monte-Carlo simulation approach generates a faster convergence rate compared to other methods (Train 2003.). Moreover, the use of Halton draws improves the performance of Monte-Carlo simulation compared to random draws (Bhat 2003). The model estimates coefficient parameter β , and μ and ϑ of the density function. For comparison purposes, a conventional multinomial logit model (MNL) is developed. The models are compared on the basis of goodness-of-fit measures of adjusted pseudo r-squared, and likelihood ratio test.

4.4.2 Model Results

This study examines the effects of life-cycle events. One of the key features of the study is to test the effects of life-oriented socio-demographic and accessibility related transitional variables. The dynamic nature of the mode transition phenomenon offers the opportunity to derive life-oriented socio-demographic transitional variables by comparing socio-demographic

information between two subsequent residential locations. Such transitional variables refer to the change in individuals' socio-demographic and dwelling characteristics in the current residential location compared to the previous location. Socio-demographic transitional variables include increase and decrease in household income, car ownership, and number of bedroom, as well as transition from rented to owned dwelling and vice versa. Similarly, transitional variables for accessibility measures to different activity points and transportation services are estimated; which include moving closer to or farther away from work location, transit station, or central business district (CBD), as well as other accessibility-related transitional variables. In addition, socio-demographic, accessibility, land use, and neighbourhood characteristics are considered during the model estimation process. Table 4-9 presents the summary statistics of the variables retained in the final model.

For comparison purposes, a multinomial logit (MNL) model is developed in addition to the RPL model. The goodness-of-fit measures suggest that the RPL model performs better with a higher adjusted pseudo r-squared value compared to the MNL model. In addition, the RPL model outperforms the MNL model with a chi-squared statistic of 388.49 (critical value of chi-square 106.32 with 75 degrees of freedom) at the 1% significance level. Therefore, the RPL model is considered as the final model. The model estimation results of the RPL model is presented in Table 4-10.

Table 4-9 Summary Statistics of Explanatory Variables used in the Estimation of Commute Mode Transition Model

Variables	Description	Mean/ Proportion
<i>Socio-demographic Characteristics</i>		
Gender (Male) (Dummy Variable)	Gender of the individual is male	38.63%
Age	Age of the individual	41.45 years
Income below 50K (Dummy Variable)	Household income below \$50,000	30.02%
Income above 75K (Dummy Variable)	Household income above \$75,000	49.44%
Income above 150K (Dummy Variable)	Household income above \$150,000	13.02%
Presence of Children (Dummy Variable)	Household with children	34.88%
No Children (Dummy Variable)	Household without children	66.12%
Owned Dwelling (Dummy Variable)	Household residing in owned dwelling	56.95%
Education up to College (Dummy Variable)	Individual's educational qualification is up to community college	15.67%
Single-Worker (Dummy Variable)	Single-worker household	50.55%
Full-Time Dual-Worker (Dummy Variable)	Two-worker household both have full time employment	30.68%
<i>Life-oriented Socio-demographic Transition</i>		
Increase in Household Income (Dummy Variable)	Increase in household income	47.02%
Decrease in Household Income (Dummy Variable)	Decrease in household income	13.69%
Decrease in Household Car Ownership (Dummy Variable)	Decrease in household car ownership	22.74%
No Car Ownership (Dummy Variable)	Household does not own car in previous and current residential location	11.26%

Table 4-9 Summary Statistics of Explanatory Variables used in the Estimation of Commute Mode Transition Model (Continued)

Variables	Description	Mean/ Proportion
<i>Life-oriented Socio-demographic Transition (Continued)</i>		
Increase in Number of Bedrooms (Dummy Variable)	Increase in number of bedrooms	39.96%
Decrease in Number of Rooms (Dummy Variable)	Decrease in number of rooms	30.02%
Moved from Rented to Owned (Dummy Variable)	Individual relocating from rented to owned dwelling	26.27%
Moved from Owned to Rented (Dummy Variable)	Individual relocating from owned to rented dwelling	10.15%
<i>Life-cycle Events</i>		
Birth of a Child_1 Year Lead (Dummy Variable)	Birth of a child 1 year prior to commute mode transition	11.04%
New Household Formation (Dummy Variable)	Reason for residential relocation is the formation of new household	10.38%
Addition of a Job_1 Year Lead (Dummy Variable)	Addition of a job 1 year prior to commute mode transition	16.56%
Addition of a Job_2 Year Lead (Dummy Variable)	Addition of a job 2 year prior to commute mode transition	12.58%
Lost Job_1 Year Lead (Dummy Variable)	Lost job 1 year prior to commute mode transition	9.71%
Lost Job_2 Year Lead (Dummy Variable)	Lost job 2 year prior to commute mode transition	6.62%
Addition of Car_Same Year (Dummy Variable)	Addition of a car to the household vehicle fleet in the same year of commute mode transition	19.42%
Traded Car_Same Year (Dummy Variable)	Household traded car in the same year of commute mode transition	18.98%

Table 4-9 Summary Statistics of Explanatory Variables used in the Estimation of Commute Mode Transition Model (Continued)

Variables	Description	Mean/ Proportion
<i>Accessibility Measures</i>		
Dist to nearest Transit Station	Distance from home to the nearest transit station in km	3.11km
Dist to nearest Park Area	Distance from home to the nearest park area in km	2.31km
Dist to CBD	Distance from home to the Central Business District (CBD) in km	10.40km
<i>Life-oriented Accessibility Transition</i>		
Moved Closer to Work Location (Dummy Variable)	Moved closer to work place compared to the previous location	77.26%
Moved Closer to School (Dummy Variable)	Moved closer to school compared to the previous location	72.41%
Moved Closer to Transit Station (Dummy Variable)	Moved closer to transit station compared to the previous location	58.28%
Moved Farther from Transit Station (Dummy Variable)	Moved farther away from transit station compared to the previous location	36.87%
Moved Closer to Park Area (Dummy Variable)	Moved closer to park area compared to the previous location	60.26%
Moved Closer to CBD (Dummy Variable)	Moved closer to CBD compared to the previous location	56.29%
Moved Farther from CBD (Dummy Variable)	Moved farther away from CBD compared to the previous location	37.97%
<i>Neighbourhood Characteristics</i>		
% of Single-detached	Percentage of single-detached dwelling in the home dissemination area	44.89%
Land-use Mix Index	Land-use mix index	0.1709
% of Transit Trips	Percentage of commute trips made by transit in the neighbourhood	12.54%
% of Active Transportation Trips	Percentage of commute trips made by walking/biking in the neighbourhood	18.78%

Table 4-10 Parameter Estimation Results of the RPL Model for Commute Mode Transition

Variables	Random-parameters Logit Model (RPL)	
	Co-efficient	t-stat
<i>Loyal to Car</i>		
Age	0.0239	1.235
Income above 150K	2.2741	3.398
Presence of Children	0.7325	1.600
Education up to College	0.8985	1.535
Full-Time Dual-Worker	0.8449	1.852
Owned Dwelling	0.3390	0.637
Traded Car_Same Year	0.9990	2.133
Moved Closer to Work Location	0.2965	0.623
<i>Loyal to Transit</i>		
Age	-0.0277	-1.138
Education up to College	2.5133	3.702
Single-Worker	0.8512	1.355
No Car Ownership	0.7883	0.935
Addition of a Job_1 Year Lead	0.7627	1.080
Dist to nearest Transit Station	-0.3229	-0.524
<i>Loyal to Active Transportation</i>		
No Children	3.5433	1.125
No Car Ownership	0.6407	0.964
Addition of a Job_1 Year Lead	-0.6260	-1.112
Dist to CBD	-0.5240	-2.660
% of Active Transportation Trips	3.8750	2.460
<i>Transition from Car to Transit</i>		
Age	-0.0159	-0.690
Income above 75K	1.1875	1.899
Decrease in Household Income	1.3222	1.606
Moved from Owned to Rented	1.9581	2.155
Lost Job_1 Year Lead	1.0167	1.314
Moved Closer to Work Location	0.6934	1.000

Table 4-10 Parameter Estimation Results of the RPL Model for Commute Mode Transition (Continued)

Variables	Random-parameters Logit Model (RPL)	
	Co-efficient	t-stat
<i>Transition from Car to Active Transportation</i>		
Gender (Male)	-0.8945	-1.216
Age	0.0336	1.247
Decrease in Household Income	1.2154	1.408
Decrease in Household Car Ownership	1.2531	1.654
Dist to CBD	-0.3523	-2.696
Moved Closer to CBD	2.1050	2.253
Moved Closer to Park Area	1.2207	1.264
<i>Transition from Transit to Car</i>		
Gender (Male)	-4.3260	-1.179
Presence of Children	3.3878	2.022
Full-Time Dual-Worker	1.5023	1.200
Moved from Rented to Owned	4.6358	2.342
Addition of Car_Same Year	2.2094	1.728
Moved Closer to CBD	2.5476	1.859
% of Single-detached	0.3543	1.600
Land-use Mix Index	1.3193	0.358
<i>Transition from Transit to Active Transportation</i>		
Income below 50K	1.4632	1.677
Education up to College	1.8856	1.885
Decrease in Household Income	1.6389	1.807
Decrease in Number of Rooms	3.0333	2.961
Lost Job_2 Year Lead	2.9367	2.619
Dist to nearest Park Area	-6.0247	-2.388
Moved Closer to School	3.1335	2.184
Moved Farther from Transit Station	1.4822	1.658
<i>Transition from Active Transportation to Car</i>		
Increase in Household Income	6.1449	2.041
Moved from Rented to Owned	2.0658	0.627
Birth of a Child_1 Year Lead	5.5368	1.000

Table 4-10 Parameter Estimation Results of the RPL Model for Commute Mode Transition (Continued)

Variables	Random-parameters Logit Model (RPL)	
	Co-efficient	t-stat
<i>Transition from Active Transportation to Car (Continued)</i>		
New Household Formation	4.7371	3.078
Moved Farther from CBD	3.2739	2.197
<i>Transition from Active Transportation to Transit</i>		
Gender (Male)	-4.1596	-1.977
Income below 50K	2.1196	2.550
Increase in Number of Bedrooms	2.0377	2.523
Addition of a Job_2 Year Lead	0.8414	1.000
Moved Closer to Transit Station	0.8858	1.167
% of Transit Trips	10.2416	2.955
<i>Constants (Reference = Transition from Transit to Car)</i>		
Loyal to Car	9.8240	2.366
Loyal to Transit	10.9956	2.578
Loyal to Active Transportation	14.0003	3.316
Transition from Car to Transit	10.1496	2.391
Transition from Car to Active Transportation	8.8482	2.101
Transition from Transit to Active Transportation	6.4415	1.453
Transition from Active Transportation to Car	1.4161	0.260
Transition from Active Transportation to Transit	7.2663	1.694
<i>Standard Deviation of the Random Parameters</i>		
Moved Closer to Work Location [Loyal to Car]	1.1434	2.261
Dist to CBD [Loyal to Active Transportation]	0.2128	2.426
Moved Closer to Park Area [Transition from Car to Active Transportation]	2.1781	3.187
Gender (Male) [Transition from Transit to Car]	6.1904	2.015
Decrease in Number of Rooms [Transition from Transit to Active Transportation]	1.4589	1.503
[] choice scenarios		

Table 4-10 Parameter Estimation Results of the RPL Model for Commute Mode Transition (Continued)

Variables	Random-parameters Logit Model (RPL)	
	Co-efficient	t-stat
<i>Standard Deviation of the Random Parameters (Continued)</i>		
Moved Farther from Transit Station [Transition from Transit to Active Transportation]	1.3034	1.635
Moved from Rented to Owned [Transition from Active Transportation to Car]	5.8190	2.160
Gender (Male) [Transition from Active Transportation to Transit]	3.2471	2.450
<i>Goodness-of-fit Measures</i>		
Log-likelihood (at Convergence)	-354.4494	
Log-likelihood (at Constant)	-548.6948	
Adjusted Pseudo R-squared	0.3540	

[] choice scenarios

4.4.2.1 Discussion of the Random-parameters Logit (RPL) Model Results

4.4.2.1.1 *Loyal to Car*

Model results suggest that older individuals are more likely to be car loyal, as probability of remaining loyal to car increases with age. Similarly, the high income group, characterized by household income above \$150000, two-worker household both having full time job status, and individual residing in an owned dwelling, prefers to be car loyal for commuting. Presence of children in the household is positively associated with car loyalty, since individuals might require a car to travel with children, for example, trip chain to day care centers/schools on their way to work. Trading (i.e., changing) car and residential relocation occurring in the same year is associated with a higher likelihood of continuing to commute by car. This result might relate to high

income individuals' self-selecting car as their commute mode following residential relocation, or it may represent a reverse causality. Surprisingly, relocating to a location closer to the workplace than the previous location reveals a higher probability to continue commuting with car. However, this variable yields a statistically significant standard deviation, with a mean and standard deviation of 0.2965 and 1.1434, respectively. This large standard deviation suggests that a sizable variation exists among the individuals in being car loyal if their commute distance is shortened. Therefore, shortening commute distance does not necessarily trigger a change in mode, arguably from car to alternative modes. Many external attributes may influence this relationship. For instance, the characteristics of the transit system and the active transportation infrastructure in the home and workplace locations might have considerable influence on the choice of commute mode.

4.4.2.1.2 Loyal to Transit

Younger individuals are more likely to be transit loyal for commuting, as are single-worker households. Both of these findings likely reflect the fact that lower income might restrict the choice of mode. Similarly, individuals with education up to community college show a positive parametric value. Individuals with no car ownership over their life-time also remain transit loyal, as expected. Interestingly, addition of a new job in the household is associated with a higher probability to continue with transit as commute mode, despite assuming the variable as a one-year lead event. Potentially, transit riders might find it challenging to make a transition to another mode (i.e., car) due to budgetary constraints, and therefore continue using transit. The model results also suggest that the shorter the distance to the nearest transit station in the new location, the higher the probability of continued transit use.

4.4.2.1.3 Loyal to Active Transportation

Individuals with no children in the household are loyal to active transportation (walk/bike) for commuting, likely because they do not need to accommodate the additional travel demand of children. Individuals not owning a car over their life-time, prefers to commute by walking/biking. The same variable represents a stronger positive relationship in the choice occasion “loyal to transit”, which indicates that individuals who do not own a car over their life-time have a higher probability of being transit loyal compared to walk/bike loyal. Addition of a job in the household increases the affordability and reveals a decreased probability of active transportation loyalty. The same variable exhibits a positive relationship for the choice occasion “loyal to transit”, such that those individuals are less likely to be loyal to active transportation and more likely to be loyal to transit with an increase in affordability. This variable exhibits a one-year lagged effect in both cases. Individuals residing closer to the CBD exhibit a higher propensity to continue with walking/biking as their commute mode. Since, the majority of the employment opportunities are located close to the CBD and individuals residing in such urban areas might have shorter commute distance, which is suitable for the use of active transportation. This variable demonstrates heterogeneity with a statistically significant standard deviation. Moreover, individuals residing in walk/bike-supportive neighbourhoods, characterized as neighbourhoods with a higher percentage of trips made by active transportation, exhibit a significantly higher probability of being loyal to active transportation for commuting.

4.4.2.1.4 Transition from Car to Transit

Younger individuals have a higher probability of making a transition in commute mode from car to transit; arguably many younger adults of this generation are environmentally concerned, and would choose sustainable

modes of transportation (Schoettle and Sivak 2014). Reduced affordability, represented by decrease in household income, a move from owned to rented dwelling, positively influences the likelihood of such transition. The loss of a job is also associated with a higher propensity of transition from car to transit, which is not surprising considering the budgetary consequences of such life-event. The model confirms a one-year lagged effect of this life-cycle event. Shortening of commute distance (i.e., relocating to a location closer to work) is associated with a transition from car to transit. Indeed, this variable reveals a two times stronger positive relationship for this transition (coefficient value 0.6934) compared to the choice occasion of “loyal to car” (coefficient value 0.2965).

4.4.2.1.5 Transition from Car to Active Transportation

Male individuals exhibit a lower preference for making a transition in commute mode from car to active transportation (walk/bike). Older individuals have a higher probability of making a transition from car to walk/bike, which might represent either their preference for healthier lifestyle or that their age is restricting them from using a car. Reduced affordability, represented by decrease in household income and decrease in household car ownership, is also associated with transition in commute mode from car to walk/bike. Individuals living closer to the CBD are more likely to make a transition from car to walk/bike, most likely due to the shorter commute distance. This hypothesis is further supported by the positive relationship of another variable, representing relocating closer to the CBD compared to the previous location. Locations closer to park area are considered as walk/bike supportive neighbourhoods; therefore, relocating closer to park area is positively associated with a transition from car to walk/bike. This variable is assumed to be a random parameter with a mean and standard deviation of 1.22047 and 2.1781, respectively. The large value of the standard deviation reveals that

individuals relocating closer to park area exhibit significant heterogeneous behaviour, such that some are less likely than others to make this transition.

4.4.2.1.6 Transition from Transit to Car

The model results suggest that female individuals have a higher probability to make a transition in commute mode from transit to car compared to their male counterparts. The large standard deviation of this random parameter indicates that females might not prefer this transition in certain cases. The presence of children exhibits a higher probability of triggering a transition to car as the commute mode. The high income group, characterized by two-worker household both having full time job status, has a higher probability of making a transition from transit to car. Increased affordability, represented by relocating from a rented to an owned dwelling, addition of a car to the household's vehicle fleet, reveals a higher propensity for transition from transit to car. The relationship associated with increased size of the household vehicle fleet might reflect self-selection of car as commute mode. Interestingly, individuals relocating closer to the CBD are more likely to make a transition from transit to car. Presumably, housing prices are higher in the peninsula Halifax (i.e., locations closer to the CBD), where higher income individuals are likely relocating. Therefore, a transition from transit to car as commute mode is observed.

4.4.2.1.7 Transition from Transit to Active Transportation

The low income group, represented by household income below \$50,000 and educational qualification up to community college, exhibits a higher probability of making a transition in commute mode from transit to active transportation (walk/bike). Reduced affordability, represented by a decrease in household income, and a decrease in number of rooms in the new dwelling, is

associated with a transition from transit to walk/bike as commute mode. A decrease in number of rooms in the new dwelling is assumed to be a random parameter. The model reveals that loss of a job triggers a transition from transit to walk/bike mode. In this case, a two-year lagged effect is observed. Locations closer to park areas show a positive influence on triggering a transition to walk/bike. Interestingly, moving closer to school shows a higher probability of making a transition from transit to walk/bike. Relocating farther away from transit stations also asserts a positive influence on the transition from transit to walk/bike. Perhaps individuals self-select their residences for commuting by active transportation.

4.4.2.1.8 Transition from Active Transportation to Car

Increased affordability, represented by an increase in household income, and relocating from a rented to an owned dwelling, is associated with a higher probability of triggering a transition from walk/bike to car as commute mode. The variable related to relocating from rented to owned dwelling is assumed as a random parameter. The large standard deviation of the variable indicates that significant heterogeneity exists among the sample individuals, such that some individuals might not prefer this transition. Life-cycle events such as, an one-year lagged effect of birth of a child and relocating due to new household formation, exhibit a positive influence on the probability of making a transition to car. Both of these life-cycle events involve an increase in household size, which might generate additional travel demand in the household necessitating a transition to car for commuting. Relocating farther from the CBD compared to the previous location reveals a strong positive effect on the probability of making a transition to car. Arguably, neighbourhoods farther away from CBD are low density areas and individuals might be self-selecting to use a car as the primary mode of transportation upon relocation.

4.4.2.1.9 Transition from Active Transportation to Transit

Males are less likely to make a commute mode transition from walk/bike to transit. However, significant heterogeneity exists, as revealed by the standard deviation of this random parameter. Addition of a new job in the household is associated with an increased probability of making a transition from walk/bike to transit. The model confirms a two-year lagged effect of this life-cycle event. Transitional variable represented by relocating to a larger dwelling with a higher number of bedrooms positively influences the transition from walk/bike to transit. Relocating closer to transit stations compared to previous location indicates shorter and more convenient access to transit services, and triggers a transition of commute mode to transit. Moreover, transit-oriented neighbourhood, represented by a higher percentage of transit trips, has a positive influence on the probability of transitioning to transit as commute mode.

In addition, this study examines a number of variables, such as job change, distance to the nearest school, and distance to the work place, among others. However, these variables could not be included in the final model due to discrepancies in prior hypothesis and poor statistical significance.

4.5 Conclusions and Summary of Contributions

This research presents the modelling of residential location choice processes, as well as investigates commute mode choice decisions after relocation. Residential location is modelled as a two-stage process of mobility and location choice. The second stage of location choice is conceptualized to have an underlying process orientation, which is a two-tier process of location search and location choice. This two-tier process of modelling location choice improves the empirical estimation of the model compared to traditional techniques. In addition, this study tests how a change in commute mode is associated with a

change in residential location. Advanced econometric models are developed to accommodate the correlated sequence of repeated choices of the households and address unobserved heterogeneity. The models accommodate interdependencies among different decisions by testing lead and lagged effects of the life-cycle events occurring at different domains and stages of the life-course.

The first stage of residential location decision is residential mobility, which is defined as the decision to move or stay at a particular location. The mobility model follows a continuous time hazard-based duration modelling technique. In the hazard setting, duration is specified as the period that a household remain in a specific residence, and the failure event is a move to a different location. Two sets of hazard models are estimated for lognormal, log logistic, and Weibull distributions. The first set of models are single episode models, which are estimated considering each duration as an independent observation. The next model set includes multiple episode shared frailty models, which accounts for the effects of the repeated duration along the housing career of the same household. The goodness-of-fit measures suggest that the multiple episode shared frailty model outperforms the single episode model. The model examines how the characteristics of life-stages, dwelling, land use, accessibility, and neighbourhood affect the termination or continuation of stay at a residential location. The model results suggest that households show a shorter duration in the case of first spell after household formation. Renters have shorter duration and move more frequently. Households residing in areas with higher land-use mix index exhibit longer duration. Households having longer commute show longer duration. Households living nearby to the CBD are likely to relocate more frequently. Longer duration is found for households residing in neighbourhoods with higher dwelling density as well as higher ratio of non-movers.

In the second stage, location choice is conceptualized as a two-tier process of location search and choice. In the first-tier of location search, households search for locations to identify potential location alternatives. Following the search, households move to one of the potential locations. The location search model is developed adopting a fuzzy logic-based modelling method. The model accommodates inter-dependencies between the stress-driven push and pull factors. The search model generates pool of alternative locations for each household on the basis of constraint and opportunity sets identified in the fuzzy logic-based model. The constraint for households' affordability is imposed by introducing constraint sets of household income and property value within the fuzzy framework. The location alternatives generated in the search model, feeds the location choice model as choice set.

The location choice model is developed adopting a latent segmentation-based logit (LSL) modelling technique. The LSL model assumes that correlated sequence of repeated choices exists due to the households housing career. The unobserved heterogeneity is addressed through formulating a flexible latent segment allocation model within the LSL framework. Households' allocation to different discrete latent segments is defined by the following variables: household income, age of the household head, percentage of owned dwelling in the neighbourhood, and distance to the CBD. The model results suggest that life-cycle events, parcel characteristics, and accessibility measures significantly influence the choice of residential locations. For instance, most households prefer larger lots. Households in general are found to prefer locations closer to work place, transit stop, and health service. Life-cycle events are found to significantly affect location preferences. For instance, birth of a child magnifies the need of larger lots. Vehicle transaction represented by vehicle acquisition, and purchase of the first vehicle in the life-time of the household show a higher propensity to choose locations farther away from work place. The adjustment period is found to be longer for the first time vehicle

purchase than that of a vehicle acquisition. The model results suggest considerable variation in location choice behaviour by the life-cycle events in the two latent segments. For example, suburbanite households in segment two show a higher likelihood to choose larger lots following the life-cycle event of a job change. On the other hand, urbanite households in segment one show a negative relationship. Interestingly, addition of a new job positively influence urbanite and suburbanite households to choose larger lots. The adjustment period for a job change is found to be longer than that of addition of a new job. Suburbanite households with children prefer to reside closer to work place. Urbanite households with children are more likely to live closer to school. Households without ownership of car in their life-time have a higher likelihood to choose locations closer to the transit stops.

For comparison purposes, another location choice model is developed utilizing choice set generated from traditional random sampling-based method. The fuzzy logic and random sampling models are compared on the basis of the predictive adjusted likelihood ratio index and average probability of correct prediction. In-terms of the above-mentioned goodness-of-fit measures, the proposed fuzzy logic-based search and location choice modelling process is found to outperform the traditional random sampling-based model.

In the case of the mode transition, this study conceptualizes that individuals reassess their commute mode when they relocate to a new residential location. Following reappraisal, they either continue using the same mode, which is considered mode loyalty, or make a transition to a new mode, which is considered mode transition. During the estimation process of mode transition, the following nine dynamic mode specific choice scenarios are considered: (1) loyal to car, (2) loyal to transit, (3) loyal to active transportation (walk/bike), (4) transition from car to transit, (5) transition from car to active transportation, (6) transition from transit to car, (7) transition from transit to active transportation, (8) transition from active transportation to car, and (9)

transition from active transportation to transit. This study develops a random-parameters logit (RPL) model, which accounts for the correlated sequence of repeated choices and unobserved heterogeneity. The model tests the influence of life-cycle events, socio-demographic transitions, and accessibility transitions. The model results suggest that moving closer to the workplace positively influences car loyalty. The large value of the standard deviation of this parameter reveals that significant heterogeneity exists among the individuals. Individuals residing closer to the transit station and those with no car ownership over the life-time exhibit a higher propensity to be transit loyal. Individuals with no children in the household and residing in neighbourhoods with a higher percentage of walk/bike trips show loyalty to active transportation. In the case of mode transitions, a decrease in household income and the loss of a job positively influence a transition from car to transit. Tenure transition from rental to owned dwelling and an increase in household vehicle fleet by addition of a car trigger a transition from transit to car. An increase in household income is associated with a higher propensity for transition from active transportation to car. Birth of a child and new household formation are positively associated with a transition from active transportation to car. Individuals relocating from rental to owned dwelling have a higher probability of making a transition from active transportation to car. The large standard deviation of this parameter suggests that significant heterogeneity exists among the individuals.

This study has certain limitations. For instance, this study could not capture the effects of historical evolution of land-use and urban form due to the unavailability of such information. Moreover, this study could not consider the historical evolution of the transportation system measures, which includes travel time, travel cost, and transit level of service (LOS), among others. Future research should focus on building a GIS database to maintain historical record of urban form and transportation system measures. Another limitation

is the use of a small sample size as longitudinal surveys are challenging and expensive. Particularly, in the case of the mode transition model, a LSL model could not be developed due to the small sample size, since analyzing different domains of contrasts with respect to multiple choice dimensions and latent segmentation are challenging with a small sample size. For the mobility model, the effects of time-varying covariates were not included in the model. Testing time-varying covariates within the duration model formulation will be an interesting future work. In the case of modelling mode transition, this study could not impose availability of car as a constraint. Future research should focus on accommodating car ownership constraint within the model estimation process.

Nevertheless, the proposed modelling framework significantly contributes to the dynamic modelling of location choice processes and commute mode transitions. The development of the two-tier fuzzy logic-based residential location model is a methodological contribution to the literature of travel demand modelling technique. The adoption of life history-oriented approach offers important behavioural insights towards understanding what triggers households' relocation and mode change decisions, which is critical for transportation and urban planning. It will also be interesting to implement such life-trajectory dynamics of the location choice decision processes within the iTLE simulation environment.

Modelling Vehicle Transactions

5.1 Introduction

This chapter focuses to model the vehicle transaction component of vehicle ownership transition module of the iTLE. The contribution of this research is four-fold: 1) investigating the transaction decisions as a process of first time vehicle purchase, vehicle acquisition, vehicle disposal, and vehicle trade, 2) examining the multi-domain decision interaction, 3) developing econometric model to accommodate the temporal dimension of the households life-time and address latent heterogeneity, and 4) accommodating the influence of adjustment period among decisions as lead and lag events. The inclusion of first vehicle purchase of the households during their lifetime is a crucial dimension, as it might be associated with a mode shift to car.

In terms of modelling methods, literature suggests that a number of methodologies are applied for vehicle ownership modelling including, unordered models ranging from conventional multinomial logit models (Bhat and Pulugurta 1998) to latent segmentation-based logit models (Anowar et al. 2014), hazard-based duration models ranging from single duration models (De Jong 1996) to competing risk models (Mohammadian and Rashidi 2007), and ordered models (Kim and Kim 2004), among others. To accommodate the life-trajectory dynamics, this study develops a latent segmentation-based logit

This chapter is largely derived from the following journal paper:

- Fatmi, M.R., and Habib, M.A. (2016). Longitudinal Vehicle Transaction Model: Assessment of Lead and Lagged Effects of Longer-Term Changes and Life-cycle Events. *Transportation Research Record: Journal of Transportation Research Board*, 2566(2), 11-21.

(LSL) model. The model accommodates repeated transaction decisions by addressing the correlated sequence of repeated choices. A flexible segment allocation component is formulated within the LSL framework to capture the unobserved heterogeneity. A life-oriented approach is taken to examine how vehicle transaction decisions are influenced by life-cycle events such as, birth of a child, death of a member, residential relocation, job relocation, addition of a job, and loss of a job, among others. The effects of adjustment period between events is accommodated as the lead and lag events. In addition, the model accommodates the effects of socio-demographic, accessibility measure, and neighbourhood characteristics.

The organization of this chapter is as follows: section 5.2 describes the modelling methods and the descriptions of vehicle transaction scenarios considered as dependent variables. Section 5.3 discusses the model estimation results. Finally, section 5.4 summarizes the contributions and limitations of this research and directions for future works.

5.2 Modelling Methods

The vehicle transaction model is developed utilizing data from the HMTS. The vehicle ownership history component of the HMTS provides information up to four current and four previous vehicle ownerships. Following the cleaning process, this study considers a total of 613 vehicle transaction instances. Out of the 613 transaction instances, 62.65% are acquisition of a vehicle, 9.13% are disposal of a vehicle, and 28.22% are trading of a vehicle. The retrospective nature of the survey enables this study to identify the first time vehicle purchase decisions from the total acquisition instances. Out of the 62.65% of acquisition instances, 17.46% are first time purchases and the remaining 45.19% are adding a vehicle to the existing vehicle fleet. This study

investigates households' vehicle transaction decisions by considering the following four transaction scenarios as the dependent variables:

1. First Time Vehicle Purchase: purchase of the first vehicle in the lifetime of the household
2. Vehicle Acquisition: addition of a vehicle to the existing vehicle fleet of the household
3. Vehicle Disposal: reduction of a vehicle from the existing vehicle fleet of the household
4. Vehicle Trade: disposal decision followed by a purchase decision within the same calendar year

A latent segmentation-based logit (LSL) model is formulated for modelling the vehicle transaction decisions, which is similar to the location choice model developed in chapter 4. Assume that household i belonging to latent segment s makes a transaction decision j at t choice occasion. The utility derived from the transaction can be expressed as:

$$U_{ijt}(i \in s) = X_{ijt}\beta_s + \varepsilon_{ijt} \quad (1)$$

Here, X is the observed attributes, β is the segment specific vector parameter, and ε is the random error term. ε is assumed to have a type I extreme value distribution and is independently and identically distributed. Due to the existence of repeated choice, the joint probability of the choice sequence can be written as following:

$$P_{ij}(i \in s) = \prod_{t=1}^T \frac{e^{X_{ict}\beta_s}}{\sum_{j=1}^J e^{X_{ijt}\beta_s}} \quad (2)$$

Here, c is the transaction made at t choice occasion from a sequence of transaction choices $c = c_{i1}, c_{i2}, \dots, \dots, c_{iT}$. The latent segment allocation model takes the following form:

$$\phi_{is} = \frac{e^{\omega_s + \theta_s Z_i}}{\sum_{s=1}^S e^{\omega_s + \theta_s Z_i}} \quad (3)$$

Here, Z is the observed attributes, ω is the segment membership constant, and θ is the segment membership vector parameter. The maximum log likelihood can be written as:

$$LL_{max} = \sum_{n=1}^N \ln \left\{ \prod_{s=1}^S \phi_{is} P_{ij} (i \in s) \right\}^{\gamma_{ij}} \quad (4)$$

Here, N is the total number of observations, and γ is a dummy variable. γ takes a value of 1 while household i makes transaction j and 0 otherwise. The parameters are estimated by maximizing the log likelihood function using expectation-maximization (EM) algorithm. Asymptotic covariance matrix for the full set of parameter estimators are determined by inverting the analytic second derivative matrix of the log likelihood function. Additionally, a MNL model is estimated for comparison purposes. The models are compared on the basis of adjusted pseudo r-squared, and Bayesian Information Criteria (BIC) measures.

5.3 Model Results

The LSL model is estimated for several number of segments. The model with the appropriate number of segments that best fits the data is determined on the basis of BIC measure. The model results suggest that the BIC value for two latent segments is 1420.47, which increases to 1594.69 for three latent segments. The lower BIC measure of the two segments indicate a better model fit. Therefore, this study assumes two segments for the final LSL model.

Table 5-1 Descriptive Statistics of Explanatory Variables used in the Estimation of Vehicle Transaction Model

Variables	Definition	Mean/ Proportion	Std. Deviation
<i>Socio-Demographic Characteristics</i>			
Gender (Male) (Dummy Variable)	Gender of the head of the household is male	53%	-
Age	Age of the head of the household in years	46.84	12.25
Education Minimum Under Graduation (Dummy Variable)	Educational qualification of the head of the household is minimum under graduation	74%	-
Income above 100K (Dummy Variable)	Household income above \$100,000	44%	-
Household Size	Number of members in the household	2.87	1.18
<i>Life-cycle Events</i>			
Birth of a Child/Member Move in _Same Year (Dummy Variable)	Birth of a child or member move in occurring in the same year of vehicle transaction	55%	-
Birth of a Child/Member Move in _1 Year Lead (Dummy Variable)	Birth of a child or member move in 1 year prior to vehicle transaction	3%	-
Birth of a Child/Member Move in _2 Year Lead (Dummy Variable)	Birth of a child or member move in 2 years prior to vehicle transaction	4%	-
Birth of a Child_1 Year Lead (Dummy Variable)	Birth of a child 1 year prior to vehicle transaction	2%	-
Birth of a Child_2 Year Lead (Dummy Variable)	Birth of a child 2 year prior to vehicle transaction	3%	-
Death/Move out of a Member _Same Year (Dummy Variable)	Death or move out of a member occurring in the same year of vehicle transaction	69%	-

Table 5-1 Descriptive Statistics of Explanatory Variables used in the Estimation of Vehicle Transaction Model (Continued)

Variables	Definition	Mean/ Proportion	Std. Deviation
<i>Life-cycle Events (Continued)</i>			
Death/Move out of a Member_1 Year Lead (Dummy Variable)	Death or move out of a member 1 year prior to vehicle transaction	2%	-
Addition of a Job_1 Year Lead (Dummy Variable)	Addition of a job 1 year prior to vehicle transaction	3%	-
Addition of a Job_3 Year Lead (Dummy Variable)	Addition of a job 3 year prior to vehicle transaction	12%	-
Lost Job_1 Year Lead (Dummy Variable)	Lost job 1 year prior to vehicle transaction	7%	-
Residential Move_1 Year Lead (Dummy Variable)	Residential relocation 1 year prior to vehicle transaction	4%	-
Residential Move_2 Year Lead (Dummy Variable)	Residential relocation 2 years prior to vehicle transaction	7%	-
Residential Move_1 Year Lag (Dummy Variable)	Residential relocation 1 year after vehicle transaction	7%	-
Residential Move_2 Year Lag (Dummy Variable)	Residential relocation 2 years after vehicle transaction	7%	-
Residential Move_3 Year Lag (Dummy Variable)	Residential relocation 3 years after vehicle transaction	5%	-
<i>Accessibility Measures</i>			
Dist to Work Location	Distance from home to work location in km	15.50	29.23
Dist to CBD	Distance from home to the Central Business District (CBD) in km	20.08	42.74
Dist to CBD above 10km (Dummy Variable)	Distance from home to the Central Business District (CBD) above 10 km	34%	-
Dist to nearest School	Distance from home to the nearest school in km	9.46	10.87

Table 5-1 Descriptive Statistics of Explanatory Variables used in the Estimation of Vehicle Transaction Model (Continued)

Variables	Definition	Mean/ Proportion	Std. Deviation
<i>Accessibility Measures (Continued)</i>			
Dist to nearest Health Service	Distance from home to the nearest health service in km	6.30	10.82
Dist to nearest Park Area	Distance from home to the nearest park area in km	5.68	29.70
Dist to nearest Park Area below 1km (Dummy Variable)	Distance from home to the nearest park area below 1km	87%	-
Dist to nearest Shopping Center	Distance from home to the nearest shopping center in km	15.07	41.51
<i>Neighbourhood Characteristics</i>			
Dwelling Density	Dwelling per acre area in the home dissemination area	1341.43	1802.92
% of Owned Dwelling	Percentage of owned dwelling in the home dissemination area	70.08%	28.81%
% of Single-detached	Percentage of single-detached dwelling in the home dissemination area	57.86%	33.25%
Avg. Property Value	Average property value (CAD) in the home dissemination area	295242	115095
Employment Rate	Employment rate in the home dissemination area	64.97%	10.64%

In addition to the LSL model, this study develops a multinomial logit (MNL) model for comparison purposes. The model results suggest that the LSL model improves the goodness-of-fit measures, as evident in the higher adjusted pseudo r-squared value (0.26) in comparison to that of the MNL model (0.10). In terms of log likelihood ratio test, the LSL model yields a chi-squared statistics of 325.32 (critical value 112.33 with 80 degrees of freedom), which confirms that the LSL model outperforms the MNL model at the 1%

significance level. Hence, this study considers the LSL model as the final model. The descriptive statistics of the variables retained in the final LSL model are presented in Table 5-1.

5.3.1 Results of the Segment Allocation Model

The model results of the segment allocation component of the LSL model is presented in Table 5-2. The results suggest that the segment membership probabilities for segment one and two are 0.54 and 0.46 respectively. Segment membership probability is the average probability over the sample households belonging to each segment.

The segment allocation model is estimated using several socio-demographics and neighbourhood characteristics. The final segment allocation model retains the following variables: household income above \$100,000, household size, dwelling density, and percentage of owned dwellings in the neighbourhood (Table 5-2). The model is estimated assuming segment two as the reference segment. The model results reveal a negative sign for household size in segment one, which refers to smaller-sized households. Moreover, membership of segment one is positively influenced by household income above \$100,000. Among the neighbourhood characteristics, the positive sign for dwelling density and negative sign for owned dwellings in segment one indicates urban dwellers. Therefore, segment one can be identified as a segment for smaller-sized urban dwellers with income above \$100,000. On the other hand, segment two can be identified as a segment for larger-sized suburban dwellers with income below \$100,000.

Table 5-2 Results for the Latent Segment Allocation Component of the Vehicle Transaction Model

	Segment 1	Segment 2
	<i>co-efficient (t-stat)</i>	<i>co-efficient (t-stat)</i>
Segment Membership Probabilities	0.54	0.46
Constant	1.47(0.60)	-
<i>Socio-demographic Characteristics</i>		
Household Size	-1.45(-2.11)	-
Income above 100K	5.90(2.14)	-
<i>Neighbourhood Characteristics</i>		
Dwelling Density	0.002(2.08)	-
% of Owned Dwelling	-0.05(-1.60)	-

5.3.2 Discussion of the Latent Segmentation-based Logit (LSL) Model Results

Table 5-3 presents the parameter estimation results of the LSL model. The majority of the variables retained in the final model exhibit statistical significance at the level of 95% confidence interval for at least one latent segment. A brief discussion of the final model results is presented below.

5.3.2.1 First Time Vehicle Purchase

Life-cycle event represented by birth of a child or member move in positively influences the transaction decision for purchasing the first vehicle. Birth of a child or member move in is a key life-event that refers to an increase in the household size, which generates an additional travel demand. Therefore, households exhibit a higher probability for purchasing their first vehicle. The model results reveal a one-year lagged effect of this life-cycle event; perhaps, households require adjustment time period following a key life-event. Interestingly, while the influence of only birth of a child is tested, the model results reveal a heterogeneous effect across the two segments. Segment one

identified to include smaller-sized urban dwellers with income above \$100,000, exhibits a higher probability for purchasing the first vehicle. In contrast, households in segment two reveal a negative relationship. The model confirms a two-year lagged effect of this variable. Death or move out of a member referring to a decrease in household size, exhibits a lower probability for purchasing the first vehicle. Another life-cycle event represented by addition of a job in the household refers to increased affordability and reveals a heterogeneous effect across the two segments. Households in segment two identified as larger-sized suburban dwellers with income below \$100,000, show a higher probability for purchasing their first vehicle. The added budgetary flexibility due to addition of a job might provide the freedom for purchasing the first vehicle to these larger-sized suburban dwellers in segment two. In contrast, households in segment one exhibit a negative relationship. The model confirms a three-year lagged effect of this variable. Residential relocation decision reveals a positive relationship in segment two, which is identified to include larger-sized suburban dwellers with income below \$100,000. Residential relocation might imply a decreased accessibility to activity locations and transportation services for these larger-sized suburban dwellers, which triggers the purchase of their first vehicle. On the other hand, households in segment one reveal a lower probability for purchasing their first vehicle. The model confirms a one-year lead and a one-year lagged effect of residential relocation decision.

Among the accessibility and neighbourhood characteristics, households residing farther away from the closest school locations have a higher probability for purchasing their first vehicle. A negative relationship is found for the accessibility measures representing distance to the CBD and distance to the nearest health services.

Table 5-3 Parameter Estimation Results of the LSL model for Vehicle Transaction

Variables	LSL	
	Segment 1	Segment 2
	<i>co-efficient</i> <i>(t-stat)</i>	<i>co-efficient</i> <i>(t-stat)</i>
<i>First Time Vehicle Purchase</i>		
Gender (Male)	-.54 (-1.25)	0.64 (1.75)
Birth of a Child/Member Move in _1 Year Lead	3.27 (3.73)	3.27 (3.73)
Birth of a Child_2 Year Lead	3.18 (2.08)	-15.17 (-0.10)
Death/Move out of a Member _Same Year	-1.72 (-2.71)	-1.66 (-4.28)
Addition of a Job_3 Year Lead	-1.27 (-1.90)	2.18 (5.44)
Residential Move_1 Year Lead	-3.41 (-2.26)	14.35 (0.10)
Residential Move_1 Year Lag	-0.67 (-0.75)	1.09 (1.40)
Dist to CBD	-0.15 (-1.83)	-0.0004 (-0.10)
Dist to nearest School	0.14 (1.72)	0.02 (1.41)
Dist to nearest Health Service	-0.23 (-1.67)	-0.02 (-1.61)
Dist to nearest Park Area	0.30 (2.79)	0.001(0.10)
Avg. Property Value	-0.00003(-1.90)	-0.00009(-3.73)
<i>Vehicle Acquisition</i>		
Age	-0.02 (-2.11)	-0.02 (-2.11)
Birth of a Child/Member Move in _Same Year	0.30 (0.60)	0.05 (0.30)
Birth of a Child_2 Year Lead	2.66 (1.73)	-1.87 (-0.71)
Addition of a Job_1 Year Lead	1.76 (1.17)	1.42 (1.98)
Residential Move_3 Year Lag	1.87 (1.98)	-0.78 (-1.10)
Dist to Work Location	0.003(0.77)	0.002(1.22)
Dist to CBD	0.02 (0.435)	0.06 (1.67)
Dist to nearest Health Service	0.10 (0.91)	0.003 (0.55)
Dist to nearest Park Area	0.02 (0.20)	-0.009 (-0.74)
Dist to nearest Shopping Center	-0.05 (-1.51)	-0.05 (-1.51)
% of Single-detached	-0.005 (-2.32)	-0.005 (-2.32)
<i>Vehicle Disposal</i>		
Gender (Male)	-1.15 (-2.98)	-1.15 (-2.98)
Education Minimum Under Graduation	0.69 (0.78)	-0.93 (-2.13)
Death/Move out of a Member _Same Year	0.60 (1.37)	0.60 (1.37)

Table 5-3 Parameter Estimation Results of the LSL model for Vehicle Transaction (Continued)

Variables	LSL	
	Segment 1	Segment 2
	<i>co-efficient</i> (<i>t-stat</i>)	<i>co-efficient</i> (<i>t-stat</i>)
<i>Vehicle Disposal (Continued)</i>		
Lost Job_1 Year Lead	0.81 (0.67)	0.84 (1.43)
Residential Move_2 Year Lead	1.27 (2.71)	1.27 (2.71)
Dist to Work Location	0.001 (0.70)	0.001 (0.70)
Dist to nearest Shopping Center	0.06 (1.00)	0.008 (2.23)
% of Single-detached	-0.002 (-0.44)	-0.002 (-0.44)
<i>Vehicle Trade</i>		
Education Minimum Under Graduation	2.80 (2.47)	0.62 (2.04)
Birth of a Child/Member Move in _2 Year Lead	0.94 (1.16)	0.94 (1.16)
Birth of a Child_1 Year Lead	3.93 (2.54)	3.93 (2.54)
Death/Move out of a Member _1 Year Lead	2.86 (1.96)	-0.05 (-0.10)
Residential Move_1 Year Lead	-3.20 (-1.32)	12.98 (0.10)
Residential Move_2 Year Lag	2.34 (2.14)	-11.56 (-0.10)
Dist to CBD above 10km	-1.12 (-1.43)	1.55 (5.05)
Dist to nearest Park Area below 1km	-0.77 (-0.65)	0.71 (1.99)
Employment Rate	0.04 (2.18)	-0.004 (-2.16)
<i>Constants (Reference = Vehicle Disposal)</i>		
<i>First Time Vehicle Purchase</i>	5.97 (4.00)	2.47 (2.56)
<i>Vehicle Acquisition</i>	3.10 (2.65)	2.17 (2.69)
<i>Vehicle Trade</i>	-2.43 (-1.00)	-0.96 (-1.26)
<i>Goodness-of-fit Measures</i>		
Log Likelihood (at convergence)	-453.50	
Log Likelihood (at constant)	-616.16	
Adjusted Pseudo R-squared	0.26	

5.3.2.2 Vehicle Acquisition

Birth of a child or member move in reveals a higher probability for vehicle acquisition. The same year effect of this variable indicates that an increase in household size triggers the requirement for immediate addition of a vehicle to the existing fleet. While birth of a child is tested separately in the model, the variable reveals a heterogeneous effect across the two segments. Addition of a job in the household reveals a higher probability for vehicle acquisition. This variable reveals a one-year lagged effect. The same variable shows a three-year lagged effect with heterogeneity across the two segments in the case of first time vehicle purchase. A change in residential location exhibits a heterogeneous effect in the two segments. For instance, smaller-sized urban dwellers with income above 100,000 belonging to segment one have a higher propensity for vehicle acquisition. On the other hand, larger-sized suburban dwellers with income below 100,000 belonging to segment two show a lower probability for adding a vehicle to the existing fleet of the household. The model confirms a three-year lead effect of this life-cycle event. The same variable reveals an opposite relationship across the two segments for a one-year lead and a one-year lagged effect in the case of first time vehicle purchase. Households residing farther away from work locations have a higher propensity for vehicle acquisition.

5.3.2.3 Vehicle Disposal

Life-cycle event represented by death or move out of a member shows a higher propensity for vehicle disposal. Death or move out of a member refers to a decrease in household size, which reflects reduced travel demand. Hence, households prefer reduction in the vehicle fleet by disposing vehicle. The model results suggest a same year effect of the occurrence of this life-cycle event and the disposal of vehicle. Loss of a job reveals a higher probability for vehicle

disposal. Loss of a job indicates reduction in the affordability of the household, which might trigger a disposal decision due to the budgetary constraints. The parameter estimates reveal a one-year lagged effect of this variable. Households prefer to dispose vehicle following a residential move with a two-year lagged effect. Neighbourhood characteristics, represented by the percentage of single-detached dwellings, exhibit a negative relationship. This result reflects that households residing in neighbourhoods with a lower percentage of single-detached dwellings are more likely to dispose vehicles. Presumably, neighbourhoods with a lower percentage of single-detached dwellings represent urban areas, which might have a well-connected alternative mode of transportation (i.e. transit, active transportation) network. Hence, households residing in such neighbourhoods prefer to dispose vehicles.

5.3.2.4 Vehicle Trade

Vehicle trade refers to a disposal decision followed by a purchase decision, which indicates no change in the vehicle ownership level. Household size increase represented by birth of a child or member move in reveals a positive relationship, which suggests a higher probability for vehicle trading. The model confirms a two-year lagged effect of this life-cycle event. A similar positive relationship is found, when only birth of a child is tested in the model. Household size decrease represented by death or move out of a member shows a heterogeneous effect across the two segments. Households prefer to trade vehicle if they belong to segment one. In contrast, segment two shows a negative relationship. Residential relocation reveals heterogeneous relationship across the two segments for a one-year lagged and a two-year lead effect. Households in segment one have a lower probability of trading a vehicle after one year of residential move. On the other hand, households in segment two prefer to trade car after one year of residential move. An opposite relationship is found across the two segments when residential relocation

decision is examined for a two-year lead effect. Accessibility measures represented by distance to the CBD above 10km and distance to the nearest park area below 1km indicate heterogeneous relationships across the two segments.

In addition to the above mentioned variables retained in the final model, this study tests a number of variables during the model estimation process. For instance, the study tests the effects of retirement, job move, distance from home to the nearest transit station, dwelling type, and percentage of different land uses in the neighbourhood, among others. Moreover, the study tests a number of variables to estimate the latent segment allocation model, such as presence of children, percentage of rented dwellings in the neighbourhood, and land-use mix index, among others. However, the above mentioned variables could not be included in the final model due to discrepancies in the hypotheses confirmation along with poor statistical significance. Additionally, the final model includes some variables below the level of 95% confidence interval as they offer important behavioural insights and have significant policy implications. These variables are retained with an assumption that they might show statistical significance if a larger dataset were available.

5.4 Conclusions and Summary of Contributions

This research presents the findings of a dynamic household-level vehicle transaction model. A latent segmentation-based logit (LSL) model is developed to investigate four types of transaction decisions, including first time vehicle purchase, vehicle acquisition, vehicle disposal, and vehicle trade. One of the unique features of this study is to identify the transaction decision of the first time vehicle purchase. The LSL model captures repeated transactions of the same households during their life-course. A segment allocation model is formulated within the LSL framework to address latent heterogeneity. The

allocation of households into different latent segments is estimated on the basis of household income, household size, dwelling density of the neighbourhood, and percentage of owned dwelling in the neighbourhood. This study tests the lead and lagged effects of life-cycle events. The model results suggest that considerable heterogeneity exists, as evident in the parametric values of two latent segments. For instance, addition of a job could trigger first time vehicle purchase in one segment and deter in another segment. Similar heterogeneous effect is found for the variable representing birth of a child for vehicle acquisition. The effect of historical deposition is also confirmed on vehicle transaction decisions. For example, birth of a child confirms a two-year lagged effect on vehicle acquisition. Interestingly, the first time vehicle purchase behaviour is found to be considerably different than vehicle acquisition decisions (addition of a vehicle to the existing vehicle fleet). For instance, addition of a job reveals significant heterogeneity across the two segments in the case of first time vehicle purchase. The model confirms that households require three years of adjustment period after getting a job to purchase their first vehicle. The same variable exhibits a higher probability for vehicle acquisition in both segments, and confirms a smaller adjustment period of one year. Additionally, the model confirms a one-year lead and a one-year lagged effect of residential move for first time vehicle purchase decisions, which exhibit heterogeneity across the two segments. On the other hand, the same variable shows an opposite relationship across the two segments for vehicle acquisition decision with a three-year lead effect.

One of the limitations of this study is that it could not consider the historical evolution of the transportation system. As a result, the effects of certain variables including transit availability, transit level of service (LOS), travel time, and travel cost, among others could not be addressed in the model. A travel demand forecasting model for Halifax is currently under development, which is expected to provide better information regarding travel time, transit

LOS, and other relevant information for further modelling. Another limitation is the use of a small sample size. Particularly, analyzing different domains of contrasts with respect to multiple choice dimensions and latent segmentation are challenging with a small sample size. If larger sample becomes available, one interesting future direction could be testing generational effects and other influences of time-varying factors. One of the future directions in the domain of model development is to consider car availability constraints during choice set formulation for the transaction instances, which might improve the model estimation results. In addition, future studies should focus on developing a latent segmentation-based nested logit modelling framework to capture endogeneity within the decision process.

In summary, this study contributes significantly towards the vehicle ownership literature by developing a life-oriented vehicle transaction model. The model disentangles a crucial behaviour regarding first time vehicle purchase decisions of the households. The study examines lead and lagged effects of life-cycle events. The historical deposition effects of the key life-events found in this study offer important behavioural insights in understanding vehicle transaction decisions. It will be interesting to microsimulate this dynamic vehicle transaction model within the iTLE framework.

Baseline Synthesis and Microsimulation of Life-stage Transitions

6.1 Introduction

This chapter presents the implementation of the baseline synthesis and life-stage transition modules of the life-oriented integrated Transport Land Use and Energy (iTLE) model. Baseline synthesis involves the generation of relevant baseline information of the agents such as demographic and vehicle ownership information. Life-stage transition includes the simulation of the demographic career of the agents. The contributions of this research is three-fold: 1) performing population synthesis at the micro-spatial resolution of parcel, 2) synthesizing vehicle ownership level, and 3) microsimulating the life-stages of the agents. A full-scale validation of the baseline synthesis and life-stage transition simulation results are also performed.

This chapter is organized as follows: section 6.2 discusses the implementation of the iTLE model. Section 6.3 presents population synthesis process and results. Section 6.4 describes the vehicle ownership level synthesis. Section 6.5 discusses the implementation of the life-stage transition module, including the microsimulation processes, validation, and simulation results. The chapter concludes with a summary of contributions in section 6.6.

The following journal paper is an earlier version of this chapter:

- Fatmi, M.R., and Habib, M.A. (2017). Baseline Synthesis and Microsimulation of Life-stage Transitions within an Agent-based Integrated Urban Model. *Procedia Computer Science*, 109, 608-315.

6.2 Implementation of the iTLE Proto-type Model

A proto-type version of the iTLE model is operationalized for Halifax, Canada. The proto-type version implements the following modules: baseline synthesis, life-stage transition, residential location transition, and vehicle ownership transition. The program code is written using C# dotNET programming language. The iTLE proto-type contains a total of approximately 1700 lines of code. The proto-type version generates baseline synthetic information for the year 2006, and runs simulation for a 15-year period from 2007 to 2021 at a yearly time-step. The run-time of the model for each simulation year is around 23 hours on a computer with Core i7-4770 processor and 16 GB of RAM, running on a 64-bit Windows 7 operating system.

The proto-type iTLE simulates agents' decisions longitudinally at each simulation year. The simulation starts with a sample of baseline population, and the relationships among the agents in the population are maintained throughout the simulation period. An agent can enter the population through birth or in-migration and exit through death or out-migration. The system state of iTLE does not hold the equilibrium assumption, rather it is always in a dynamic dis-equilibrium state. iTLE is designed as a modular-based modelling system, which allows the application of each module and subsequent micro-models in isolation and offers the opportunity to improve any component without affecting the whole simulation framework. All urban form elements are considered as exogenous in the current version of iTLE software. Following the simulation at each time-step, the system output is stored at the individual agent- and object-level; which can be used to generate numerous statistics and maps at different aggregation levels. This chapter presents the results of population synthesis, vehicle ownership level synthesis, and life-stage transition components of the iTLE model.

6.3 Population Synthesis

6.3.1 Synthesis Process

The population for the base year is generated in the following two-stages: (1) generation of synthetic population at the zonal-level, and (2) allocation of the synthetic population at the micro-spatial unit of parcel. The first stage involves synthesizing the population at the zonal-level of dissemination area (DA). A 100% synthetic population is generated following an Iterative Proportional Updating (IPU) technique (Ye et al., 2009) for the base year 2006. In the IPU technique, control for both household-level and individual-level characteristics is maintained by adjusting weights iteratively among the attribute types of the households until attribute types at the household- and individual-level are matched. The synthesis is performed using an open source population synthesizer, PopGen. For the synthesis, the household-level control variables include, household income, household size, tenure type, and dwelling type; and the individual-level control variables include, age, sex, marital status, and employment status. A list of categories for the household-level and individual-level control variables are presented in Table 6-1.

The iTLE model is designed to operate at the finest disaggregate spatial unit of parcel. Hence, the second stage involves allocation of the households into the parcels using a logit link model. To control the allocation of the households into parcels of the DA it belongs (according to stage one), a constraint is introduced in the logit link model. This constraint generates household-specific choice set, which only includes the parcels of the specific DA that the household is allocated through synthesis. A multinomial logit model (MNL) is developed to generate the initial parcel-level residential locations (Table 6-2). The allocation of households into the parcels is determined based on parcel characteristics and its interaction with households' socio-economic characteristics.

Table 6-1 List of Categories of the Household-level and Individual-level Control Variables for Population Synthesis

Control Variables			
Household-level		Individual-level	
<i>Attributes</i>	<i>Categories</i>	<i>Attributes</i>	<i>Categories</i>
Household Income X 1000 CAD (5 Categories)	under 20, 20-49, 50-79, 80-99, 100 and above	Age (years) (13 Categories)	under 9, 10-14, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-64, 65-74, 75 and above
Household Size (5 Categories)	1 person, 2 person, 3 person, 4-5 person, 6 person and above	Gender (2 Categories)	female, male
Tenure Type (2 Categories)	own, rent	Marital Status (5 Categories)	single, married, separated, divorced, widowed
Dwelling Type (8 Categories)	single-detached, semi-detached, row, apt above 5 storeys, apt less than 5 storeys, duplex, movable, others	Employment Status (3 Categories)	Employed, unemployed, not in the labour force

Table 6-2 Parameter Estimation Results of the Base Year Logit-link Model for the Population Synthesis Procedure

Explanatory Variables	Variable Description	Multinomial Logit Model	
		<i>co-efficient</i>	<i>t-stat</i>
Parcel Size	Size of the property (acres)	6.23440	8.16
Parcel Size X Income below 50k	Size of the property (acres) interacted with household income below \$50,000 (CAD)	-4.31527	-1.60
<i>Goodness-of-fit Measures</i>			
Log-likelihood (at convergence)		-827.880	
Log-likelihood (at constant)		-881.890	
Adjusted Pseudo R-squared		0.061	

6.3.2 Synthesis Results

The results suggest that the population synthesis module generates a synthetic population of 155,140 households in comparison to the observed total households of 155,060 in 2006 for Halifax. This is a slight over-representation by only 0.05%. The number of synthetic individuals is 363,820, which is an under-representation of the observed number of individuals by 2.38%. The performance of the population synthesis is evaluated on the basis of the following two goodness-of-fit measures: (1) Standard Root Mean Square Error (SRMSE)¹⁰, and (2) Absolute Percent Error (APE)¹¹. The SRMSE value for the overall synthetic population is 0.37. The APE measures evaluate the performance of the spatial distribution of the synthetic population in comparison to the observed population. The APE measures are determined at the DA-level, which is shown in Figure 6-1. The analysis results suggest that around 89% of the DAs show an APE value of less than 5%. Only around 2.5% of the DAs show an APE value of greater than 10%.

$$^{10} SRMSE = \frac{\left[\sum_{j=1}^m \dots \sum_{k=1}^n (S_{j\dots k} - O_{j\dots k})^2 / N \right]^{1/2}}{\sum_{j=1}^m \dots \sum_{k=1}^n (S_{j\dots k}) / N}, \text{ Here, } S_{j\dots k} \text{ is the synthesized number of agents}$$

with attribute categories $j\dots k$, $O_{j\dots k}$ is the observed number of agents with attribute categories $j\dots k$, and N is the total number of agents (Farooq et al., 2013). SRMSE value generally ranges from 0 to 1. A value of 0 represents a perfect fit.

¹¹ $APE_i = \left| \left(\frac{S_i - O_i}{O_i} \right) \right| * 100$, Here, S_i is the synthesized number of agents in DA i , and O_i is the observed number of the agents in DA i (Chen, 2009). APE value ranges from 0% to 100%. A value of 0% represents a perfect fit.

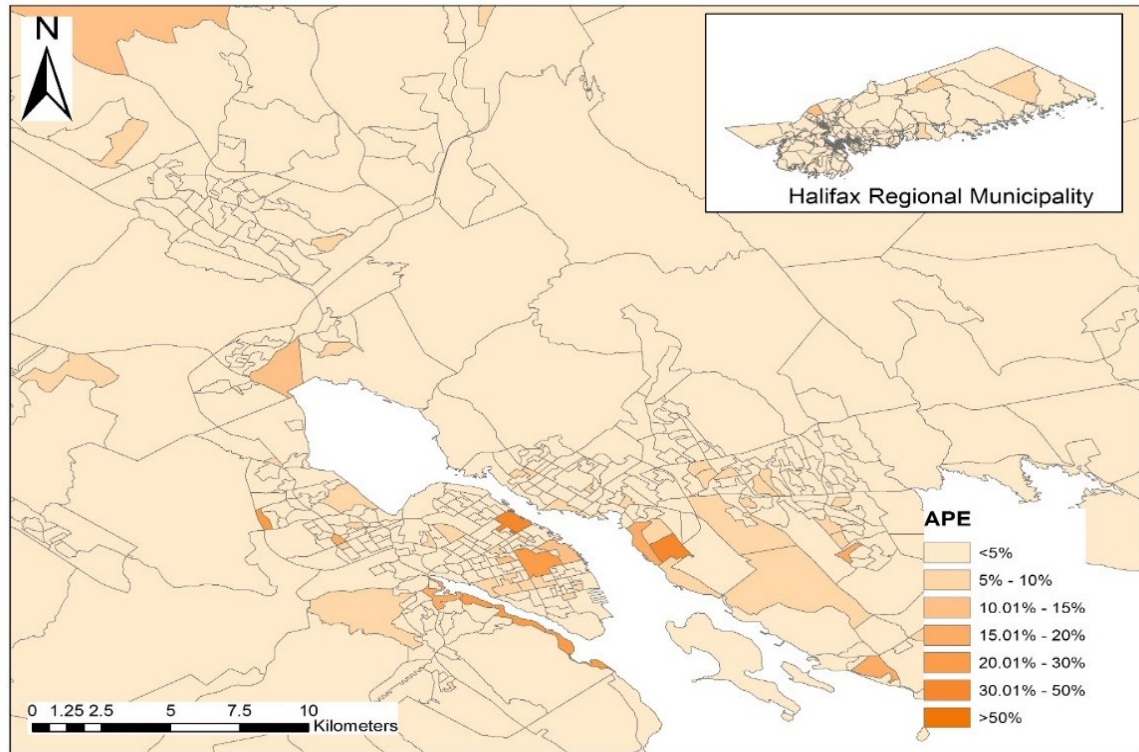


Figure 6-1 APE measures of the Synthetic Population for the Base Year 2006

Furthermore, a comparison between the characteristics of the synthetic and observed population is presented in Table 6-3. The results reveal that majority of the characteristics of the synthetic population represent a slight difference from the observed population, which is less than 1%. For example, in the case of gender, the synthetic female population share slightly over-represents observed female share by 0.53% only. In the case of tenure type, the synthetic owned households over-represent observed owned households by 0.06%, only. Similar results are found for most of the categories of the individual- and household-level attributes. Only “single persons” category of marital status and “not in the labour force” category of employment status show a difference of greater than 1%, to be specific 1.02% and 1.08% respectively. Hence, it can be concluded that the synthetic population module generates satisfactory estimates of population.

Table 6-3 Comparison of the Synthetic and Observed Population Characteristics for the Base Year 2006

Variables	Synthetic Population (%)	Observed Population (%)	Difference (%)
<i>Gender</i>			
Female	52.55	52.02	0.53
Male	47.45	47.98	-0.53
<i>Age (years)</i>			
0 to 9	10.39	10.16	0.23
10 to 14	6.14	5.99	0.15
15 to 19	6.06	6.53	-0.47
20 to 24	7.49	7.55	-0.06
25 to 29	6.94	6.98	-0.04
30 to 34	7.02	6.93	0.09
35 to 39	7.58	7.35	0.22
40 to 44	8.93	8.79	0.14
45 to 49	8.50	8.47	0.03
50 to 54	7.66	7.57	0.09
55 to 64	11.65	11.62	0.03
65 to 74	6.36	6.50	-0.14
75 and Above	5.29	5.56	-0.26
<i>Marital Status</i>			
Single	37.04	36.01	1.02
Married	47.06	47.27	-0.21
Separated	3.26	3.44	-0.18
Divorced	7.54	7.73	-0.19
Widowed	5.10	5.55	-0.45
<i>Employment Status</i>			
Employed	63.58	64.55	-0.97
Unemployed	4.21	4.32	-0.11
Not in Labour Force	32.21	31.13	1.08

Table 6-3 Comparison of the Synthetic and Observed Population Characteristics for the Base Year 2006 (Continued)

Variables	Synthetic Population (%)	Observed Population (%)	Difference (%)
<i>Household Size</i>			
1 person	27.76	27.74	0.03
2 person	35.57	35.56	0.00
3 person	16.67	16.65	0.02
4-5 person	18.54	18.51	0.03
6 person and Above	1.46	1.54	-0.07
<i>Household Income (1000 \$CAD)</i>			
Under 20	15.31	15.36	-0.04
20 to 49	30.90	30.96	-0.06
50 to 79	24.11	24.06	0.05
80 to 99	10.89	10.97	-0.08
100 and Above	18.79	18.65	0.14
<i>Tenure Type</i>			
Own	64.07	64.01	0.06
Rent	35.93	35.99	-0.06
<i>Dwelling Type</i>			
Single-detached	51.52	51.57	-0.05
Semi-detached	6.74	6.81	-0.07
Row House	3.51	3.51	0.00
Apartment with 5 and Above Storey	9.59	9.53	0.06
Apartment with Less than 5 Storey	22.15	22.09	0.06
Duplex Apartment	4.04	4.04	0.01
Movable	2.26	2.28	-0.02
Other	0.19	0.19	0.01

6.4 Vehicle Ownership Level Synthesis

Vehicle ownership level synthesis component generates the vehicle ownership level for the baseline population in the following four classes: zero vehicle, one vehicle, two vehicle, and three or more vehicle. Since, vehicle ownership information is not available in the census and Public Use Microdata File (PUMF), the population synthesis procedure does not include vehicle ownership as a control variable. A multinomial logit (MNL) model is developed to generate the baseline vehicle ownership level utilizing the HMTS data.

6.4.1 Model Estimation

The parameter estimation results of the vehicle ownership synthesis model is presented in Table 6-4. The model results suggest that socio-demographic characteristics significantly influence vehicle ownership level. For example, in the case of zero vehicle ownership, the model confirms the effects of age, income, and household size. Younger head households represented by age below 30 years show a higher likelihood to have zero vehicle ownership, which is aligned with the past literature. For instance, Kuhnimhof et al. (2012) found a reduction in vehicle ownership, and Schoettle and Sivak (2014) revealed a higher use of sustainable modes among the younger population. Such lower vehicle ownership might be triggered by the change in transportation and communication technologies, and growing environmental concern among the younger adults. Low income population represented by household income below \$50,000 reveals a higher probability to have zero vehicle. Constrained affordability of the low income households might limit their vehicle ownership level. Single person households are more likely to have zero vehicle, which is intuitive for smaller sized households and aligned with the findings of Anastasopoulos et al. (2012).

Table 6-4 Parameter Estimation Results of the Vehicle Ownership Level Synthesis Model

Explanatory Variables	Variable Description	Multinomial Logit Model <i>co-efficient (t-stat)</i>
<i>Zero Vehicle Ownership</i>		
Constant		0.08135 (0.32)
Age below 30 Years	Age of the head of the household below 30 years	0.69595 (3.43)
Income below 50k	Household income below \$50,000(CAD)	1.89429 (7.66)
Household Size 1	Single person household	1.07394 (4.53)
<i>One Vehicle Ownership</i>		
Constant		1.75972 (8.34)
Income below 50k	Household income below \$50,000(CAD)	0.60362 (2.98)
Presence of Children	Households with children	1.10638 (4.56)
Rented Dwelling	Household residing in rented dwelling	0.26514 (1.63)
<i>Two Vehicle Ownership</i>		
Constant		1.14346 (5.47)
Age above 50 Years	Age of the head of the household above 50 years	0.39609 (2.34)
Income above 100k	Household income above \$100,000(CAD)	0.56649 (3.19)
Presence of Children	Households with children	1.53327 (6.20)
<i>Three or More Vehicle Ownership (Constant = Reference)</i>		
Income above 100k	Household income above \$100,000(CAD)	1.60610 (5.11)
Household Size > 3	Number of persons in the household more than 3	0.88812 (3.03)
<i>Goodness-of-fit Measures</i>		
Log-likelihood (at convergence)		-987.439
Log-likelihood (at constant)		-1142.241
Adjusted Pseudo R-squared		0.131

The model results reveal that the vehicle ownership level increases as household income, age, and household size increases, which is expected. For instance, households with income above \$100,000 show a higher likelihood for

two vehicle ownership. In the case of three or more vehicles, the effect of the same variable representing income above \$100,000 increases by 3 times. Older head households with age above 50 years show a positive association with two vehicle ownership; since, older population of this generation are more dependent on cars and prefer higher vehicle ownership (Hjorthol et al., 2010). Interestingly, presence of children in the household show a positive relationship for one vehicle ownership and two vehicle ownership. Arguably, individuals with children might require to trip chain to day care centers/schools on their way to work, and require car for convenience. This variable shows a 1.5 times stronger relationship for two vehicle ownership than one, which is expected as multiple vehicles might offer added flexibility to both the parents or other members of the household to travel with children. All the variables retained in the final model exhibit statistical significance at the level of 95% confidence interval.

6.4.2 Vehicle Ownership Level Synthesis Results

The MNL model described above is utilized to determine the probability of a household to own zero, one, two, and three or more vehicles. Households are assigned to a vehicle ownership level following the order of probability estimation. The distribution of the generated baseline vehicle ownership level for 2006 is illustrated in Figure 6-2. The results suggest that 22.55% of the households do not own a vehicle, 37.40% own one vehicle, 32.16% own two vehicles, and 7.89% own three or more vehicles. Due to the unavailability of the actual vehicle ownership information in 2006 for Halifax, the results could not be validated.

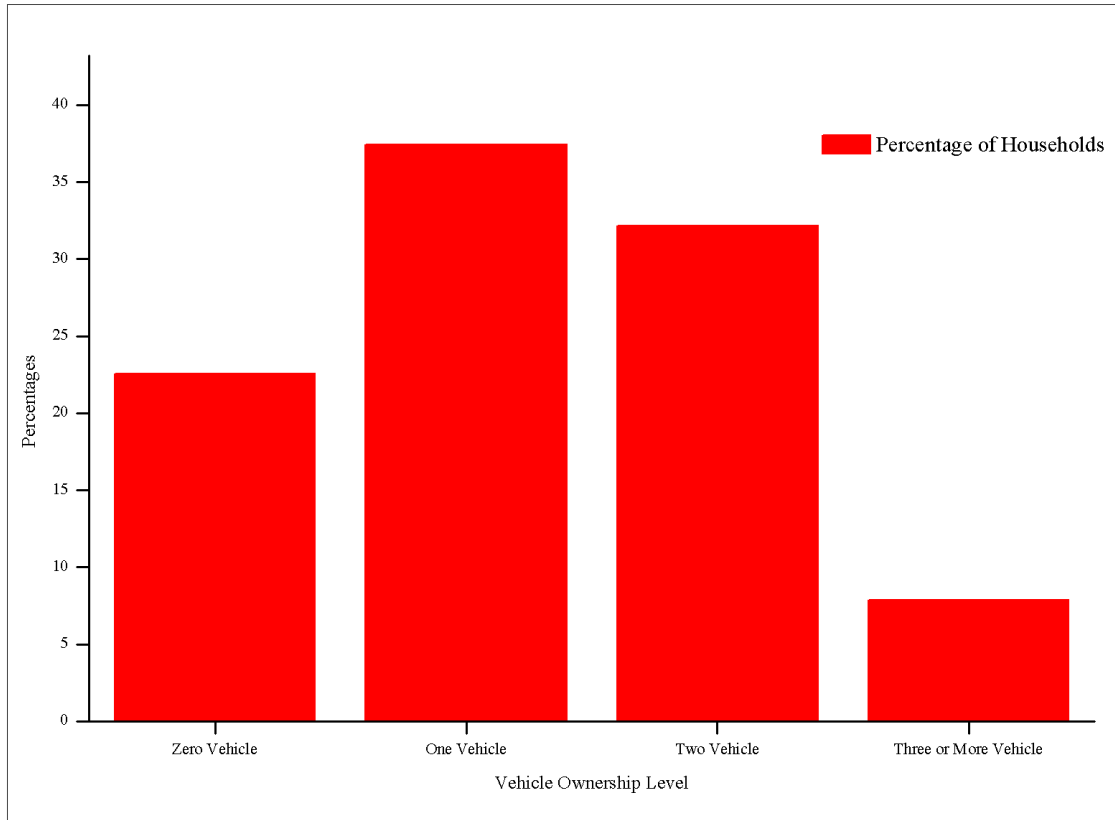


Figure 6-2 Vehicle Ownership Level Synthesis Results for the Year 2006

6.5 Population Life-stage Transition Module

6.5.1 Microsimulation Process

The current version of iTLE simulates the following six life-stage transitions: ageing, death, birth, out-migration, in-migration, and household formation. The proto-type implements this module at a yearly time-step for the simulation years 2007 to 2021. A 10% sample of the synthesized Halifax population is used for the simulation.

The life-stage transitions are simulated as binary probabilities of a transition to occur or not. This module follows a heuristic modelling approaches, where average of the historical rates (Appendix A) are used to determine the rate of

an event and consequently develop the rules. For example, the microsimulation process of the birth component is presented in Figure 6-3.

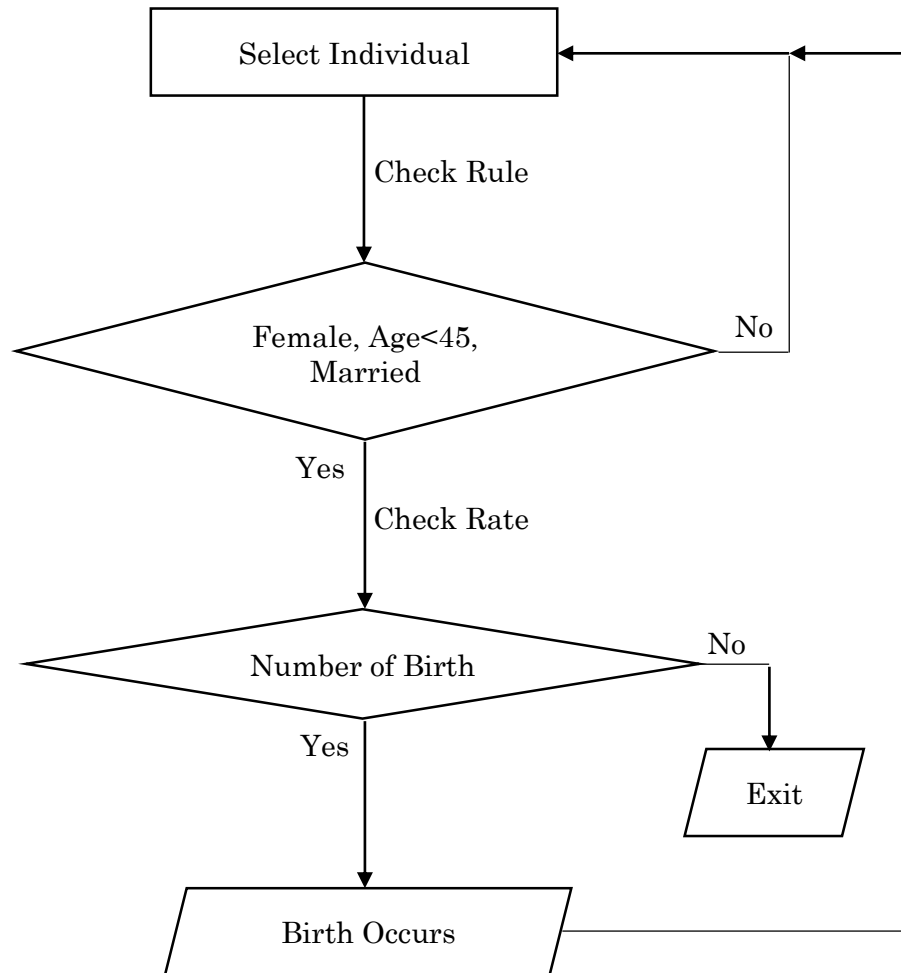


Figure 6-3 Process Diagram for the Birth Component of the Life-stage Transition Module

Figure 6-3 depicts that the birth component heuristically evaluates the candidacy of a household based on the presence of female in the household, their age, and marital status. Then, a child birth is assigned to a household controlling for the historical birth rate from Statistics Canada. The simulation of rest of the life-stage elements follows a similar technique. For the death component, individuals above a lower limit cut-off point of age are only

considered. The number of individuals to experience the death event in a year is determined by using the historical death rate information.

The out-migration and in-migration simulate the migration of the entire household in the study area and update of the lists, including individual, household, and location lists, subsequently. The household formation component determines the occurrence of marriage between two adult candidates of opposite sex. The candidacy of a male and a female for a marriage is evaluated on the basis of their age, age difference, and marital status. Finally, marriage is assigned to occur between two potential individual candidates using historical marriage rate. Following the formation of a new household, both individuals are assumed to leave their former household and move to a new location, which is determined during the residential location transition module. Subsequently, individual and household lists are updated. Moreover, individuals' age is updated by following a deterministic process. In this technique, the age of all individuals in the system is increased by one in each simulation year.

6.5.2 Validation Results

The simulation results of the life-stage transition module is validated at the 2011 time point using the census information. The results suggest that the iTLE under-represents the total number of population by 3.86%. Since the synthetic population under-represented the observed population in 2006 and the simulation for each year is processed using information from the previous simulation year, the error propagation causes a systematic under-estimation of population over time. A comparison between the characteristics of the simulated and observed population is presented in Table 6-5. The comparative results suggest that the iTLE performs reasonably well, as majority of the categories of the population attributes show a difference of less than 1%. For

example, in the case of marital status, the simulated single population share slightly under-represents observed single population by 0.40% only.

Table 6-5 Comparison of Simulated and Observed Population Characteristics for the Year 2011

Variables	Simulated Population (%)	Observed Population (%)	Difference (%)
<i>Gender</i>			
Female	52.77	51.65	1.12
Male	47.23	48.35	-1.12
<i>Age (years)</i>			
0 to 9	5.51	10.03	-4.52
10 to 14	10.24	5.25	4.99
15 to 19	5.90	6.11	-0.21
20 to 24	5.63	8.01	-2.38
25 to 29	7.50	7.29	0.21
30 to 34	7.37	6.68	0.69
35 to 39	7.10	6.79	0.31
40 to 44	7.18	7.14	0.04
45 to 49	8.68	8.49	0.19
50 to 54	7.87	8.11	-0.24
55 to 64	6.68	13.14	-6.46
65 to 74	10.27	7.30	2.97
75 and Above	10.06	5.64	4.42
<i>Marital Status</i>			
Single	39.92	40.32	-0.40
Married	45.77	45.95	-0.18
Separated	2.98	2.83	0.15
Divorced	6.95	5.91	1.04
Widowed	4.39	5.00	-0.61
<i>Household Size</i>			
1 person	29.19	28.56	0.63
2 person	34.26	36.50	-2.24
3 person	15.61	16.35	-0.74
4-5 person	18.25	17.06	1.19
6 person and Above	2.70	1.54	1.16

Table 6-5 Comparison of Simulated and Observed Population Characteristics for the Year 2011 (Continued)

Variables	Simulated Population (%)	Observed Population (%)	Difference (%)
<i>Household Income (1000 \$CAD)</i>			
Under 20	14.53	7.60	6.93
20 to 49	33.15	26.98	6.17
50 to 79	23.49	25.07	-1.58
80 to 99	10.57	13.42	-2.85
100 and Above	18.27	26.93	-8.66
<i>Tenure Type</i>			
Own	58.31	63.42	-5.11
Rent	41.69	36.58	5.11
<i>Dwelling Type</i>			
Single-detached	50.87	51.00	-0.13
Semi-detached	6.27	6.84	-0.57
Row House	3.19	3.73	-0.54
Apartment with 5 and Above Storey	12.73	10.67	2.06
Apartment with Less than 5 Storey	20.48	21.46	-0.98
Duplex Apartment	4.09	3.80	0.29
Movable	2.18	2.39	-0.21
Other	0.18	0.14	0.04

The iTLE model is also validated by performing a cross comparative analysis of the simulated and observed population attributes, as shown in Figure 6-4 to 6-7. The age distribution of the predicted female and male is compared with the Census (Figure 6-4). The iTLE generates reasonably accurate distribution of the age cohorts for both female and male population, with a difference of less than 1% in majority of the cases. For example, the simulation performs reasonably well for males and females in different age cohorts between 15 to 54 years. However, males and females below 10 years of age, and above 64

years show a difference of more than 1%. Figure 6-5 and 6-6 demonstrate the distribution of marital status by age for female and male, respectively. Majority of the attributes show a difference of less than 1%. However, the results show a slightly higher under-representation of single population under 10 years of age, and over-representation of married and divorced population over 64 years, which correspond to the under- and over-representation of male and female of the same age cohorts in Figure 6-4. Similarly, the iTLE produces reasonably representative distribution of household income by dwelling type, as shown in Figure 6-7.

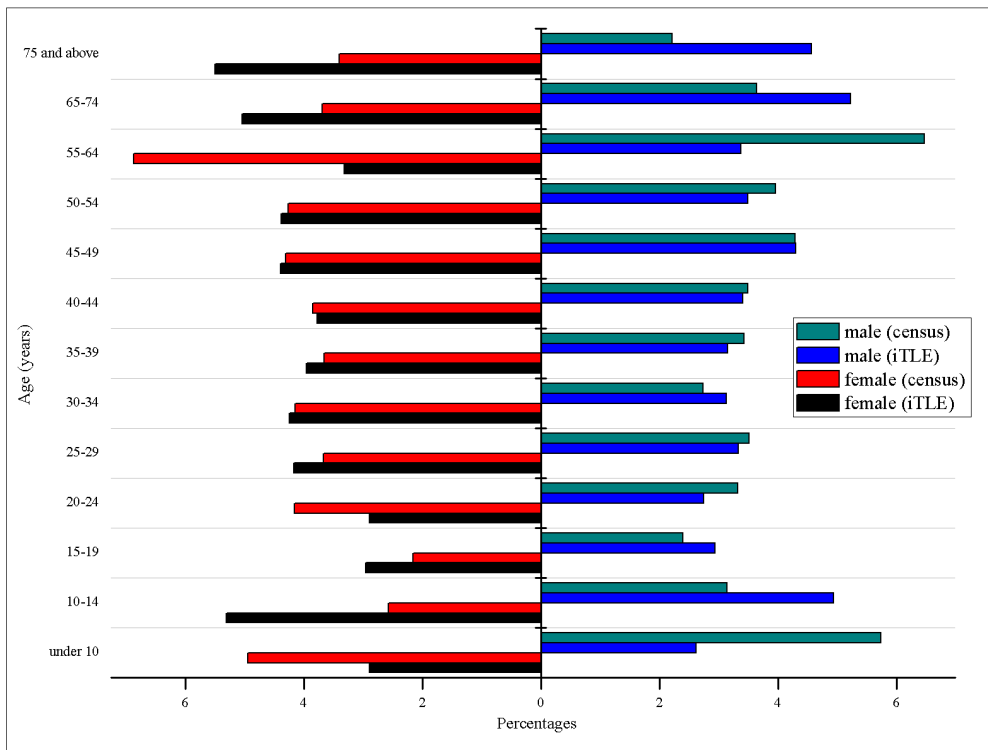


Figure 6-4 Age Distribution of Female and Male of Simulated and Observed Population for the Year 2011

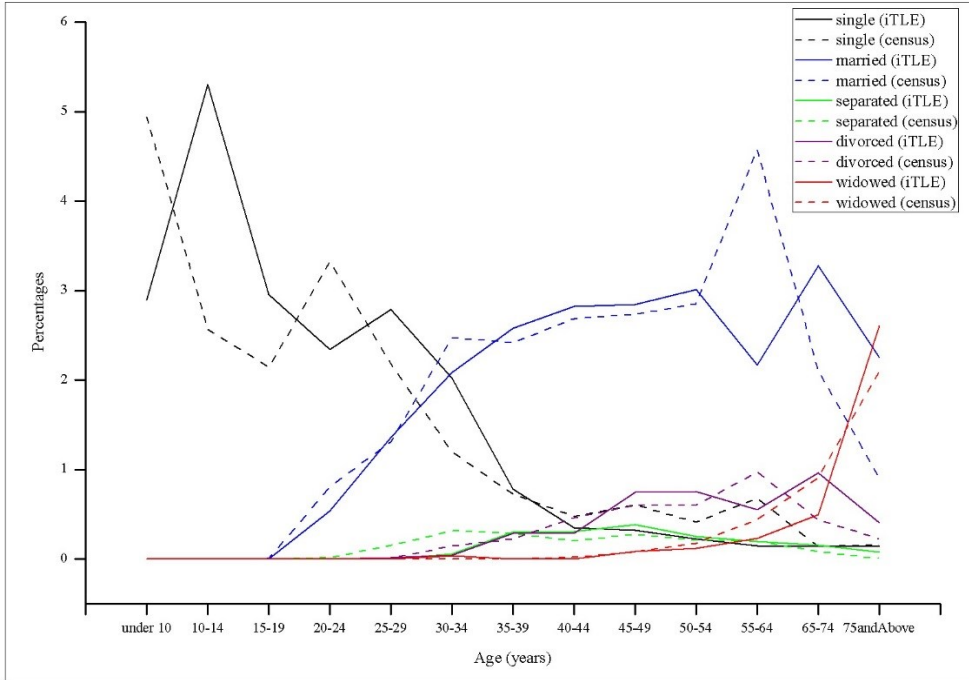


Figure 6-5 Age and Marital Status Distribution of Female of Simulated and Observed Population for the Year 2011

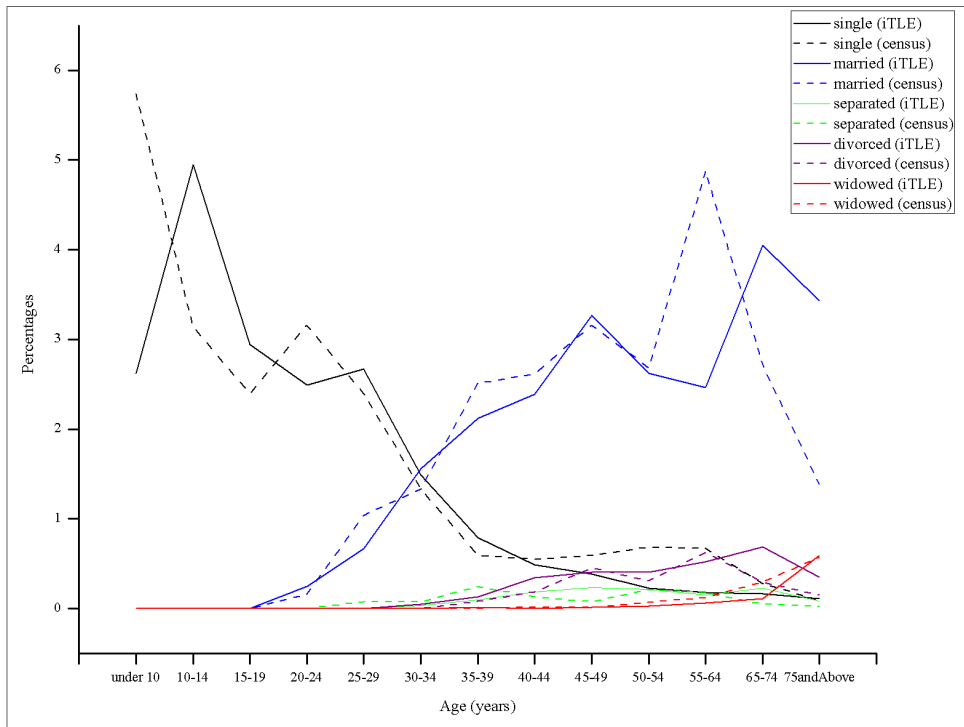


Figure 6-6 Age and Marital Status Distribution of Male of Simulated and Observed Population for the Year

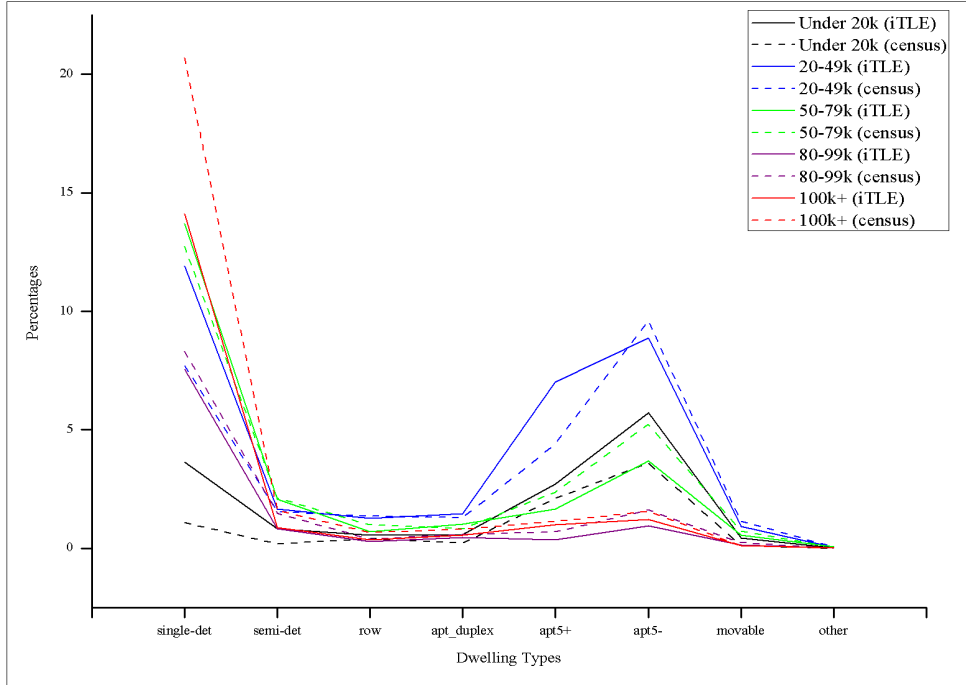


Figure 6-7 Household Income and Dwelling Type Distribution of Simulated and Observed Population for the Year 2011

6.5.3 Microsimulation Results

The predicted life-stage transition rates from 2007 to 2021 are presented in Figure 6-8. Note the two Y-axis and the scale difference. The black lines in the graph represent rates for different demographic events per 1000 population and correspond to the Y-axis on the left side. The red lines represent rates per 1000 households and correspond to the Y-axis on the right side. The iTLE predicts an increase of population in each simulation years. A total of 14.08% population is predicted to increase in 2021 compared to 2006. This net increase is attributed by a consistent higher rate of birth and in-migration compared to death and out-migration over the years, as illustrated in Figure 6-8. In 2021, the iTLE predicts the rates for birth, death, and marriage to be 11.73, 6.72, and 5.97 per 1000 individual, respectively. The predicted rates for in-

migration, out-migration, and movers are 40.71, 24.33, and 152.04 per 1000 households respectively in 2021.

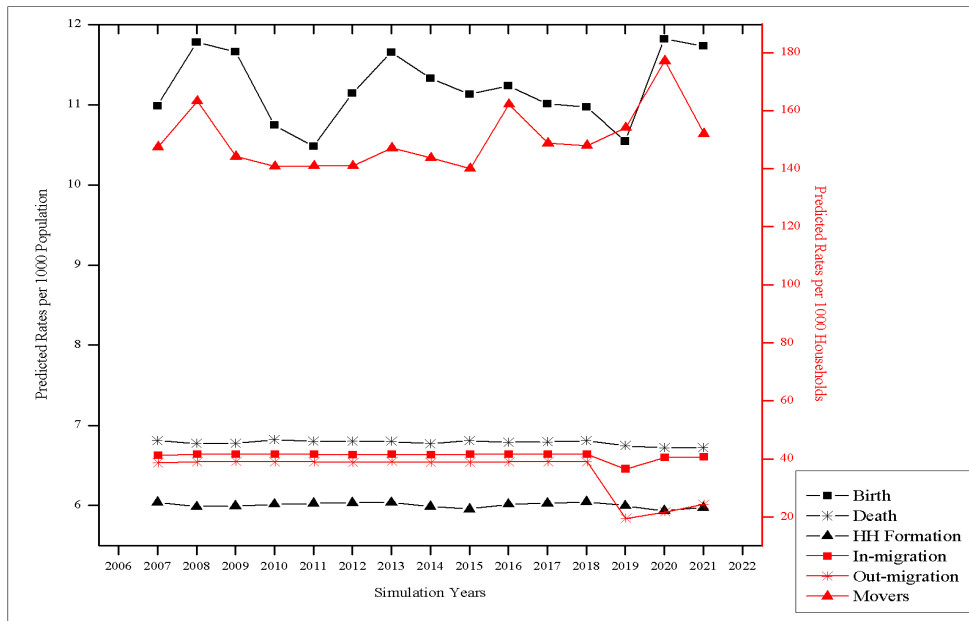


Figure 6-8 Predicted Life-stage Transition Rates for the Years 2007-2021

6.6 Conclusions and Summary of Contributions

This study contributes to the integrated urban modelling literature by developing micro-level population synthesis, vehicle synthesis, and microsimulation of life-stage transitions within a life-oriented agent-based iTLE model. A proto-type version of the iTLE is implemented for Halifax, Canada. Baseline information is generated for 2006, and simulation is run for a 15-year period from 2007 to 2021. The baseline synthesis includes, population synthesis at the parcel-level and vehicle ownership level synthesis. Population synthesis for the iTLE is a two-stage process: 1) population synthesis at the DA-level following an Iterative Proportional Updating (IPU) technique, and 2) allocation of the synthetic population to the parcels utilizing a logit link model. The iTLE generates a 100% synthetic population. The goodness-of-fit measures of the population synthesis results suggest a SRMSE value of 0.37. In addition,

around 89% of the DAs are found to show an APE measure of less than 5%. In the case of vehicle ownership level synthesis, a MNL model is developed to generate vehicle ownership in the following four levels: zero, one, two, and three or more vehicle. The synthesis results suggest that 22.55%, 37.40%, 32.16%, and 7.859% of the households own zero, one, two, and three or more vehicles, respectively.

The population life-stage transition module simulates a number of life-stages, such as ageing, birth, death, in-migration, out-migration, and household formation. Population life-stages are simulated following a heuristic modelling approaches. In this process, historical rates and rules are developed to determine the occurrence of an event for an individual/household in a particular simulation year. The life-stage transition module is validated with the Census 2011 information. A cross comparative analysis of the simulated and observed population attributes is performed. The cross comparative validation results suggest that majority of the categories of the population socio-demographic attributes show a difference of less than 1%. In the case of forecasting, the iTLE predicts an increase of 14.08% population in 2021 compared to 2006. The results suggest that the iTLE generates reasonably satisfactory population estimates for further model development and implementation.

In summary, the baseline synthesis and life-stage transition module developed in this study resolve some key issues in integrated urban modelling, which will assist in implementing state-of-the-art residential location and vehicle transaction decision components within the iTLE framework. For example, the life-stage transition component will assist in maintaining the multi-domain decision interactions along the life-course of the agents. In addition, population synthesis at the micro-spatial level enables iTLE to simulate agents decisions and changes at the disaggregate spatial-level. Finally, the vehicle ownership

synthesis adds the capacity to the iTLE to perform vehicle ownership simulation.

Microsimulation of Residential Location Processes

7.1 Introduction

This chapter presents the microsimulation of residential location transition module of the iTLE model. The residential location module is implemented by utilizing the micro-behavioural models developed in Chapter 4. This research contributes to the microsimulation paradigm of residential location in the following three dimensions: 1) addressing the multi-domain interactions and life-course dynamics during the simulation procedure, 2) accommodating the process orientation of the phenomenon by implementing location decision as a two-stage process of mobility and location choice, and 3) predicting the spatio-temporal evolution of the population and demographic configuration of the neighbourhoods. This study also offers a validation of the residential location simulation results.

The organization of this chapter is as follows: section 7.2 discusses the microsimulation processes of the mobility and location choice components of the location transition module. Section 7.3 provides the validation results of the module. Section 7.4 presents the microsimulation results, particularly, prediction of the evolution of urban population. Finally, section 7.5 concludes with a summary and potential use of the model.

The following paper is an earlier version of this chapter:

- Fatmi, M.R., and Habib, M.A. (2017). Development of a Proto-type Integrated Urban Model: Microsimulation of Life-stage Transitions and Residential Location Transitions. Published in the peer-reviewed proceedings of the 96th Annual Meeting of Transportation Research Board, Washington DC, USA, January 8-12.

7.2 Microsimulation Processes

The residential location transition module determines the choice of location as a process of mobility and location choice. To reduce the computational complexity, more compatible and simplified versions of the micro-behavioural models developed in Chapter 4 are considered for the implementation within the iTLE proto-type model system (Appendix B). The models maintain the basic principle of the life-course perspective through accommodating the effects of life-cycle events as lead and lag events. A description of the microsimulation processes is provided below.

7.2.1 Residential Mobility

The household-level residential mobility decision is simulated in each year by implementing a discrete time binomial logit model (Appendix B). The purpose for developing this discrete time binomial logit model is that it is more compatible for implementing within the discrete time simulation framework of the iTLE than the continuous time duration model developed in Chapter 4. The mobility model determines the probability of move of a household at a particular simulation year. The predictors' equation for the mobility model is written below:

$$Y_i = c + \alpha X_i + \varepsilon \quad (1)$$

Here, i is household, X is the predictor, c is the constant term, ε is the random error term, and α is the coefficient of the parameter to be estimated. Now the probability equation can be written as:

$$P(Y_i) = \frac{e^{c+\alpha X_i}}{1+e^{c+\alpha X_i}} \quad (2)$$

Households are assigned to move or stay list by comparing the estimated probability of the move against a randomly generated probability using Monte

Carlo Simulation technique. If the estimated probability is higher than the random probability, then households are assigned to move list and enter the location choice process. In contrary, households are assigned to stay list and exit the location transition module.

7.2.2 Residential Location Choice

The location choice of the households is simulated by using a multinomial logit (MNL) model (Appendix B), which is a simplified version of the model developed in Chapter 4. The spatial unit of simulation is at the parcel-level. The utility function for the location choice model can be written as:

$$V_{ij} = \alpha_j X_j + \alpha_{ji} X_j X_i + \varepsilon \quad (3)$$

Here, i is household, j is parcel, X is the predictor, ε is the random error term, and α is the coefficient of the parameter to be estimated. The term $X_j X_i$ represents interaction variables. The probability function can be written in the following logit form:

$$P_{ij} = \frac{\alpha_j X_j + \alpha_{ji} X_j X_i}{\sum_j \alpha_j X_j + \alpha_{ji} X_j X_i} \quad (4)$$

This location choice model determines the probability of choosing a location from a pool of randomly generated alternative locations. Based on the probability estimation, households are either assigned to move to the new location or stay at their current location. The allocation of a parcel to a household is sequential and follows the order of probability estimation. If a parcel is allocated to a household, it is made unavailable for other households. Based on the choice of new location, household, individual, and parcel lists are updated accordingly. The current version of the model only estimates location choice of the home owners'. Renters' location are simulated using a simplified heuristic process.

7.3 Validation Results

The performance evaluation of the location transition module is shown in Figure 7-1 and 7-2. Figure 7-1 shows the APE measures at the DA-level. The results suggest that around 21% of the DAs show an APE value of less than 10%. Moreover, around 31% of the DAs show an APE measures of 10%-30%.

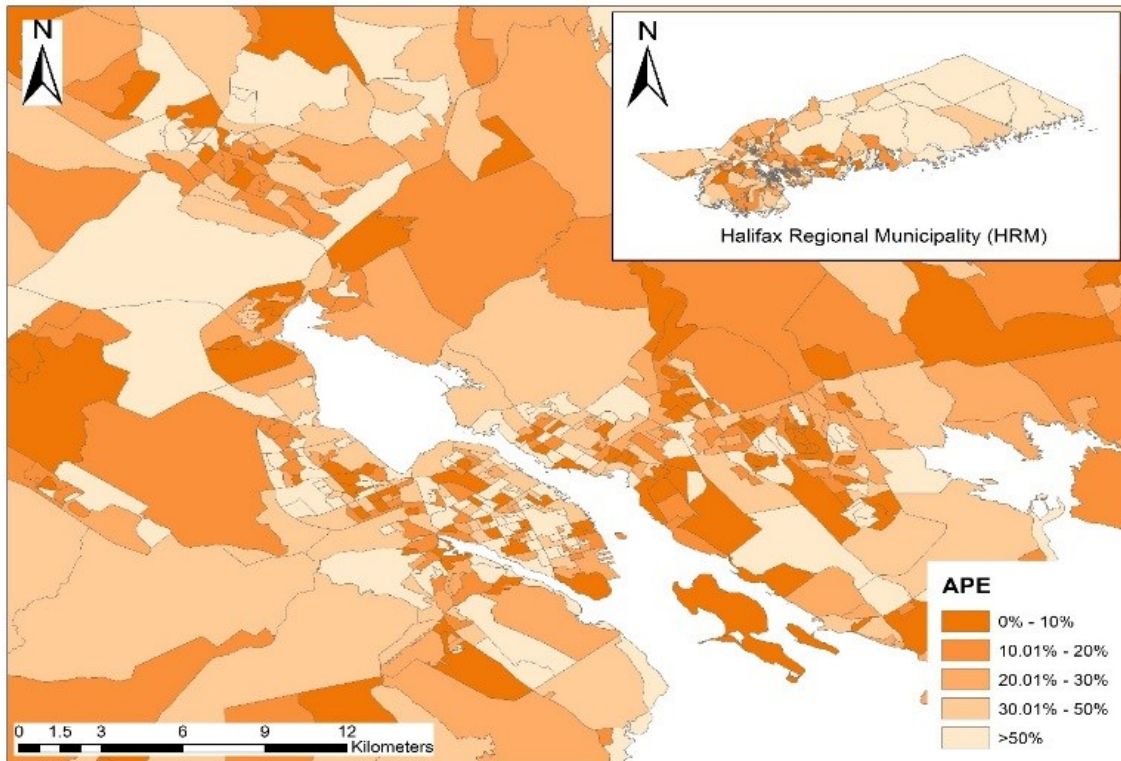


Figure 7-1 APE measures of the Simulated Households for the Year 2011

Figure 7-2 illustrates the difference in the number of households in each DA between the simulated and observed population. The graph shows the percentage of DAs falling under different categories of difference bands. The model predicts that around 37% of the DAs represent the observed population within the difference range of ± 50 number of households. Only 8% of the DAs show a difference of greater than ± 300 . In summary, it can be concluded that the iTLE performs reasonably well in predicting the residential location of the population.

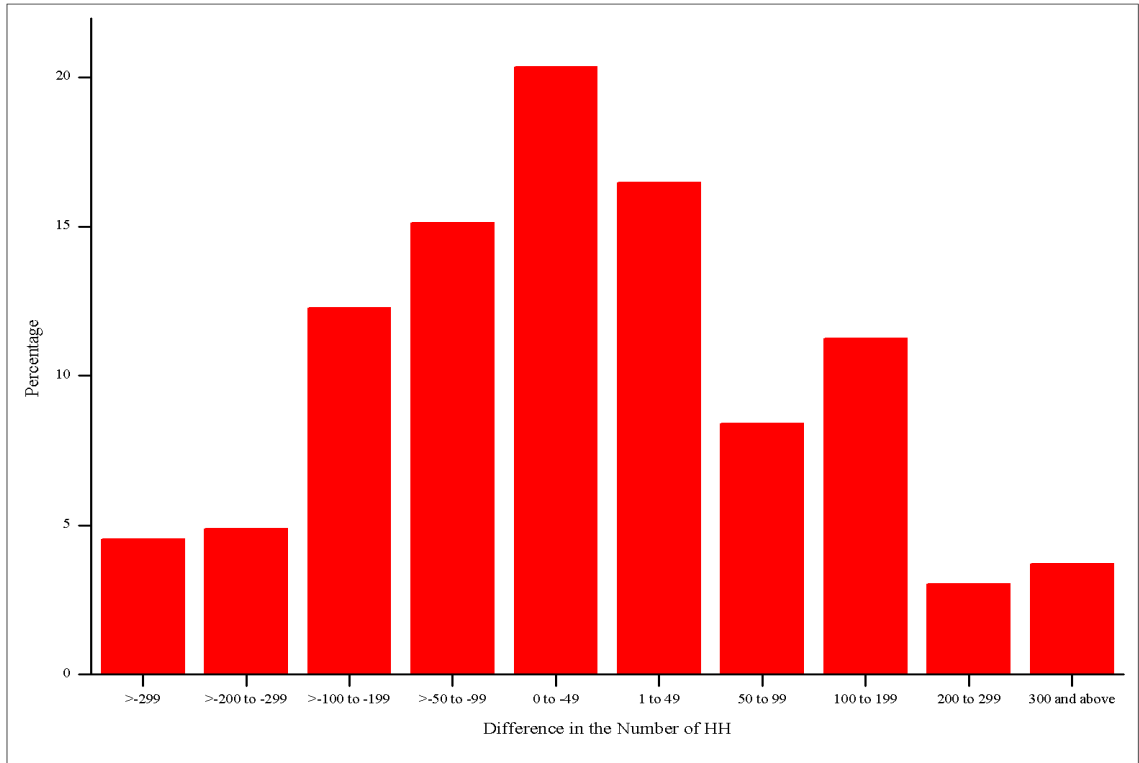


Figure 7-2 Difference between the Simulated and Observed Number of Households in the DAs for the Year 2011

7.4 Predicted Evolution of the Halifax Population Behaviour

This section presents the predicted temporal and spatial evolution of the mobility, housing pattern, and neighbourhood compositions for Halifax.

7.4.1 Predicted Evolution of Duration of Stay

To evaluate the demographic distribution of the predicted residential movers over the simulation years, a non-parametric density function for the duration of stay is utilized. Particularly, a kernel density estimation technique is adopted with the assumption of Gaussian kernel function for optimal bandwidth selection (Silverman 1986). Figure 7-3 to 7-6 present the kernel

density plots of the predicted duration of stay for different age groups. Here, age represents the age of the head of the household. The results suggest that the density is skewed to the left for households with younger head. The density is skewed to the right and is more variable as age increases. This implies that younger head households are predicted to be more frequent movers than their older counterpart. The mean of the duration for population with age <40, 40-54, 55-64, and 65 and above are predicted to be 3.53, 6.05, 6.60, and 7.24 years respectively.

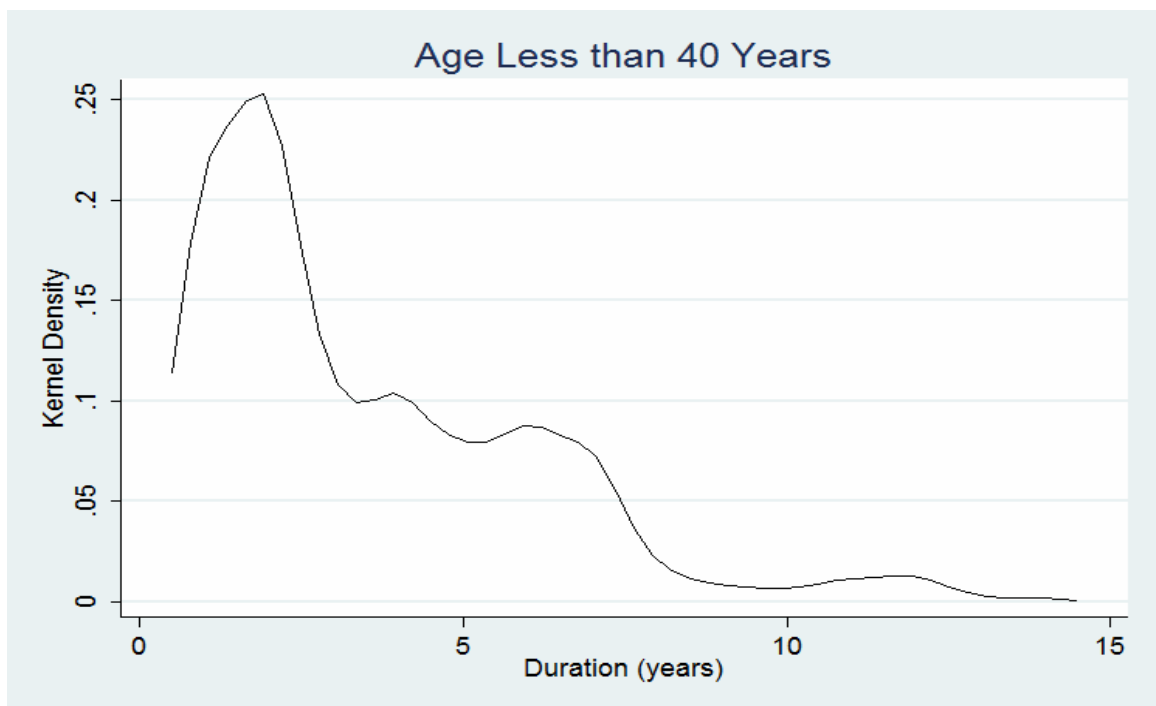


Figure 7-3 Predicted Duration of Stay of Population Aged < 40 Years for the Years 2007-2021

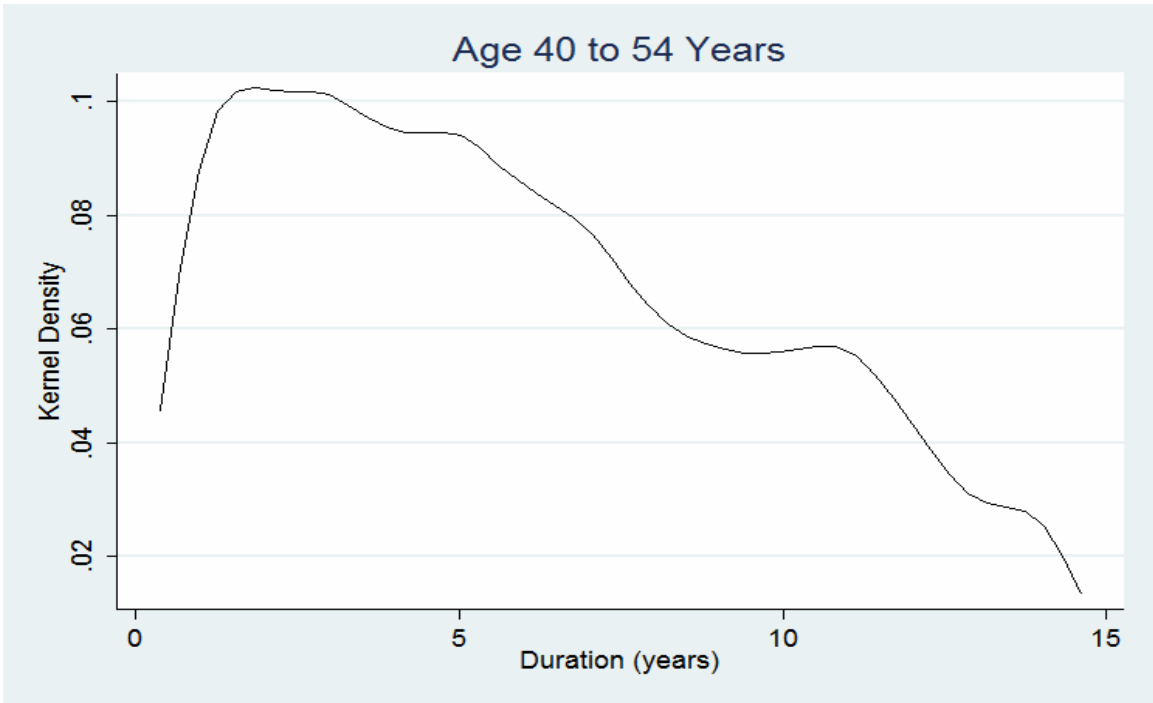


Figure 7-4 Predicted Duration of Stay of Population Aged 40-54 Years for the Years 2007-2021

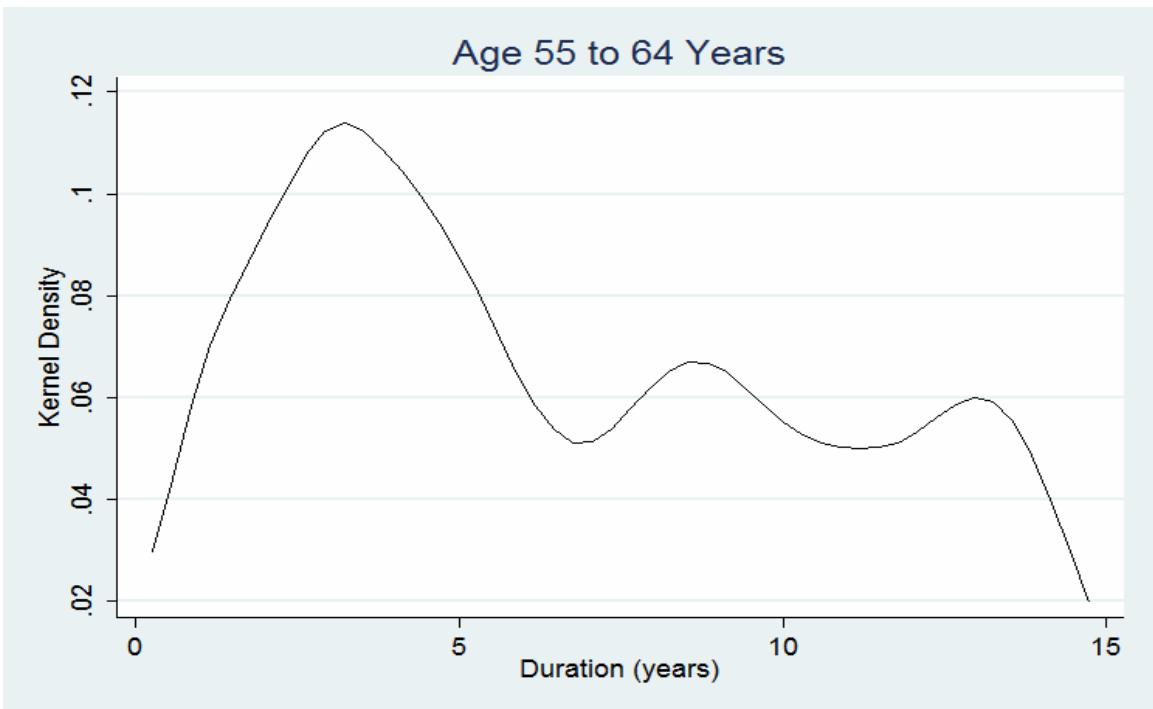


Figure 7-5 Predicted Duration of Stay of Population Aged 55-64 Years for the Years 2007-2021

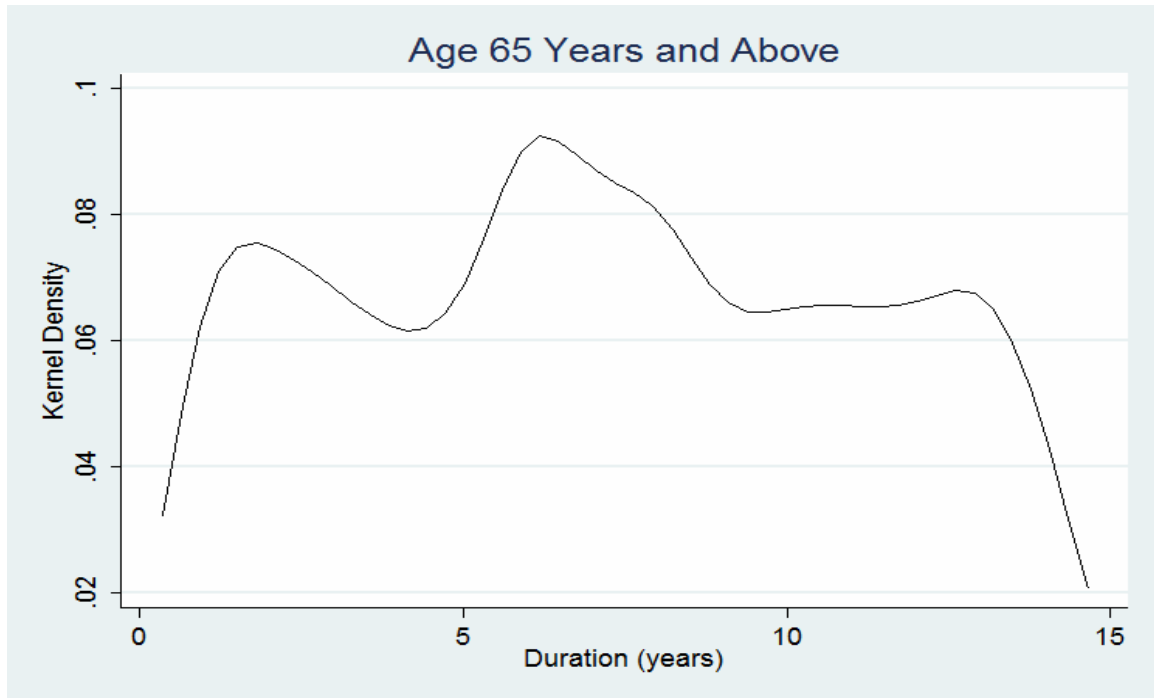


Figure 7-6 Predicted Duration of Stay of Population Aged > 64 Years for the Years 2007-2021

To evaluate the predicted spatial evolution of duration of stay by demographics, duration plot by location distance from CBD and age is demonstrated in Figure 7-7. Location distance from CBD refers to the distance of home parcel to the CBD, and age refers to the age of the head of the household. Duration is predicted to increase as age and location distance from CBD increases. This implies that younger head households residing closer to the CBD are predicted to be more frequent movers than older head households residing farther away from the CBD. As illustrated, duration is predicted to be substantially high to the right of 45 years and above 10 km from the CBD, revealing middle aged to older population residing in the suburban and rural neighbourhoods are predicted to be less frequent movers. Similarly, the plot of duration by location distance from CBD and household income in Figure 7-8 suggests that duration increases with household income and distance from CBD. This implies that low income households residing closer to the CBD are more frequent movers than their high income suburban and rural counterpart.

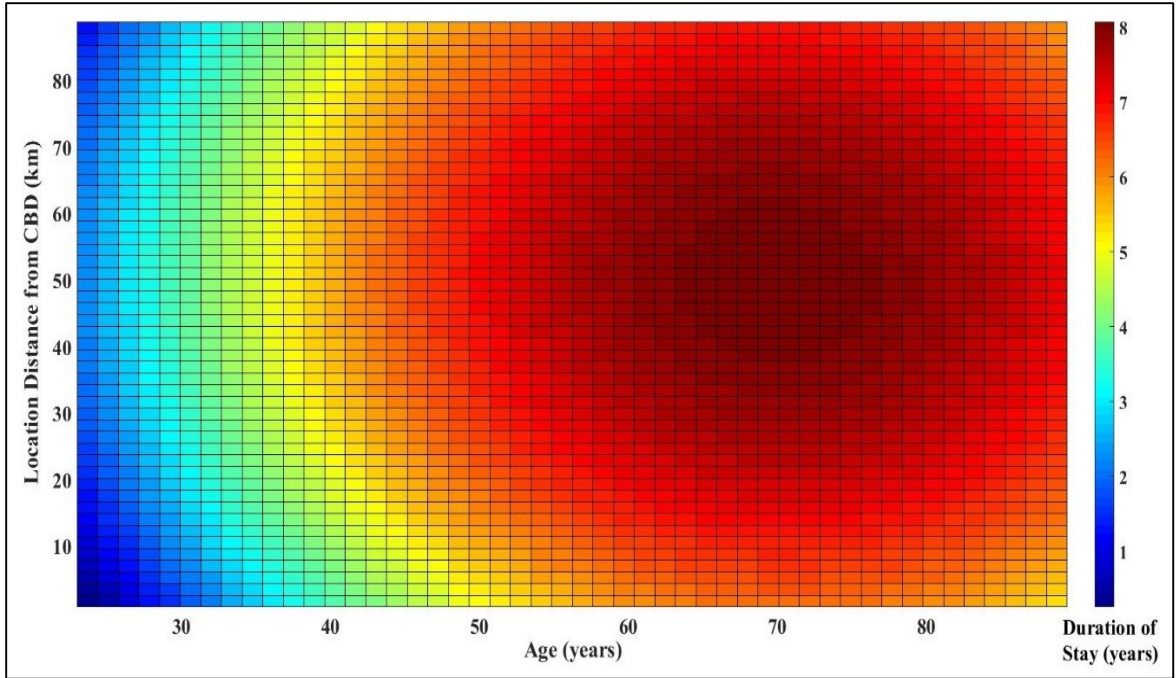


Figure 7-7 Predicted Duration of Stay of Population by Age and Location of the Residence for the Years 2007-2021

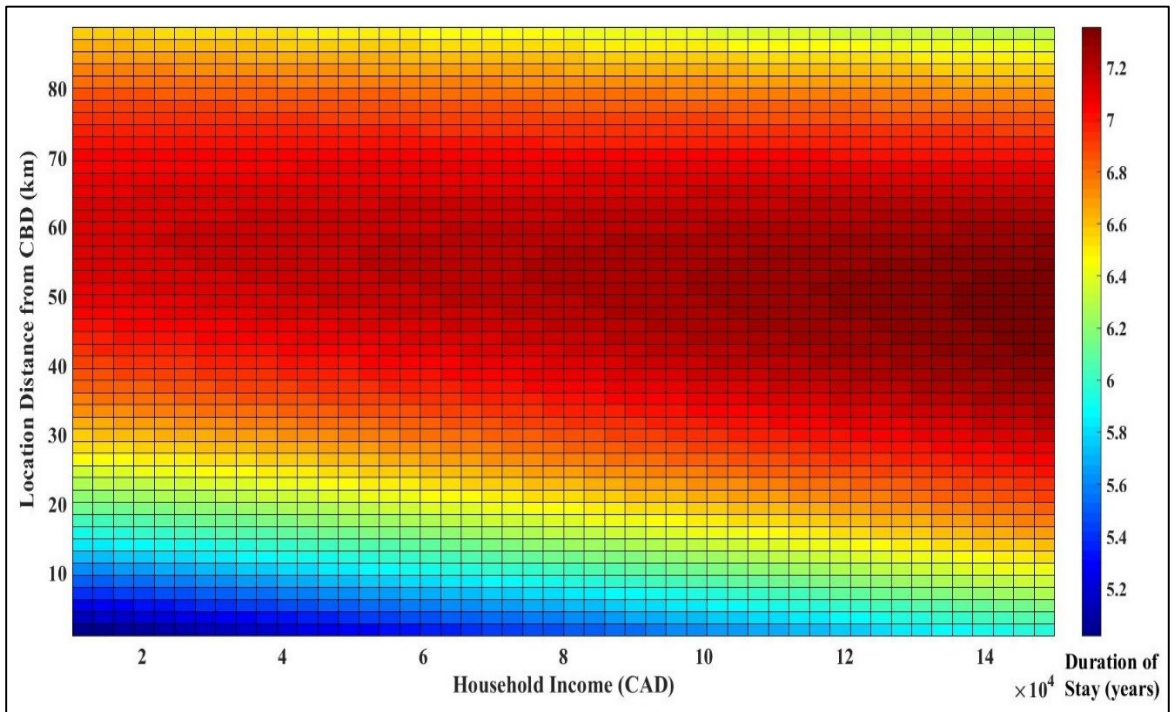


Figure 7-8 Predicted Duration of Stay of Population by Household Income and Location of Residence for the Years 2007-2021

7.4.2 Predicted Evolution of the Spatial Distribution of the Halifax Population

Figure 7-9 illustrates population density change at the DA-level from 2006 to 2021. A higher increase in density is predicted in the high density urban core (i.e. Halifax and Dartmouth urban core) and close by suburban areas (i.e. Clayton Park, Bedford, and Sackville). Interestingly, a higher density increase is predicted in the North End neighbourhoods of the Halifax Peninsula, which is documented by Roth, (2013) as neighbourhoods experiencing gentrification.

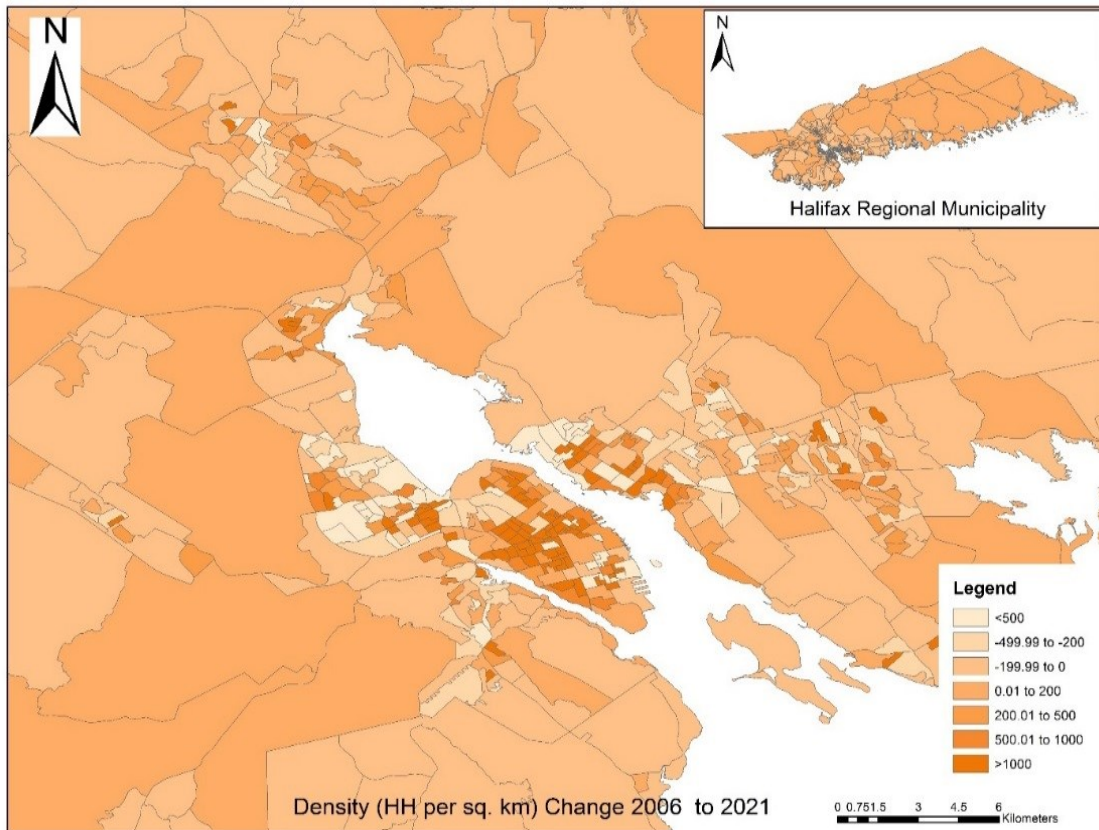


Figure 7-9 Predicted Household Density Change from 2006 to 2021

The spatial distribution of the Halifax population in 2021 is presented in Figure 7-10. The plot depicts the density of the households based on the location (parcel) distance from the CBD. A higher proportion of the households

is predicted in the locations within 25km from the CBD. Similar findings can be observed for the years 2007-2020, as reported in Appendix C. In the context of Halifax, these are the high density urban core and nearby suburban neighbourhoods, which corresponds to the high density areas in Figure 7-9. The proportion of the population residing in these high density neighbourhoods has increased over the 15 year periods. For example, 68% of the total households were predicted in these high density areas in 2007, which increased to 71% in 2021. The predicted evolution of the demographic composition of the high density neighbourhoods is discussed in the next section.

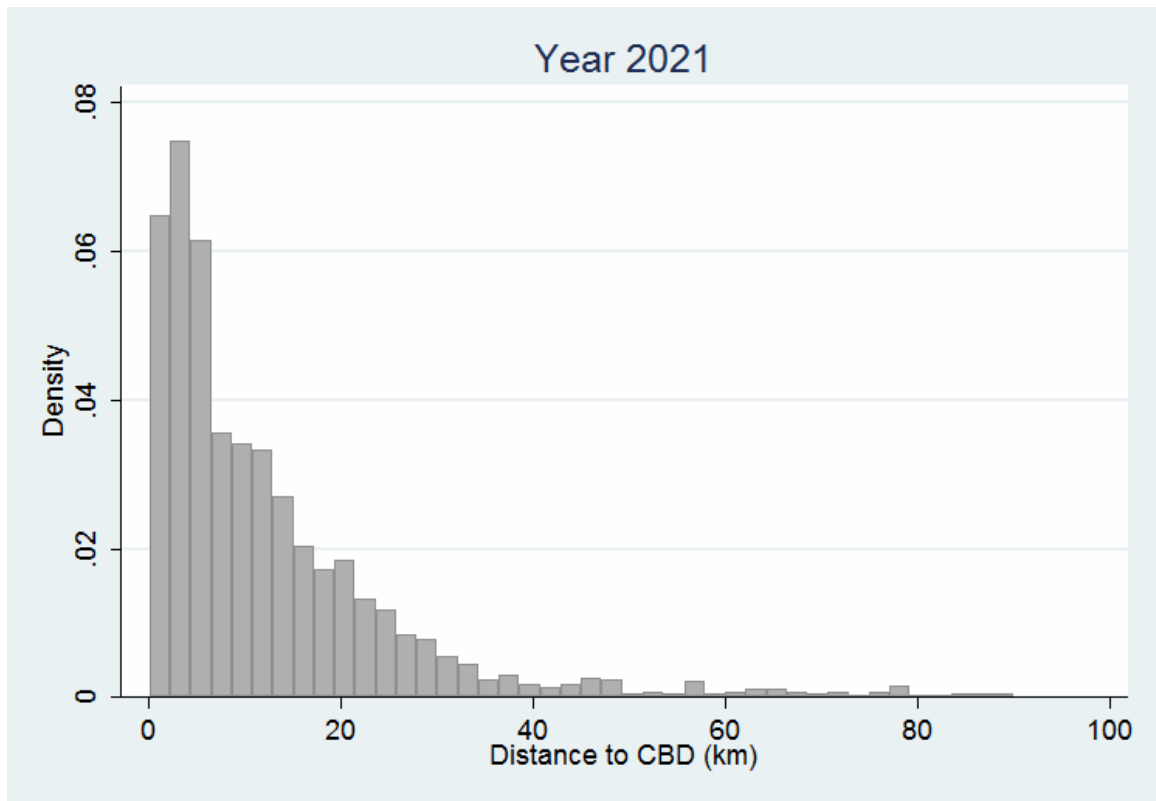


Figure 7-10 Predicted Spatial Distribution of the Halifax Population for the Year 2021

7.4.3 Predicted Demographic Composition of the High Density Neighbourhoods in Halifax

The predicted average density of the high density¹² neighbourhoods over the simulation years is presented in Figure 7-11. The plot shows the yearly average of the household density in each DA that falls under the high density category. As illustrated, average household density is predicted to increase in the high density DAs; to be specific, an average increase by around 632 household/sqkm in 2021 compared to 2007.

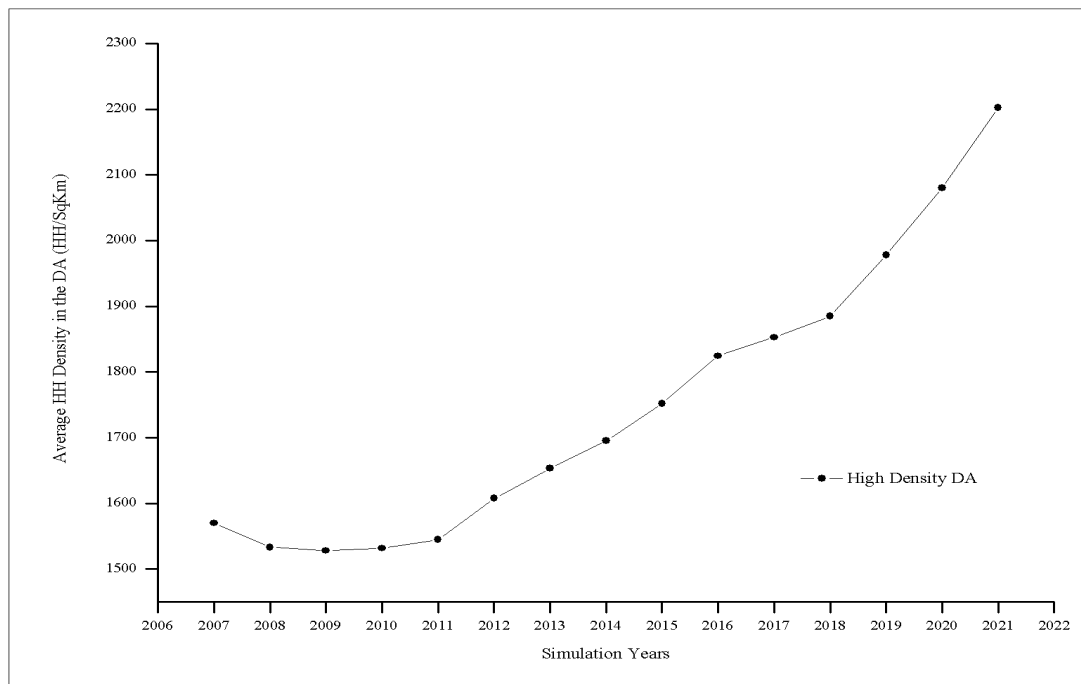


Figure 7-11 Predicted Yearly Avg. Household Density of the High Density DAs in Halifax for the Years 2007-2021

The distribution of the predicted average household income and average age in the high density DAs from 2007-2021 is shown in Figure 7-12 to 7-15. The

¹² High density neighbourhoods refer to the DAs with greater than 600 households per square km.

high density DAs are classified into low income¹³ and high income¹⁴ DAs. Figure 7-12 and 7-13 illustrate the yearly distribution of the average household income by DA in low income and high income high density DAs respectively. The average household income in low income DAs is predicted to increase over the years. The mean value of average income increased from around \$40,000 in 2007 to \$50,000 in 2021. The average household income in the high income DAs is predicted to be stable over the years. The mean value is around \$70,000.

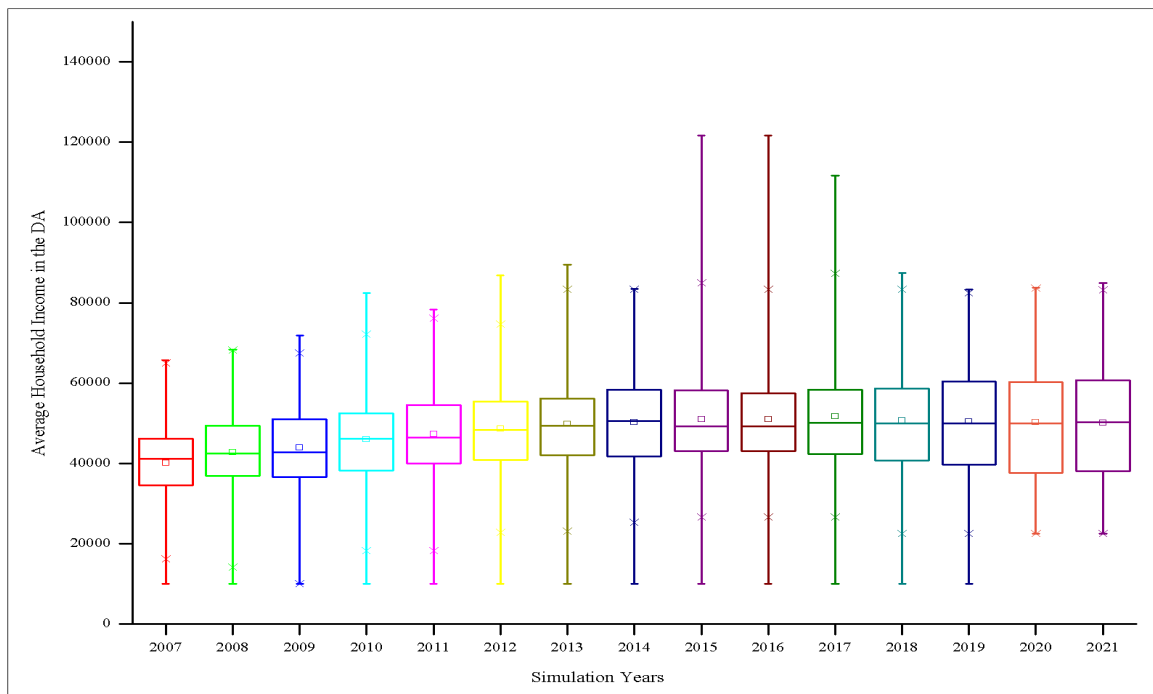


Figure 7-12 Predicted Yearly Avg. HH Income in Low Income High Density DAs in Halifax for the Years 2007-2021

¹³ Low income high density DAs refer to the high density DAs with average household income less than \$50,000

¹⁴ High income high density DAs refer to the high density DAs with average household income greater than \$50,000

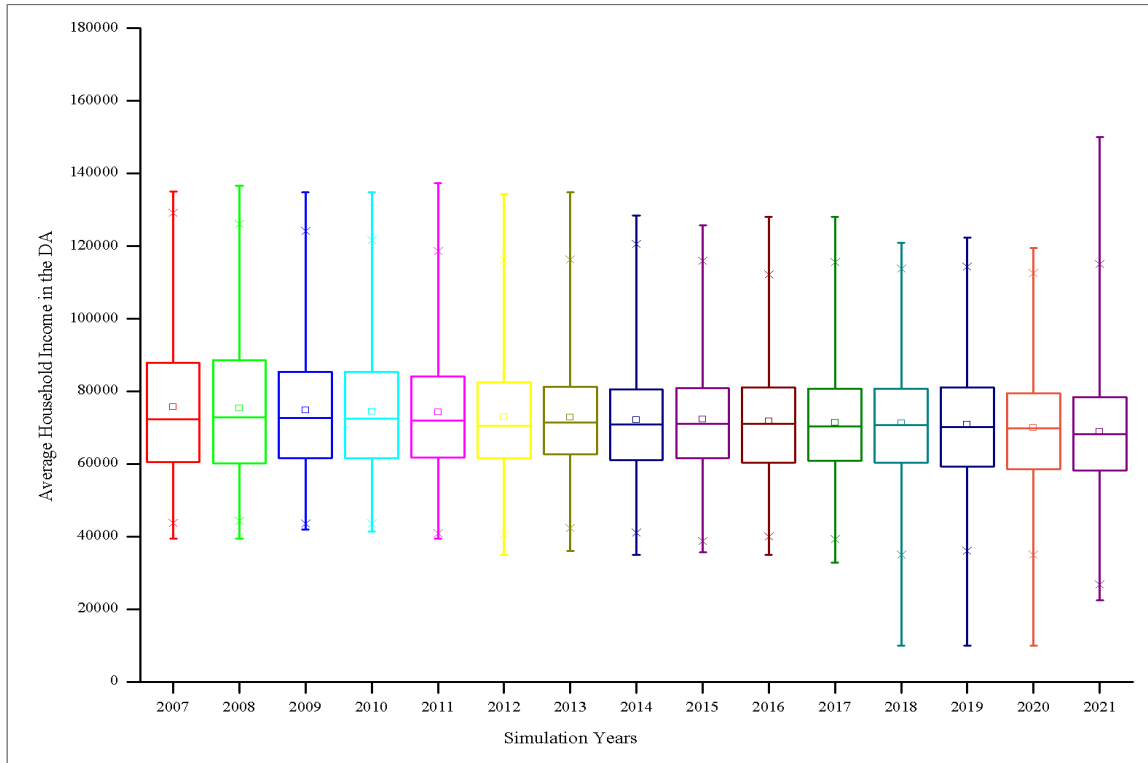


Figure 7-13 Predicted Yearly Avg. HH Income in High Income High Density DAs in Halifax for the Years 2007-2021

Figure 7-14 and 7-15 portray the yearly distribution of the average age by DA in low income and high income high density DAs respectively. Note that age refers to the age of the head of the household. Average age of the head of the household is predicted to increase in both the low and high income DAs. In the case of the low income DAs, the mean value of average age increased from around 50 years in 2007 to 58 years in 2021. For high income DAs, the mean value increased from around 52 years in 2007 to 61 years in 2021.

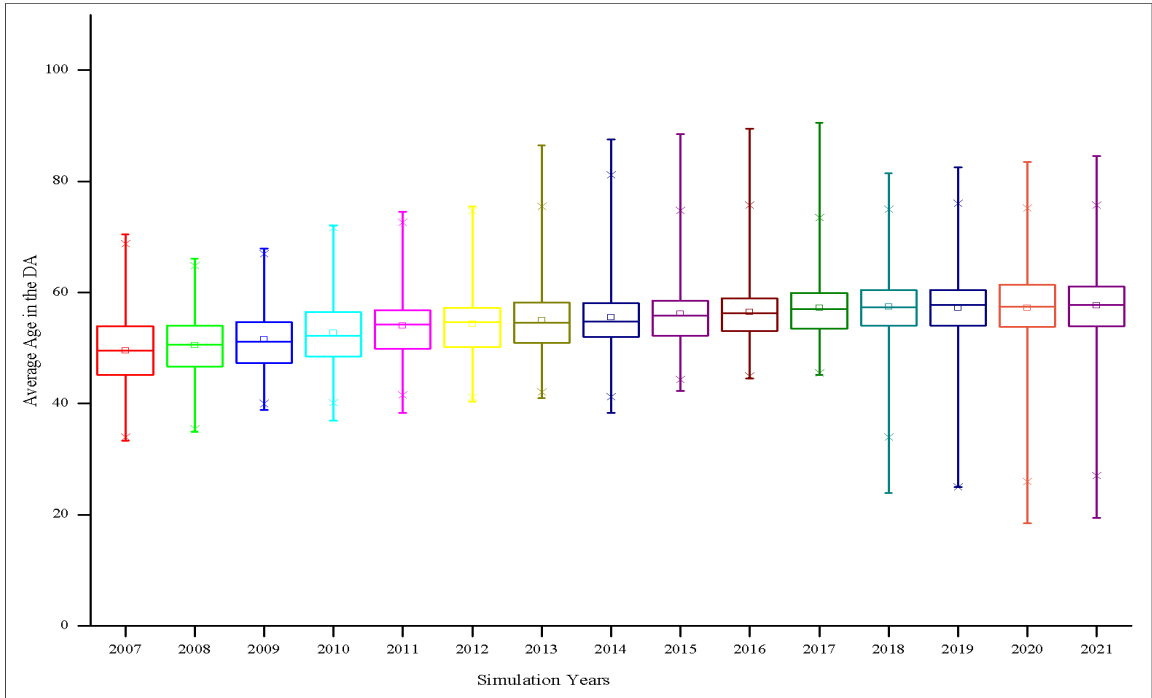


Figure 7-14 Predicted Yearly Avg. Age of HH Head in Low Income High Density DAs in Halifax for the Years 2007-2021

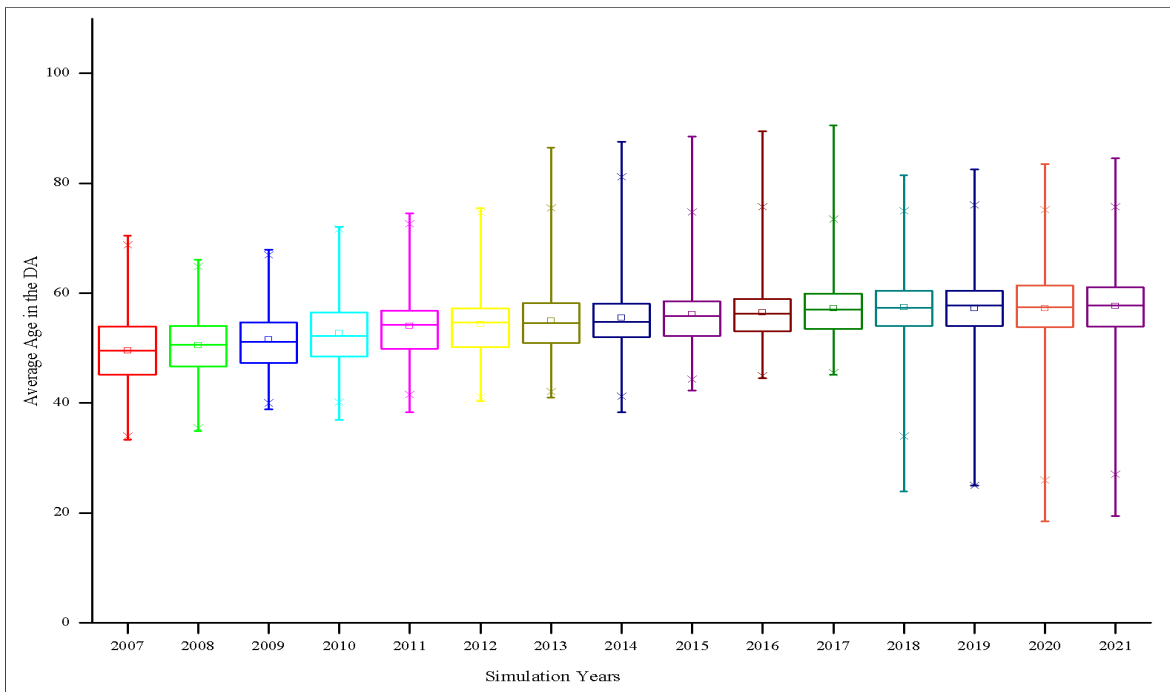


Figure 7-15 Predicted Yearly Avg. Age of HH Head in High Income High Density DAs in Halifax for the Years 2007-2021

The configuration of the high density neighbourhoods in terms of its population's demographics and household composition in 2021 is illustrated in Figure 7-16 to 7-20. Kernel density is plotted against the home location (parcel) distance from CBD for population with different household composition. In each figure from 7-16 to 7-20, three kernel density are estimated for low income¹⁵, medium income¹⁶, and high income¹⁷ households. The kernel density estimation assumes a Gaussian kernel function for optimal bandwidth selection. Fig 7-16 depicts that the density is skewed towards the left of 5km for single person households. Interestingly, the density is predicted to be more variable and skewed towards the right of 5km as household composition changes through life-events (i.e. marriage, having children), as shown in Fig 7-17 to 7-20. For example, a secondary peak in the density is predicted for couple without children for locations within 10-15km. Locations within 10-15km from the CBD in Halifax refer to suburban neighbourhoods. This implies that as household composition changes through marriage and birth of a child, households' density is skewed towards the suburban neighbourhoods. In the case of variation by household income, the density of high income households is skewed to the left of 5km and within 10-15km. For low and medium income households, density is skewed to the left of 10km. Interestingly, for couple with more than two children, the variation by income is predicted to be relatively small. Similar observations can be made for other simulation years as well.

¹⁵ Low income refers to household income less than \$50,000

¹⁶ Medium income refers to household income between \$50,000 and \$100,000

¹⁷ High income refers to household income above \$100,000

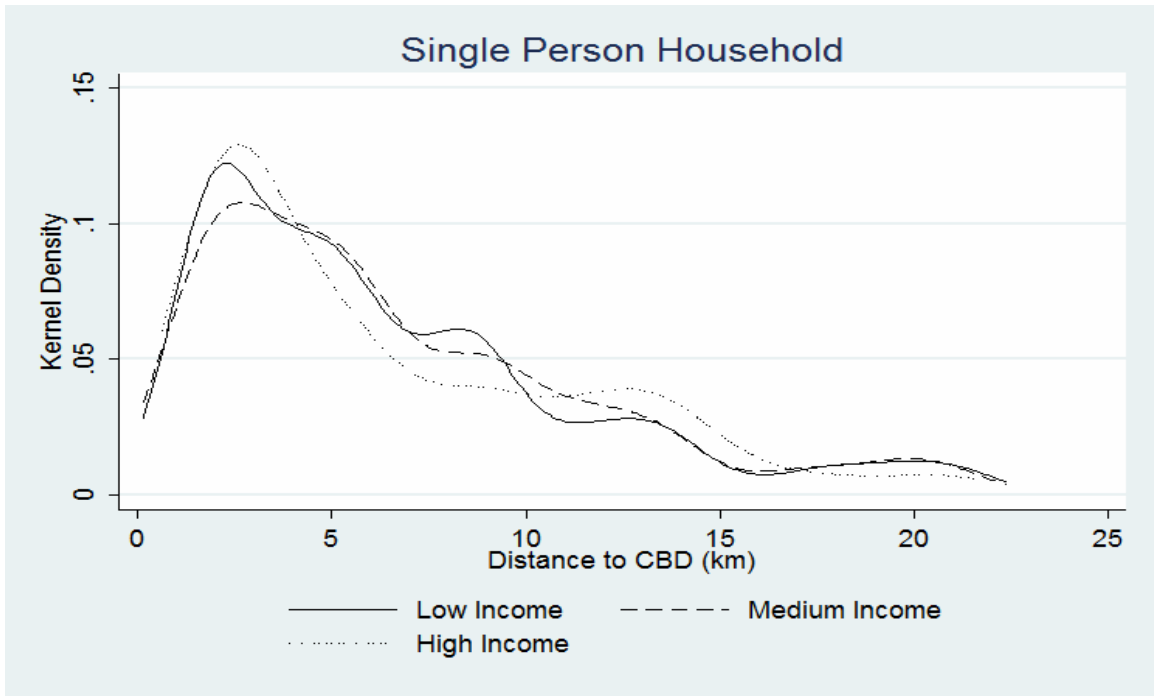


Figure 7-16 Predicted Distribution of Single Person HH in the High Density Neighbourhoods of Halifax for the Year 2021

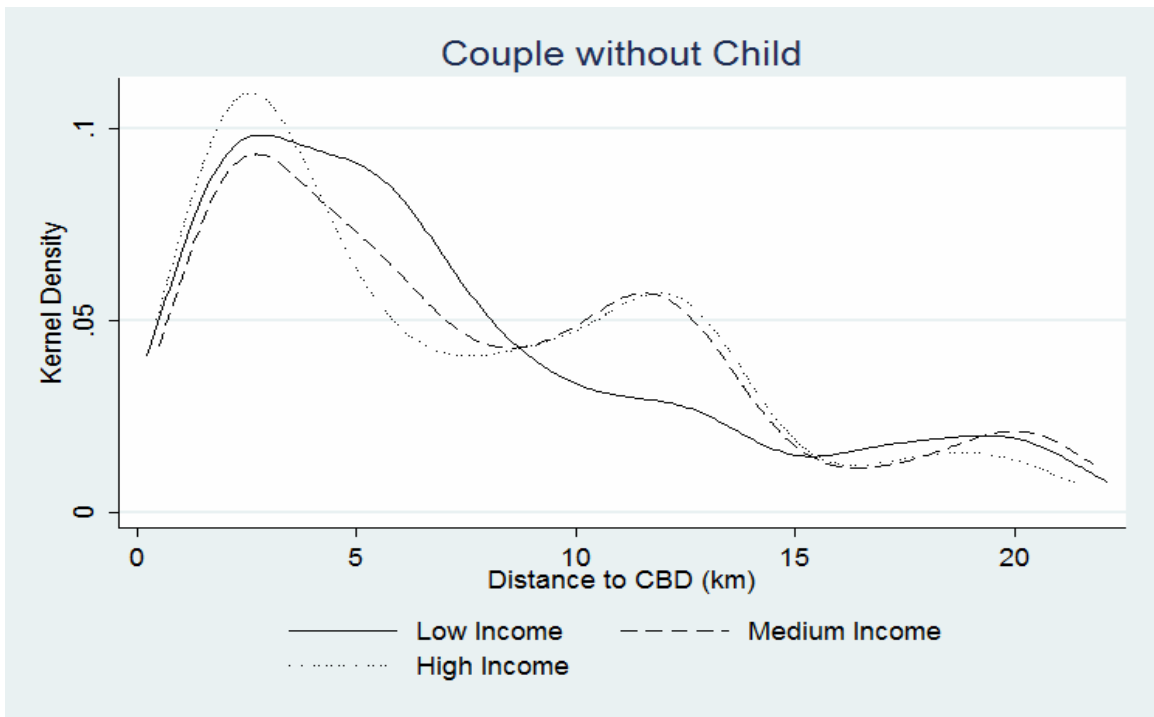


Figure 7-17 Predicted Distribution of Couple without Child HH in the High Density Neighbourhoods of Halifax for the Year 2021

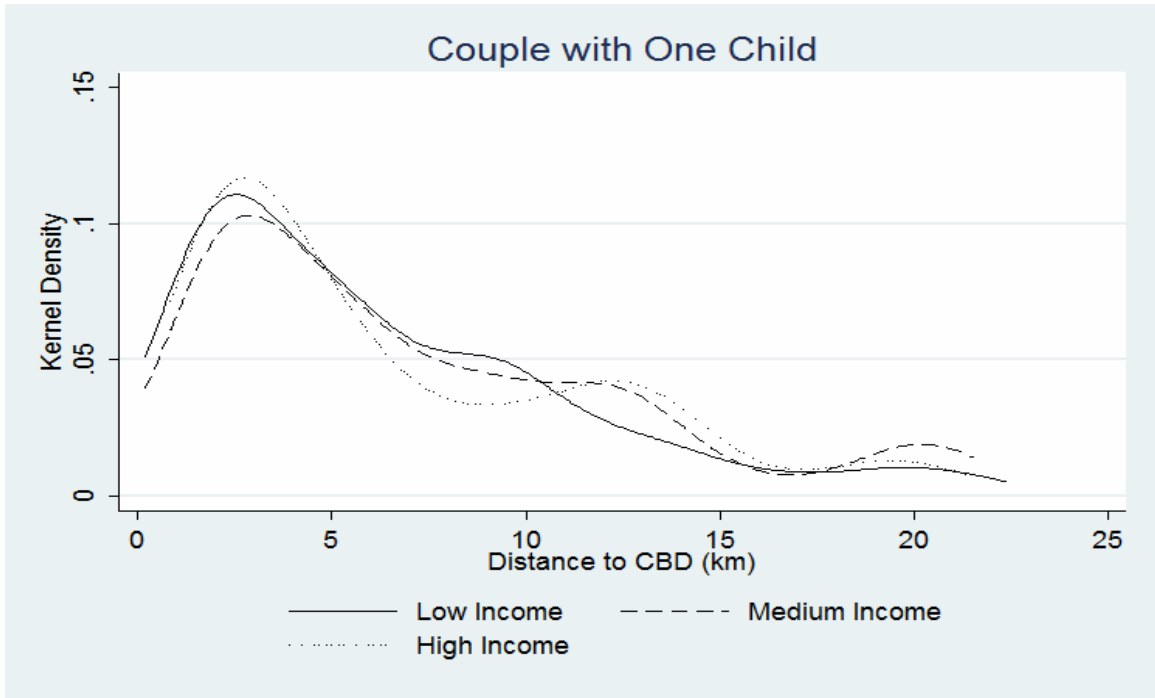


Figure 7-18 Predicted Distribution of Couple with One Child HH in the High Density Neighbourhoods of Halifax for the Year 2021

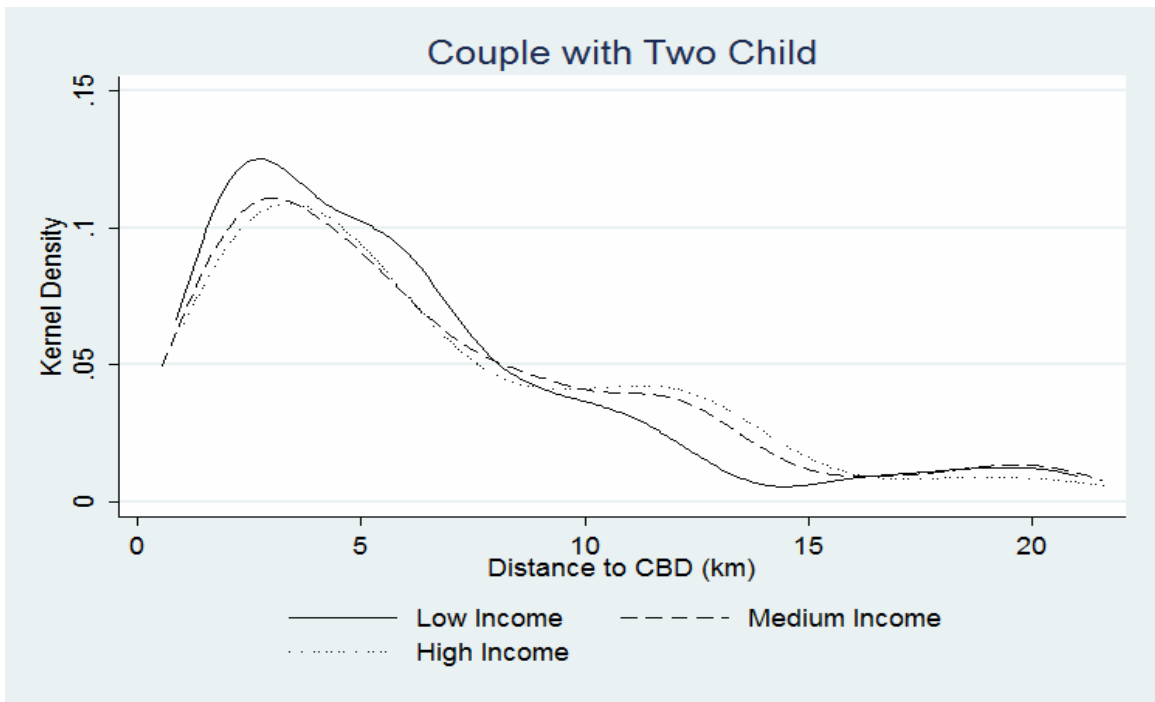


Figure 7-19 Predicted Distribution of Couple with Two Child HH in the High Density Neighbourhoods of Halifax for the Year 2021

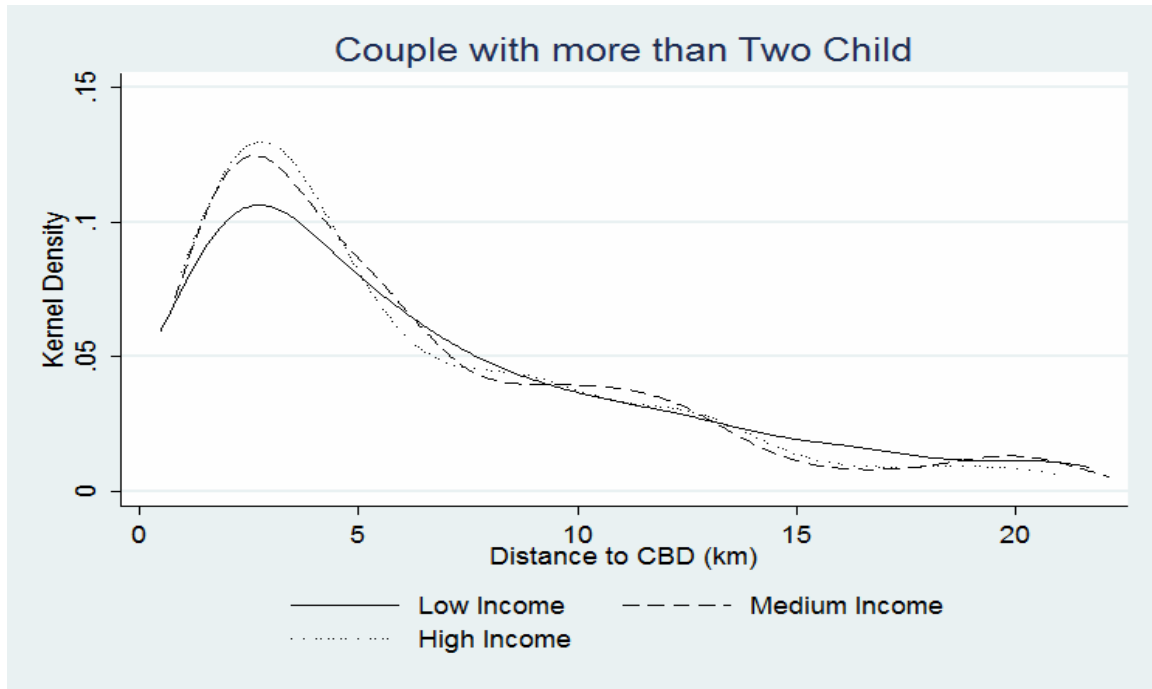


Figure 7-20 Predicted Distribution of Couple with more than Two Child HH in the High Density Neighbourhoods of Halifax for the Year 2021

7.5 Conclusions and Summary of Contributions

This research presents the microsimulation of residential location transition processes within a proto-type version of the iTLE model. A life history-oriented perspective is adopted to address the interactions and feedbacks among the multi-domain decisions and transitions during the simulation of residential locations. Residential location is simulated as a two-stage process of mobility and location choice. The mobility and location choice models are implemented from 2007-2021 for Halifax, Canada. This research presents microsimulation results regarding residential mobility, micro-level spatial distribution of the population, and demographic compositions of the neighbourhoods. A validation of the simulation results of location transition module is performed. The spatial analysis results suggest that around 21% of the DAs show an APE value of less than 10%. Around 37% of the DAs represent the observed population within

the difference range ± 50 number of households. Hence, the simulation results are considered as satisfactory.

Further microsimulation results provide interesting insights towards the micro-level spatio-temporal evolution of population mobility, housing pattern, and household compositions of the neighbourhoods. The mobility results suggest that younger head households are more frequent movers than their older counterpart. The mean duration of stay of the population with age <40, 40-54, 55-64, and 65 and above are predicted to be 3.53, 6.05, 6.60, and 7.24 years, respectively. Particularly, younger head households residing closer to the CBD are predicted to be more frequent movers than older head households residing farther away from the CBD. The spatial distribution suggests that a higher density of the households is consistently predicted in the locations within 25km from the CBD over the simulation years of 2007-2021. The proportion of total households is predicted to increase from 68% in 2007 to 71% in 2021 in these high density neighbourhoods. In terms of the DA-level demographics and household compositional configuration of the high density neighbourhoods, higher density of single person households are predicted in the urban core. As household composition changes through marriage and having child, the density is predicted to be more variable and skewed towards the suburban neighbourhoods.

The capacity of iTLE to generate micro-level spatial distribution of the population will be useful for testing alternative land use and transport policies. It will also feed important information to develop state-of-the-art activity-based travel models. For instance, the micro-level prediction of the spatio-temporal evolution of population demographics will be useful for destination choice procedure. It will assist in addressing the variation in activity generation and scheduling procedure for population at different life-stages residing in different locations. Moreover, the iTLE will support substantial

intra-household interactions during the simulation of travel activities, such as scheduling, vehicle allocation, and mode choice.

Microsimulation of Vehicle Transactions

8.1 Introduction

This chapter presents the microsimulation of vehicle transaction component of the iTLE model. The contributions of this research is three-fold: 1) microsimulating vehicle transaction decisions, 2) addressing the process orientation of the phenomenon through simulating first time purchase, transaction or do nothing, acquisition, trade, and disposal decisions, and 3) accommodating the multi-way interaction of various life-cycle events and decisions during the simulation procedure. This research presents the validation results and offers insights towards how vehicle transaction as well as ownership is spatio-temporally evolving by population demographics.

This chapter is organized as follows: section 8.2 discusses the microsimulation processes of the vehicle transaction component within the iTLE. Section 8.3 describes the simulation results including validation and predicted evolution of vehicle ownership for the Halifax population. Finally, section 8.4 concludes with a summary of key findings.

The following paper is an earlier version of this chapter:

- Fatmi, M.R., and Habib, M.A. (2017). Microsimulation of Vehicle Transaction Decisions within an Integrated Urban Modeling Framework. Published in the peer-reviewed proceedings of the 96th Annual Meeting of Transportation Research Board, Washington DC, USA, January 8-12.

8.2 Microsimulation Processes

The operational framework of the vehicle transaction component within the iTLE model is presented in Figure 8-1. The process starts with a vehicle ownership synthesis component to generate baseline vehicle ownership information. Description of this component is provided in Chapter 6. Following the generation of baseline vehicle information, vehicle transaction component operates as a sequential process of vehicle ownership state and transaction. The first step in this process is to assign households into the following two categories of vehicle ownership state: no vehicle ownership state, and transient ownership state. The next step is to determine the following vehicle transaction decisions: first time purchase, transaction or do nothing, acquisition, disposal, and trade. Simplified version of the model developed in Chapter 5 are implemented within the iTLE proto-type. Discussion on the microsimulation processes and methods are provided below.

8.2.1 Vehicle Ownership State

In this stage, the vehicle ownership state of each household is determined in each simulation year. Households are heuristically assigned into one of the following two categories of vehicle ownership state: no vehicle ownership state, and transient ownership state. Households without a vehicle transaction history in their life-time are assigned to the list of no vehicle ownership state, and households with a transaction history are assigned to the list of transient ownership state.

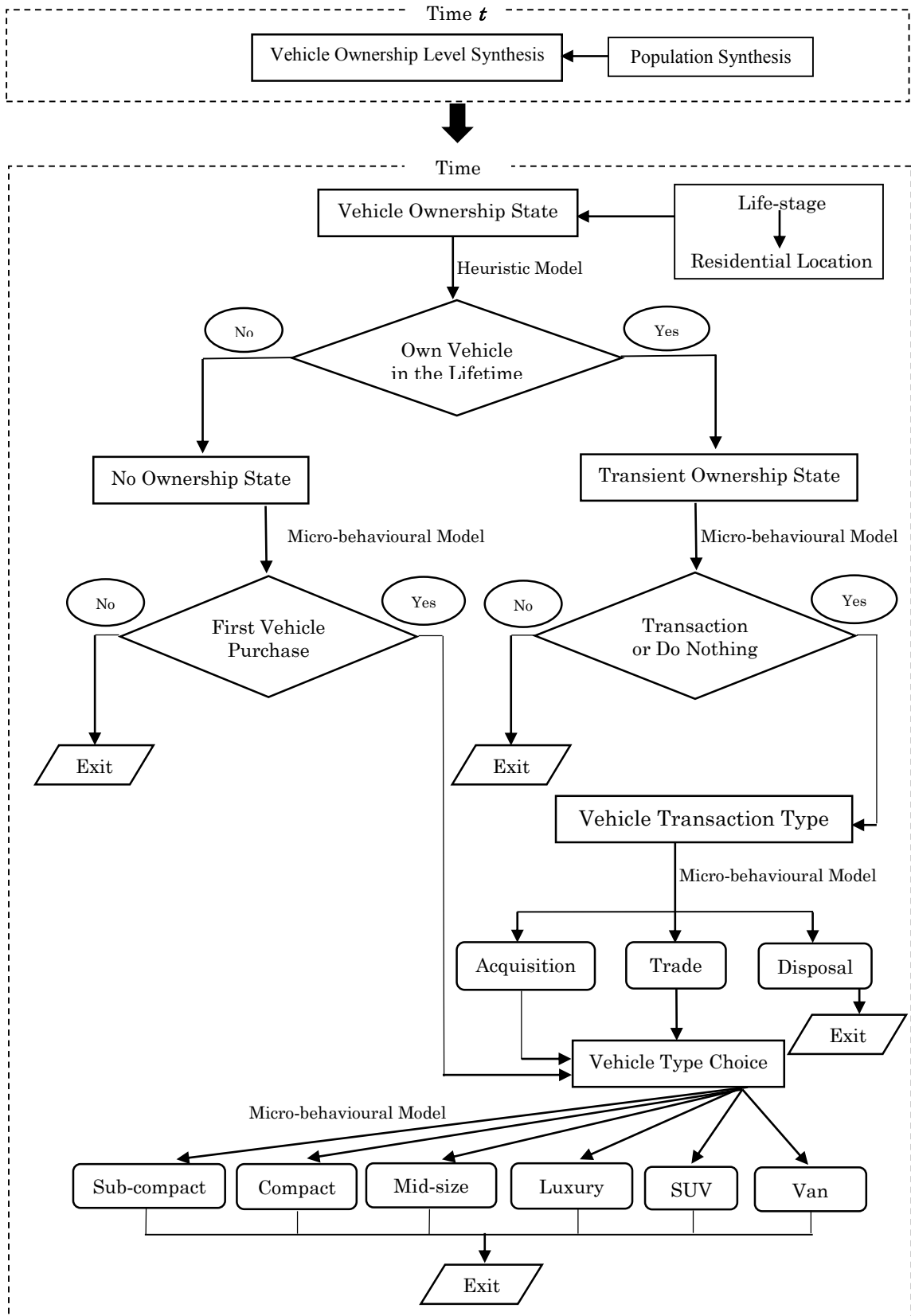


Figure 8-1 Operational Framework of the Vehicle Transaction Component of iTLE

8.2.2 First Time Vehicle Purchase

In each simulation year, the first time vehicle purchase decision is simulated for the households in the no vehicle ownership state list, since they never owned a vehicle in their life-time. For the first vehicle purchase, a discrete time binomial logit model is developed utilizing the HMTS data (Appendix B). Households are identified to purchase the first vehicle or not by comparing the estimated probability with a randomly generated probability using Monte Carlo Simulation technique. If the estimated probability is higher, households are assigned to the list of first vehicle purchase and enter vehicle type choice component. Otherwise, households exit the vehicle ownership transition module.

8.2.3 Vehicle Transaction or Do Nothing

In the case of the households in the list of transient ownership state, their transaction or do nothing decisions are simulated. A discrete time binomial logit modelling technique (similar method to the first vehicle purchase model) is utilized to determine the probability of a household to make a transaction (Appendix B). The estimated probability is compared with a random probability to identify whether households make a transaction or not in a year. Households assigned to the list of transaction, enter vehicle transaction type component. Households assigned to the list of no transaction, exit the module.

8.2.4 Vehicle Transaction Type

Vehicle transaction type component involves the simulation of acquisition, disposal, and trade. Transaction type model is developed utilizing a multinomial logit modelling technique (Appendix B). The model determines the probability of a household to make one of the three transactions following

the order of probability estimation. Households assigned to acquire or trade enter vehicle type choice component. Households assigned to make a disposal exit the module. Subsequently, the vehicle ownership level of the households making a transaction is updated accordingly.

The next step is to simulate vehicle type choice. In this stage, the simulation determines the choice among the following six vehicle types: sub-compact, compact, mid-size, luxury, SUV, and van. The micro-behavioural model of the vehicle type choice component is recently developed (Khan and Habib 2016), and will be implemented later.

8.3 Validation Results

The iTLE proto-type runs vehicle transaction simulation from 2007 to 2021. The simulation results of the vehicle transaction component are validated for the 2016 simulation year using the NovaTRAC¹⁸ 2016 survey data. A comparison of the vehicle ownership level between the predicted and observed population is presented in Figure 8-2. The comparative analysis suggests that the iTLE under-represents zero vehicle ownership by 1%. Two, and three or more vehicle ownerships are over-represented by 2%, and 3% respectively. The largest difference is found for one vehicle ownership, which is an under-representation of 4%, only. Therefore, the validation results reveal that the performance of the vehicle transaction component can be considered reasonably satisfactory.

¹⁸ NovaTRAC is a travel activity survey conducted in the Province of Nova Scotia. The survey collected vehicle ownership information as well as travel activities of the population.

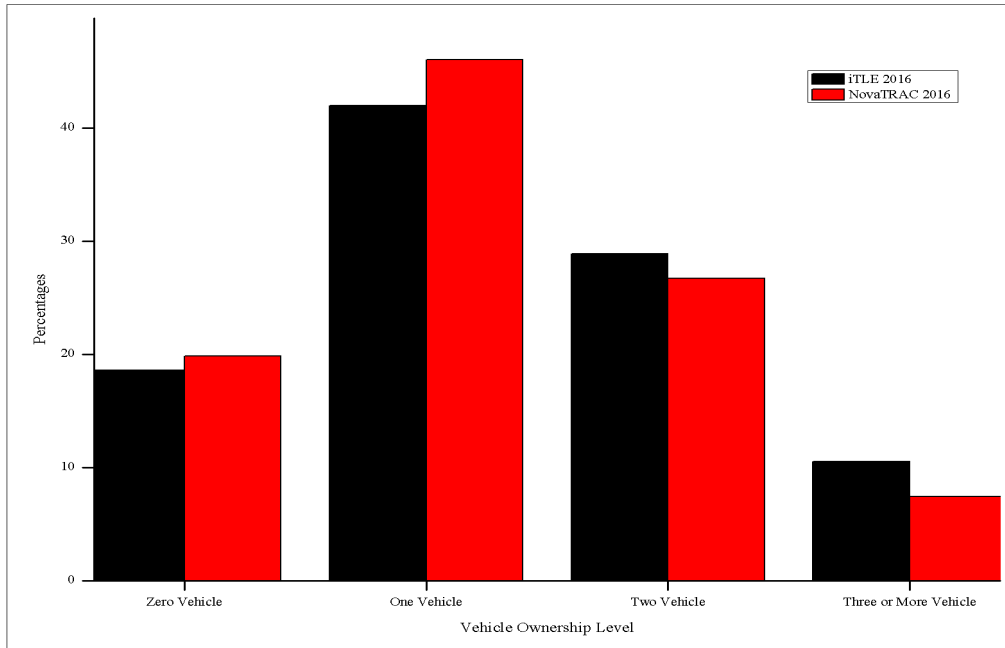


Figure 8-2 Vehicle Ownership Level Comparison of the Predicted and Observed Halifax Population for the Year 2016

8.4 Predicted Evolution of Vehicle Ownership in Halifax

8.4.1 Predicted Spatial Distribution of the Household Vehicle Ownership Level

The predicted spatial distribution of the vehicle ownership level of the households are shown in Figure 8-3. This figure only depicts the results for the year 2007. The results for the rest of the simulation years (2008-2021) are presented in Appendix D. A non-parametric density function for different vehicle ownership levels; particularly, kernel density estimates are plotted against the home location (parcel) distance from CBD. One of the major advantages of the non-parametric kernel density function is to identify bimodality in the distribution. For each year, four kernel density are estimated for zero vehicle, one vehicle, two vehicle, and three or more vehicle ownership. A Gaussian kernel function is assumed for optimal bandwidth selection. The figure 8-3 shows that the density for zero vehicle ownership is predicted to be

skewed to the left of 10km over the years, which are urban core neighbourhoods in Halifax. The density is predicted to be more variable as households' vehicle ownership level goes higher. For example, two, and three or more vehicle ownership are predicted to be more variable and skewed to the left of 25km. In the context of Halifax, parcels within 25km of the CBD represent both urban and suburban neighbourhoods. This implies that households with higher vehicle ownership are not only distributed in the suburban neighbourhoods, a reasonable share is distributed in the urban core as well. Interestingly, the density of households with three or more vehicle ownership is predicted to increase to the left of 10km over the years. This increase of three or more vehicle ownership in the Halifax urban core over the years might be attributed by the positive relationship of the variable “distance from home to CBD less than 10km”, retained in the vehicle acquisition choice scenario of the transaction type model (see Appendix B).

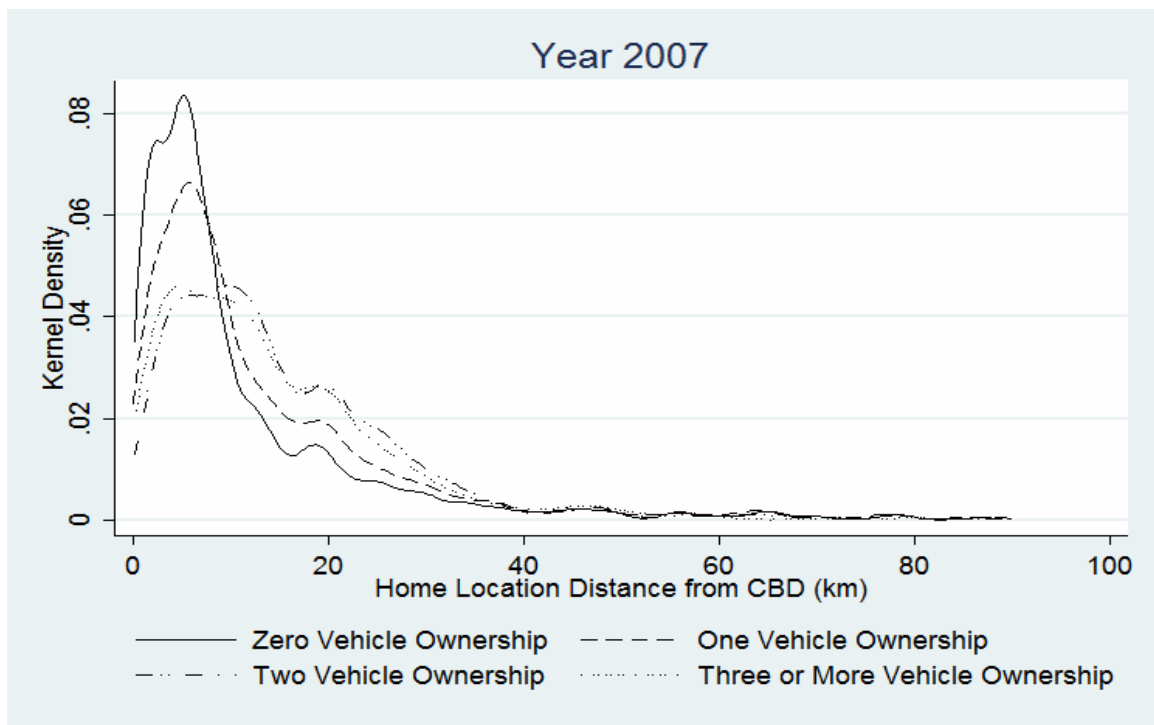


Figure 8-3 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2007

Figure 8-4 to 8-7 add another dimension by representing households' vehicle ownership levels in each DA through maps. The figure focuses on the urban core and surrounding suburban DAs in Halifax for the year 2021. Fig 8-4, 8-5, 8-6, and 8-7 represent the percentages of total households' in a DA with zero vehicle ownership, one vehicle ownership, two vehicle ownership, and three or more vehicle ownership, respectively. The spatial distribution shows that a higher percentage of households in the urban DAs are predicted to have zero vehicle ownership, which include DAs of the Halifax and Dartmouth Downtown (Figure 8-4). A higher percentage of households in the DAs throughout the urban core and surrounding suburban areas are predicted to have one vehicle ownership (Figure 8-5). A significantly higher proportion of one vehicle ownership is predicted in some of the suburban areas. For instance, above 50% of the households are predicted to have one vehicle ownership in some DAs of Bedford, Clayton Park, and Herring Cove areas. A higher percentage of two vehicle ownership is predicted in the suburban areas (Figure 8-6). A higher percentage of three or more vehicle ownership is predicted in the suburban areas as well as in some specific urban areas, which are well known as high income neighbourhoods (Figure 8-7). For example, more than 25% of the households in some of the South End DAs of the Halifax Peninsula are predicted to have three or more vehicles. Note that the South End of the Halifax Peninsula is known as one of the richest neighbourhoods in Canada.

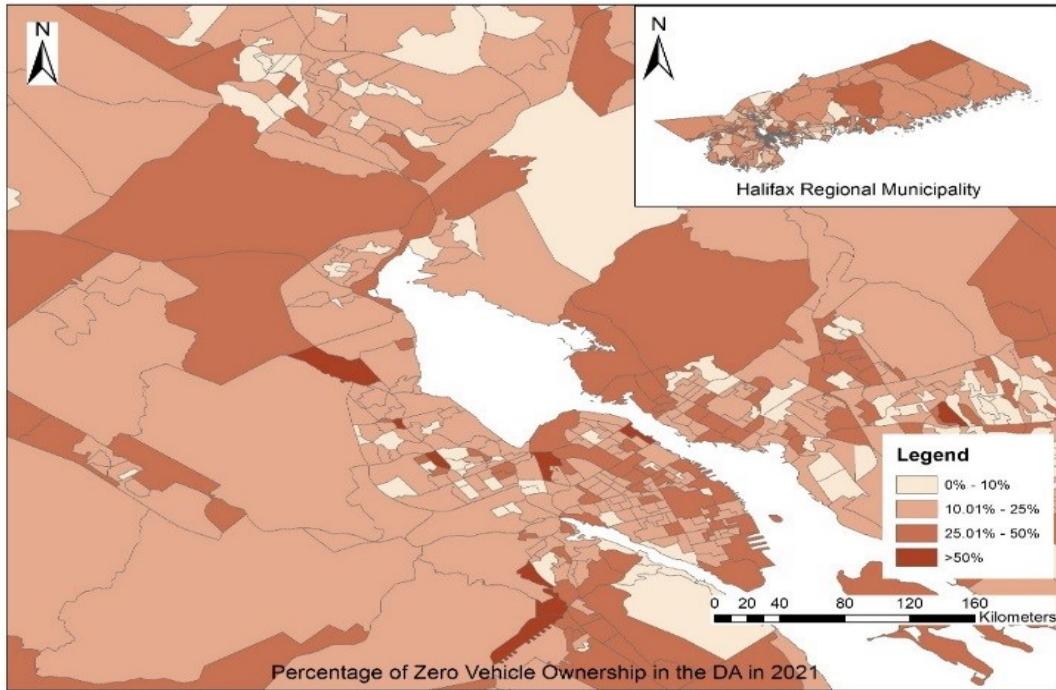


Figure 8-4 Predicted Spatial Distribution of Zero Vehicle Ownership Households in the DA for the Year 2021

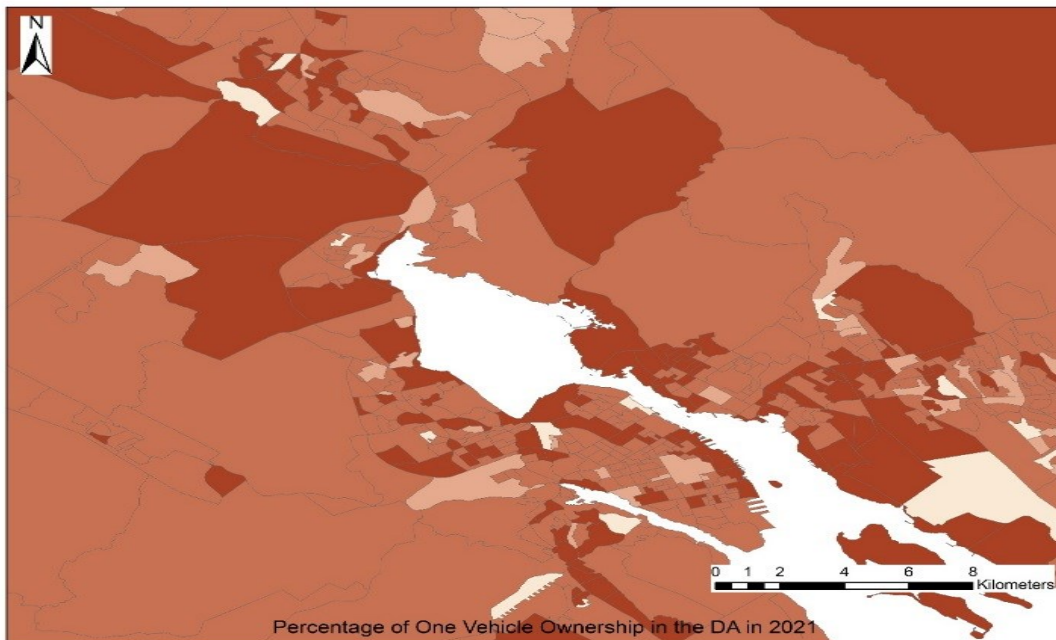


Figure 8-5 Predicted Spatial Distribution of One Vehicle Ownership Households in the DA for the Year 2021

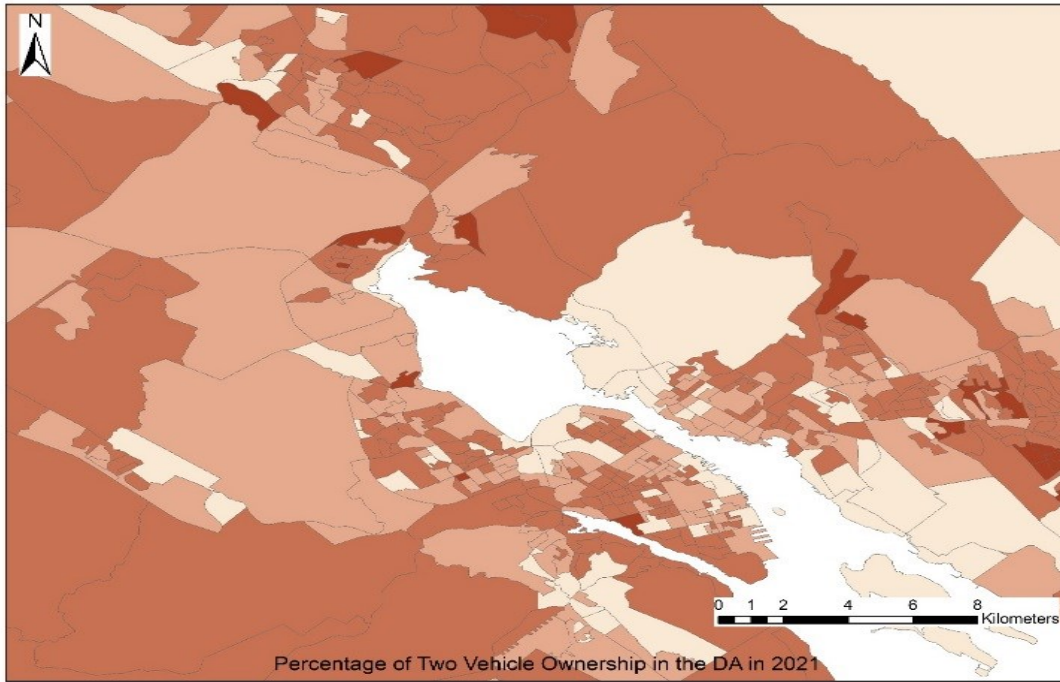


Figure 8-6 Predicted Spatial Distribution of Two Vehicle Ownership Households in the DA for the Year 2021

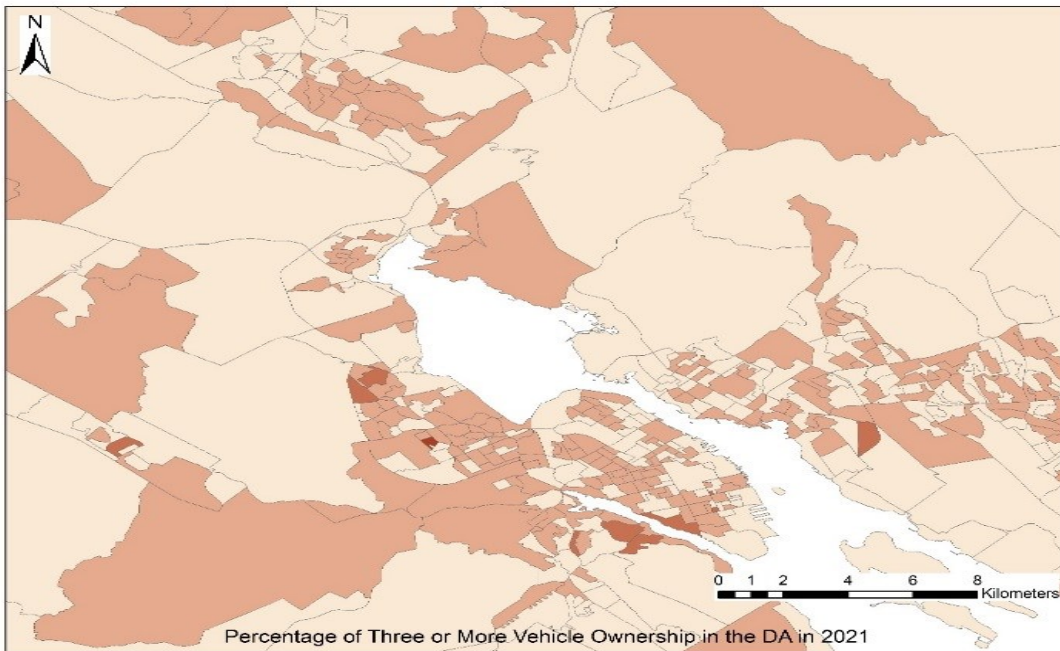


Figure 8-7 Predicted Spatial Distribution of Three or More Vehicle Ownership Households in the DA for the Year 2021

8.4.2 Predicted Vehicle Transactions by Population Demographics

A 2-dimensional kernel density is estimated to evaluate the predicted vehicle transaction types by population demographics. Similar to the above kernel estimates, a Gaussian kernel function for optimal bandwidth selection is assumed. Figure 8-8 to 8-11 illustrate the 2-dimensional kernel estimates for different transaction types for the year 2021. The kernel plots for the first purchase, acquisition, disposal, and trade are shown in Figure 8-8, 8-9, 8-10, and 8-11, respectively. In each figure, x-axis represents age of the head of the household, y-axis represents household income, and z-axis is the color bar representing kernel density. For the first vehicle purchase, density is skewed to the left of 45 years and household income of less than \$80,000 (Figure 8-8). This implies that higher proportion of the first vehicle purchase is made by younger head households with lower and middle income. The average age and household income for first vehicle purchase is 39 years and \$33,000 respectively, which further indicates a higher share of lower income younger groups. In the case of vehicle acquisition, the density is predicted to be more variable than first purchase. The density is skewed within the age range of 35-65 years and income of less than \$120,000 (Figure 8-9). This reflects that population with a wider range of demographics are predicted to be involved in vehicle acquisition. The average age and household income for acquisition is 49 years and \$47,000 respectively. For disposal, density is skewed within 35-65 years and \$30,000-\$110,000 (Figure 8-10). The average age is 53 years and household income is \$73,000. In the case of trade, density is skewed within 40-80 years and within the income range of \$130,000-\$170,000 (Figure 8-11). This implies that older head high income households are predicted to make a higher proportion of vehicle trade. The average age is 60 years and household income is \$80,000 for the trade. The average income of \$80,000 is lower than the skewed range of \$130,000-\$170,000. This can be explained by the secondary peaks in the kernel estimates for the same age range but lower income range.

For instance, a secondary peak is observed for household income of \$30,000-\$100,000 and age range 40-80 years. Similar findings can be drawn from the plots for the rest of the simulation years.

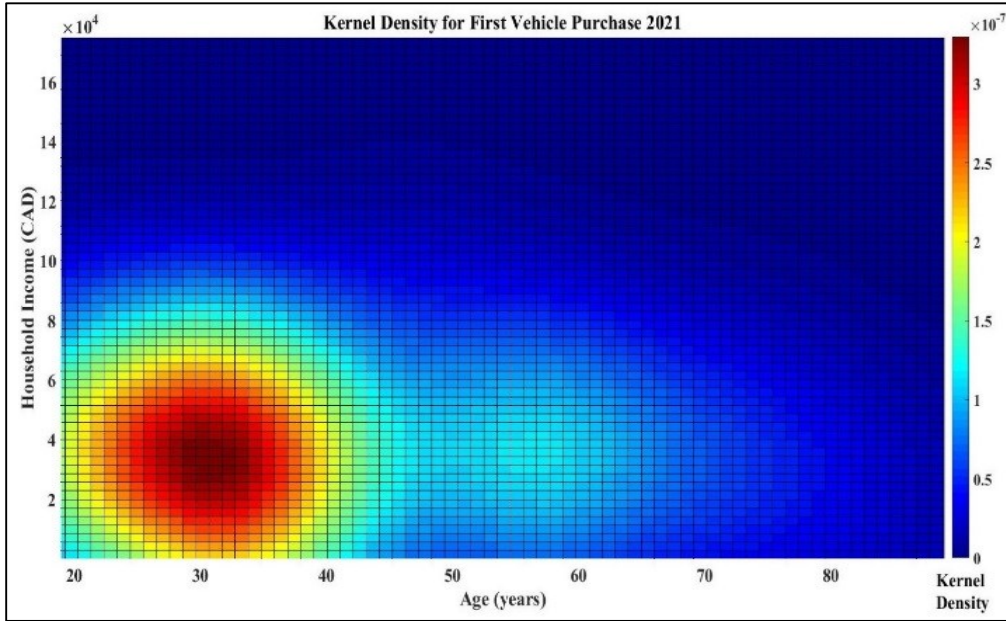


Figure 8-8 Predicted Distribution of Age and Income of Households Purchasing First Vehicle for the Year 2021

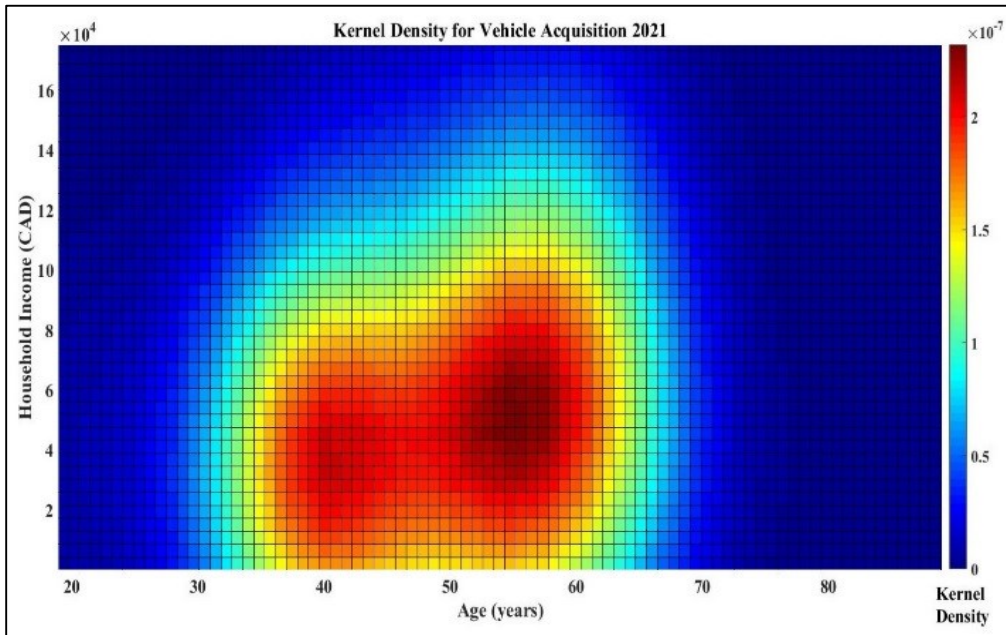


Figure 8-9 Predicted Distribution of Age and Income of Households Acquiring Vehicles for the Year 2021

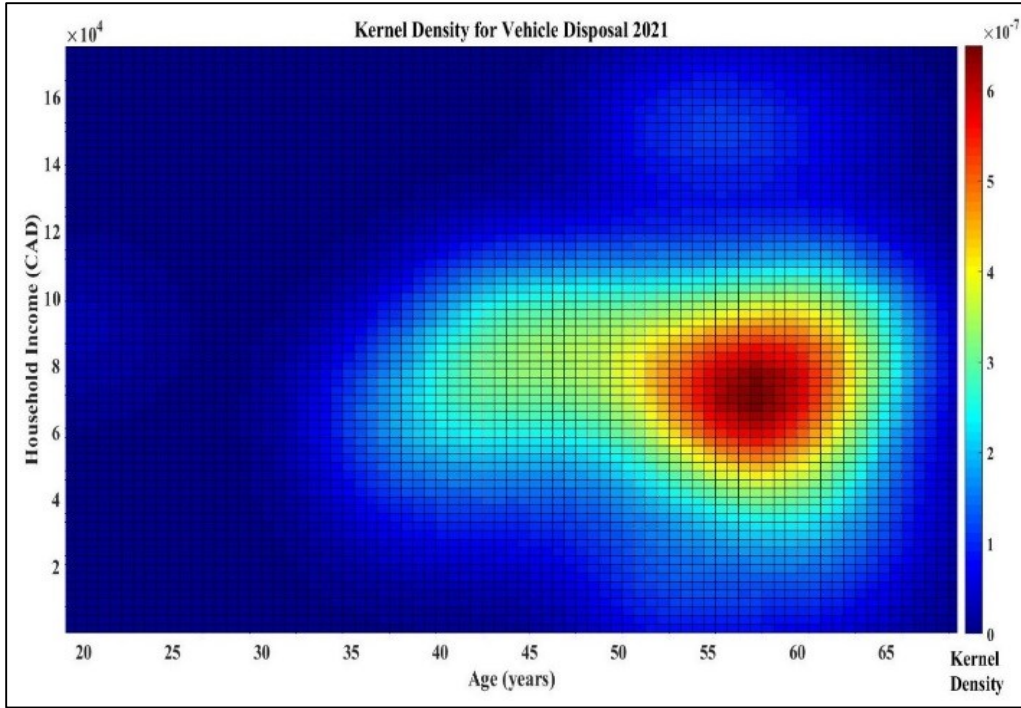


Figure 8-10 Predicted Distribution of Age and Income of Households Disposing Vehicles for the Year 2021

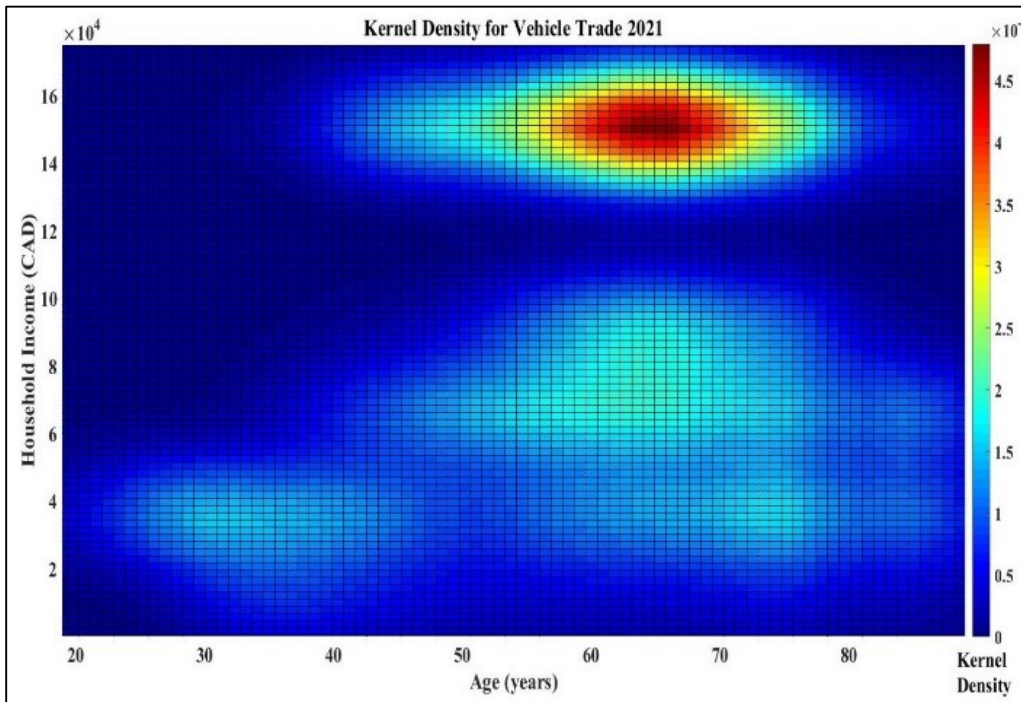


Figure 8-11 Predicted Distribution of Age and Income of Households Trading Vehicles for the Year 2021

8.4.3 Predicted Vehicle Ownership per Household Member

The average vehicle per household member is predicted to be 0.72 in 2021. Around 75% of the households are predicted to own at least one vehicle per household member in 2021. Figure 8-12 represents the plot of vehicle ownership per household member by location (parcel) distance from CBD and household income for 2021. Vehicle per household member is predicted to increase with the increase in household income and decrease in location distance from the CBD. Vehicle per household member is predicted to be significantly higher to the right of \$120,000 and below 20km, which reflects high income suburban and urban dwellers. Ownership of vehicles per member is as high as 1 for these affluent suburban and urban dwellers. Interestingly, low and middle income suburban and urban dwellers are predicted to have around 1 vehicle ownership for every 2 household members. Similarly, Figure 8-13 represents vehicle ownership per household member by location distance from CBD and age for 2021. Vehicle per household member is predicted to increase with the increase in age and decrease in location distance from the CBD.

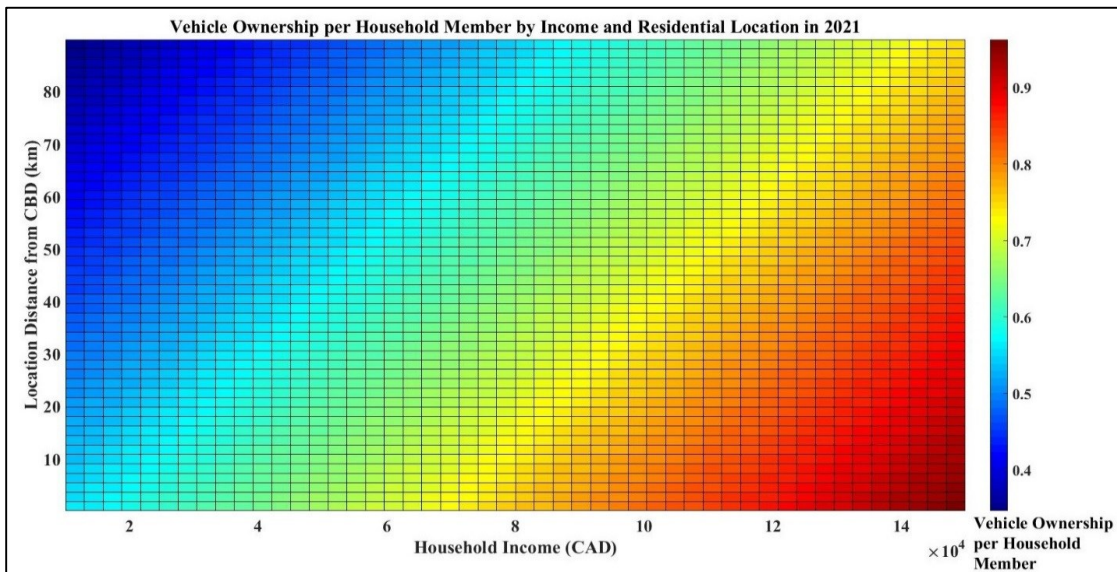


Figure 8-12 Predicted Spatial Distribution of Vehicle Ownership per Household Member by Income for the Year 2021

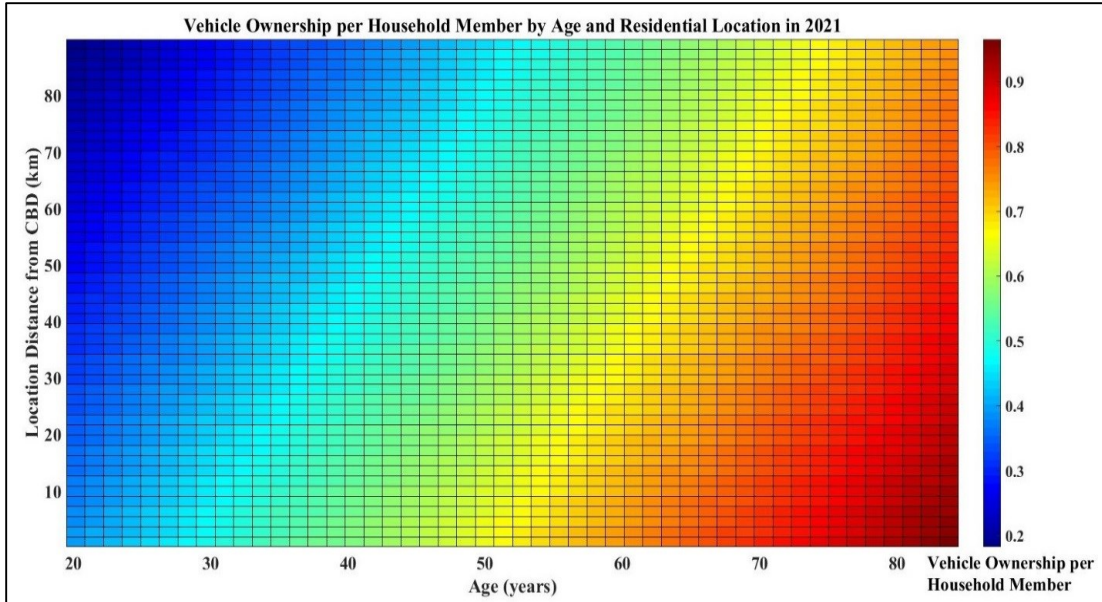


Figure 8-13 Predicted Spatial Distribution of Vehicle Ownership per Household Member by Age for the Year 2021

8.4.4 Predicted Vehicle Ownership Composition of the Neighbourhoods

Figure 8-14 shows a 15 year evolution of the average vehicle ownership per household in the DA between 2007 and 2021. For the overall Halifax DAs, the median value of the average vehicle ownership per household is predicted to increase from 1.37 in 2007 to 1.41 in 2021; however, the 75th percentile decreases from 1.67 in 2007 to 1.63 in 2021. Interestingly, the average vehicle per household is predicted to increase in the Halifax urban core DAs during this period. The median value increases from 1.21 in 2007 to 1.5 in 2021, and the 75th percentile value increases from 1.53 in 2007 to 1.69 in 2021.

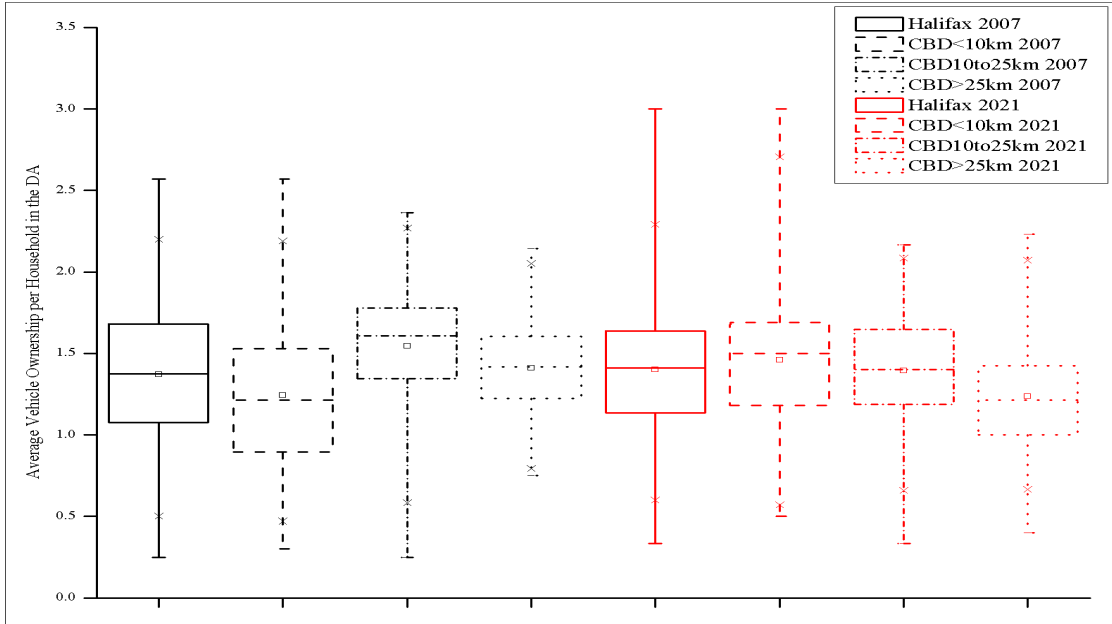


Figure 8-14 Predicted 15 Year Evolution of Average Vehicle Ownership per Household in the DA for the Years 2007-2021

Another dimension is added by plotting average vehicle ownership per household in the DA with the location and average household income of the DAs for 2021 (Figure 8-15). The figure illustrates that the average vehicle per household in the DA increases with an increase in average household income in the DA and a decrease in distance of the DA from CBD. The average ownership is significantly higher for the DAs with average income above \$130,000 and distance from CBD below 20km. This implies that higher income DAs in the urban core and surrounding suburban areas are predicted to have higher average vehicle ownership per household, which is as high as 2.2. High income rural DAs (distance more than 50km) are predicted to have less than 1.8 vehicles per household on an average.

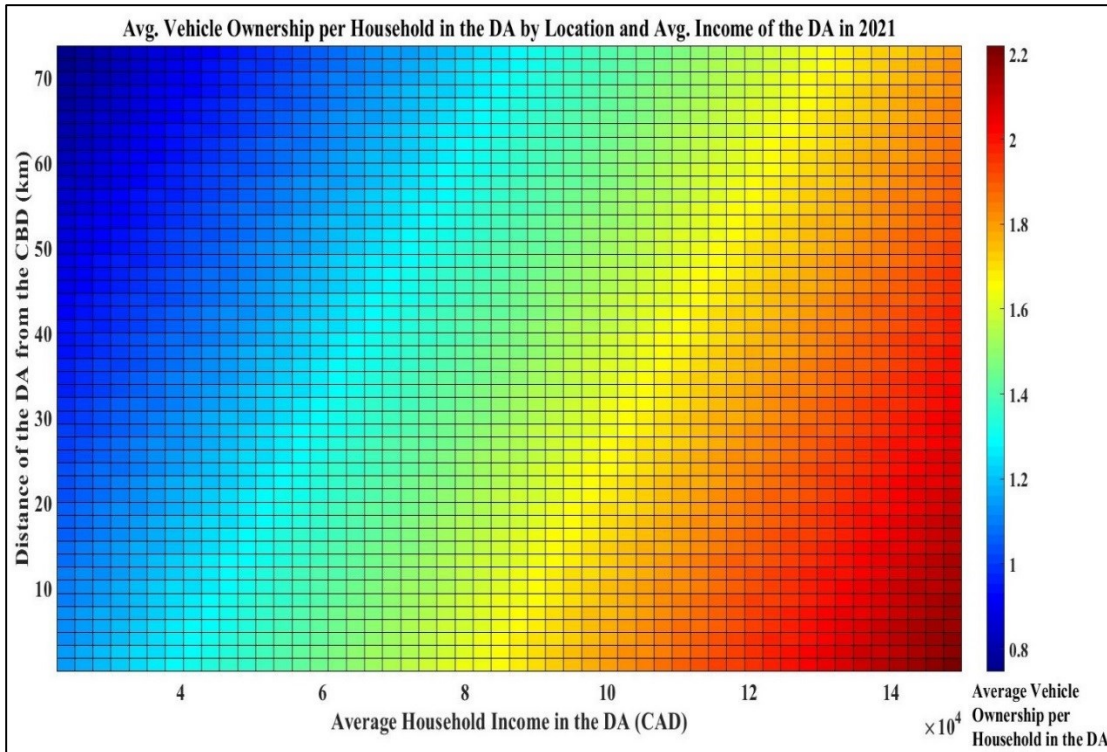


Figure 8-15 Predicted Spatial Distribution of the Avg. Vehicle Ownership per Household in the DA by Avg. Household Income in the DA for the Year 2021

8.5 Conclusion

This research presents the findings of the microsimulation of vehicle transaction component within the iTLE proto-type model. The process orientation of vehicle transaction is addressed by microsimulating first time purchase, transaction or do nothing, acquisition, trade, and disposal decisions. The effects of multi-domain decision interactions and life-stage transitions on vehicle transaction decisions is accommodated within the simulation framework.

The iTLE proto-type simulates vehicle transactions for 2007-2021 for Halifax. The validation results at the 2016 time point suggests that majority of the categories of the predicted vehicle ownership levels lie within a few percentage

point of the observed ownership level. For example, zero vehicle ownership is under represented by 1%, only. Therefore, it can be concluded that the iTLE generates reasonably representative vehicle ownership estimates for the population.

This research also presents simulation results regarding the spatio-temporal distribution of vehicle ownership for the Halifax population. A yearly spatial variation of different vehicle ownership levels is presented by kernel density estimates. It is found that higher proportion of the households with zero vehicle ownership is predicted in the Halifax urban core. The density is predicted to be more variable and distributed in the suburban areas as well as urban areas with the increase in vehicle ownership level. One of the interesting findings is that an increase in density of three or more vehicle ownership households is predicted in the urban core areas over the years. Similar distribution is found while the percentage of different vehicle ownership level in the DAs is represented through maps for the year 2021. The map shows that a higher percentage of three or more vehicle ownership is predicted in some specific urban areas, which are well known as high income neighbourhoods. The demographic distribution of the vehicle transaction types suggests that higher proportion of the first vehicle purchase involves younger head (average age 39 years) lower income (average household income \$33,000) households. The distribution of acquisition suggests that population with a wider range of demographics are involved in acquisition, such as age range of 35-65 years and income of less than \$120,000. The average vehicle per household member is predicted to be 0.72 in 2021 and around 75% of the households are predicted to own at least one vehicle per household member in 2021. High income urban dwellers are predicted to have a higher number of vehicles per member, which is as high as 1 in 2021. The vehicle ownership level composition analysis of the neighbourhoods (DA-level) suggests that the higher income DAs in the urban

core and surrounding suburban areas are predicted to have higher average vehicle ownership per household, which is as high as 2.2 in 2021.

In summary, this study contributes significantly to the literature by simulating vehicle transaction decisions as a process of first time purchase, acquisition, disposal, trade, and transaction or do nothing decisions, within an integrated urban modelling platform. Multi-way decision dynamics are accommodated within the simulation procedure. The simulation results of vehicle transaction decisions are reasonably satisfactory and offers promising insights towards the spatio-temporal evolution of vehicle ownership in an urban region. Future research should focus on the implementation of vehicle type choice model. Finally, the implementation of vehicle transaction decisions promises to improve the prediction of travel activities and facilitates the opportunity to extend iTLE into the prediction of emission and energy use under different policy scenarios.

Conclusions

9.1 Summary

The development of integrated urban models have emerged from the need to predict the evolution of urban region, and test alternative land use and transport policy scenarios. Integrated urban models simulate a wide range of household- and individual-level decision processes. Residential location and vehicle ownership are two most critical components of integrated urban models, since these are crucial household-level long-term and medium-term decisions. One of the major limitations of the existing urban models is their lack of behavioural representation during the modelling and simulation of essential decision components. Unless the behaviour of the individuals/households are reasonably addressed, the purpose for developing integrated urban models will be challenging to achieve. This research contributes to the modelling and microsimulation paradigms of integrated urban models by representing greater behaviour of the population. Particularly, this study presents the development and implementation of the residential location and vehicle transaction components within an integrated Transport Land Use and Energy (iTLE) modelling system. This study also presents the implementation of population synthesis, vehicle ownership level synthesis, and life-stage transition components within the iTLE model.

The research gaps in integrated urban modelling are identified through a review of the literature. The literature review suggests that the existing integrated urban models lack in addressing the multi-way interactions among different decision components such as residential location and vehicle

transaction. These longer-term decisions have a time dimension as they evolve over the life-course of the population, which is not well addressed in the literature. To microsimulate the decision interactions along the life-time, population life-stages are required to be simulated. Microsimulation of demographic career of the population is rare in the current integrated urban modelling literature. Further, there is a process orientation of the longer-term decisions like residential location and vehicle transaction. Accommodating the process orientation within the integrated modelling framework is also limited in the existing literature. Moreover, investigation of how a change in long-term state such as residential location influences a change in decision in another life-domain such as mode choice has not occurred to any significant extent. Modelling and predicting vehicle transaction demands further investigation as limited of the existing urban models include this component. Nonetheless, advanced econometric models need to be developed that are capable of accommodating the life-trajectory dynamics of the decision processes.

Based on the needs and gaps identified in the literature review, this research proposes a life-oriented agent-based integrated urban model, known as integrated Transport Land Use and Energy (iTLE) model. The proposed model adopts the theory of life-course perspectives to accommodate the multi-way feedback mechanism among decisions along the life-time of the agents. The model is conceptualized to microsimulate agents' life-stages and associated changes and decisions longitudinally at each simulation time-step. The core components of the model includes: baseline synthesis, life-stage transition, residential location transition, and vehicle transaction. Baseline synthesis involves the generation of population synthesis and vehicle ownership level synthesis. Life-stage transition module addresses the evolution of demographic career of the agents. Household location is conceptualized as a two-stage process of mobility and location choice. The second stage of location choice is assumed as a two-tier process of location search and choice. This study tests

how a relocation influences commute model choice decisions. Vehicle transaction is assumed as a process of first time vehicle purchase, vehicle acquisition, disposal, and trade decisions. One of the mechanisms adopted to address multi-way decision interactions is through introducing lead and lag events.

The development of a life-oriented urban system simulation platform such as the iTLE is a data intensive effort. The primary data source for developing the micro-models of residential location, vehicle transaction and mode transition is a retrospective Household Mobility and Travel Survey (HMTS) conducted in Halifax, Canada. The survey collected life-history information of the respondents, including housing history, vehicle ownership history, employment records, household and employment compositional change, and socio-demographics, among others. The HMTS data provides information on the life-cycle events including, birth of a child, death of a member, move-in of a member, move-out of a member, household formation, residential relocation, addition of a job, loss of a job, job change, retirement, and vehicle transaction, among others. In addition, secondary data includes parcel information from the Nova Scotia Property Database 2013, location of different activity points and transportation services from the Desktop Mapping Technologies Inc. (DMTI), land use information from the Halifax Regional Municipality (HRM), and neighbourhood characteristics from the 2011 Census tabulations. Independent variables such as life-cycle events, accessibility measures, neighbourhood, and land use characteristics are derived from the above mentioned data, and tested during the model estimation process. In addition, 2006 Public Use Microdata File (PUMF), and 2006 Census information are utilized to develop the population synthesis component.

The residential location decision is modelled as a two-stage process: 1) residential mobility, and 2) residential location choice. The first stage of mobility refers to the decision to move or stay at a particular location. The

mobility model is developed utilizing a continuous time hazard-based duration modelling technique. According to the hazard formulation, duration is considered to be the continuous time-period a household has spent at a location and the termination is the event where a household moves to a new location. Single episode models are extended towards multiple episode models to accommodate the repeated duration along the housing career of the same households. Multiple episode shared frailty models are estimated for different distributions. The goodness-of-fit-measures suggest that the multiple episode shared frailty model outperforms the single episode model. Particularly, multiple episode gamma shared frailty model with Weibull distribution is considered as the final model. The model results suggest that life-stages, dwelling, land use, accessibility, and neighbourhood characteristics significantly affect mobility decisions. For example, households in their first spell after formation show a shorter duration. Households residing in higher mixed land use areas have a longer duration. Households having longer commute show a longer duration. Households residing closer to the CBD reveal a shorter duration.

The second stage of location choice is modelled as a two-tier process of: 1) location search, and 2) location choice. Based on this concept, following a decision to move in the mobility stage, households first undertake a search process to generate a pool of potential alternative locations and finally move to a location from the pool. The search model is developed utilizing a fuzzy logic-based modelling technique that accommodates the stress-driven push and pull factors. The search model assumes that households' search process is constrained by their affordability. Hence, constraints regarding household income and property value are imposed within the fuzzy framework. The pool of locations generated in the search process are used as the choice set for the location choice model in the second tier. The model is developed at the micro-spatial resolution of parcel. For comparison purposes, a traditional location

choice model is developed utilizing choice set generated from a random sampling technique. The goodness-of-fit measures suggest that the proposed fuzzy logic-based search and location choice modelling process outperforms the traditional model.

The location choice model utilizes a latent segmentation-based logit (LSL) modelling technique. The LSL model accommodates the correlated sequence of repeated choices of the households during their housing career. The model captures latent heterogeneity by allocating households into flexible discrete latent segments. The segment allocation model is defined on the basis of household income, age of the household head, percentage of owned dwelling in the neighbourhood, and distance to the CBD. The LSL model results suggest that life-cycle events, parcel characteristics, and accessibility measures significantly influence the location choice decisions. For instance, birth of a child magnifies the need of larger lots. The influence of vehicle transaction is tested by considering vehicle acquisition, and purchase of the first vehicle in the life-time of the household. Both the variables reveal a higher propensity to choose locations farther away from work place. In the case of first vehicle purchase, a longer adjustment period is found than that of a vehicle acquisition. The model results suggest significant variation in location choice by life-history attributes. For example, suburbanite households in segment two exhibit a higher probability to choose larger lots following a job change. In contrast, urbanite households in segment one show a negative relationship. Interestingly, addition of a new job positively influence the choice for larger lots. Households are found to require longer adjustment period following a job change than that of addition of a new job. Moreover, most households are found to prefer larger lots. Households in general show a higher likelihood to choose locations closer to work place, transit stop, and health service.

This study examines how a change in residential location influences the choice of commute mode. It is conceptualized that individuals reassess their commute

mode following a long-term change of state such as residential location. Following the reappraisal, continuation with the same mode is considered as mode loyalty; whereas, a change is considered as mode transition. This study investigates mode specific mode transition and loyalty decisions by comparing the choice of commute mode between two distinct temporal points of consecutive residential locations. The following nine dynamic choice scenarios are considered: (1) loyal to car, (2) loyal to transit, (3) loyal to active transportation (walk/bike), (4) transition from car to transit, (5) transition from car to active transportation, (6) transition from transit to car, (7) transition from transit to active transportation, (8) transition from active transportation to car, and (9) transition from active transportation to transit. A random-parameters logit (RPL) model is developed to account for the correlated sequence of repeated choices and unobserved heterogeneity. The model results suggest that life-cycle events significantly affect commute mode choice decisions. For instance, birth of a child, and new household formation are found to positively influence a transition from active transportation to car. Loss of a job is associated with a transition from car to transit. One of the key features of this study is to examine the effects of temporal changes in socio-demographic and accessibility as households change their location. For instance, a decrease in household income positively influence a transition from car to transit. Tenure transition from rental to owned dwelling trigger a transition from transit to car. The model results suggest that considerable heterogeneity exists among the sample individuals. For example, moving closer to the workplace is positively associated with car loyalty. A large value of the standard deviation of this parameter reveals the existence of significant heterogeneity among the individuals.

In the case of vehicle transaction, a dynamic model is developed to investigate the following four types of transactions: first time vehicle purchase, vehicle acquisition, vehicle disposal, and vehicle trade. One of the key features of this

study is to examine the first time vehicle purchase decisions of the households during their lifetime. The purchase of the first vehicle might be associated with a mode shift to car; therefore, it is important to examine the first time vehicle purchase decisions. A latent segmentation-based logit (LSL) model is developed to investigate the vehicle transaction decisions. The model addresses repeated transactions of the same households during their life-course, as well as accommodates latent heterogeneity through allocating households into flexible discrete latent segments. The households are allocated to different segments based on household income, household size, dwelling density of the neighbourhood, and percentage of owned dwelling in the neighbourhood. The model results suggest that life-cycle events, accessibility measures, neighbourhoods, and socio-demographic characteristics considerably influence vehicle transaction decisions. Significant heterogeneity is found across the two latent segments. For example, birth of a child or member move in positively influences vehicle acquisition in segment two and deter in segment one. The temporal dynamics of the inter-dependencies among decisions is confirmed through lead and lagged effects of the life-cycle events. For instance, birth of a child confirms a two-year lagged effect on vehicle acquisition. The model results suggest that first vehicle purchase behaviour is significantly different than vehicle acquisition. For example, addition of a job exhibits heterogeneous relationship in the two segments for first time vehicle purchase with an adjustment period of three years. The same variable exhibits a positive relationship for vehicle acquisition in both segments with a smaller adjustment period of one year.

In the case of developing the integrated Transport Land Use and Energy (iTLE) modelling system, a proto-type version of the iTLE model is implemented for Halifax, Canada. The program code is written using C# dotNET programming language. The iTLE proto-type starts with generating the baseline information for 2006, and runs simulation for a 15-year period

from 2007 to 2021 at a yearly time-step. The baseline synthesis includes, population synthesis and vehicle ownership level synthesis. Population synthesis is performed in the following two-stages: 1) population synthesis at the zonal level of dissemination area (DA) following an Iterative Proportional Updating (IPU) technique, and 2) allocation of the synthetic population to the micro-spatial level of parcels utilizing a logit link model. The population synthesis engine generates a 100% synthetic population for Halifax. The goodness-of-fit measures suggest a SRMSE value of 0.37. In terms of the spatial distribution, around 89% of the DAs show an APE measure of less 5%. The vehicle ownership synthesis is performed utilizing a MNL model. The synthesis results suggest the following baseline distribution for zero, one, two, and three or more vehicle ownership: 22.55%, 37.40%, 32.16%, and 7.859%. In the case of microsimulating population demographic career, the iTLE simulates the following life-stages: ageing, birth, death, in-migration, out-migration, and household formation. This module follows a heuristic modelling approach that utilizes historical rates and rules to determine the occurrence of an event for an individual/household in a simulation year. The life-stage transition module is validated with the 2011 Census information. For example, a cross comparative analysis results suggest that majority of the simulated population attribute categories show a difference of less than 1% with the observed population. Therefore, it can be concluded that the iTLE generates reasonably satisfactory population estimates for further model development and implementation. In the case of microsimulation results, the iTLE predicts an increase of 14.08% population in 2021 compared to 2006.

This study presents the microsimulation results of residential mobility and location choice models within the iTLE proto-type. The models are implemented for a 15-year simulation run, starting from 2007 to 2021. The location choice simulation results are validated for the 2011 time point. The validation results suggest that around 21% of the DAs show an APE value of

less than 10%. Around 37% of the DAs represent the observed population within the difference range of ± 50 number of households. The validation results suggest that the iTLE generates reasonably satisfactory spatial distribution of the population. Furthermore, this study presents a 15-year prediction results regarding residential mobility, housing pattern of the population, and demographic composition of the neighbourhoods. The mobility results suggest that younger head households are more frequent movers than their older counterpart. The mean duration of stay of the population with age <40, 40-54, 55-64, and 65 and above are predicted to be 3.53, 6.05, 6.60, and 7.24 years, respectively. Adding a spatial dimension to the mobility analysis suggests that younger head households residing closer to the CBD are predicted to be more frequent movers than older head households residing farther away from the CBD. The spatial distribution of the population from 2007-2021 suggests that a higher density of the households is consistently predicted in the locations within 25km from the CBD. The proportion of total households in these high density neighbourhoods is predicted to increase from 68% in 2007 to 71% in 2021. In terms of the DA-level demographics and household compositional configuration of the high density neighbourhoods, higher density of single person households are predicted to live in the urban core. As household composition changes through marriage and having child, the density is predicted to be more variable and skewed towards suburban neighbourhoods.

Finally, vehicle transaction is simulated within the iTLE proto-type as a process of first time purchase, transaction or do nothing, acquisition, trade, and disposal decisions. The iTLE proto-type generates a 15-year vehicle transaction simulation results, starting from 2007 to 2021. The model is validated at the 2016 time point. The validation results suggest that majority categories of the predicted vehicle ownership levels lie within a few percentage points of the observed population. For instance, zero vehicle ownership shows

a deviation of 1%, only. This research also discusses the spatio-temporal distribution of vehicle ownership for the Halifax population. The results suggest that a higher proportion of zero vehicle ownership households is predicted in the Halifax urban core. The density is predicted to be more variable and distributed in the suburban areas with the increase in vehicle ownership level. The demographic distribution of the vehicle transaction suggests that the first vehicle purchase involves a higher proportion of younger head (average age 39 years) and lower income (average household income \$33,000) households. The results reveal that the average vehicle per household member will be 0.72 in 2021 and around 75% of the households will own at least one vehicle per household member. The vehicle ownership level composition analysis at the DA-level suggests that the higher income DAs in the urban core and surrounding suburban areas are predicted to have higher average vehicle ownership per household, which is as high as 2.2 in 2021.

9.2 Contributions of this Research

The contributions of this research encompass the modelling and microsimulation paradigms of integrated urban modelling literature. Overall, this study tackles the notion to accommodate life-trajectory dynamics of longer-term decision processes within the empirical and computational procedure of an integrated Transport Land Use and Energy (iTLE) modelling system. Innovative and advanced econometric modelling methods are developed to disentangle the interactions among decisions in different life-domains along the life-course of the population, as well as address the process orientation of the decisions. The computational procedure of the iTLE is developed to microsimulate agents' longer-term decisions longitudinally along their life-course. The major contributions of this research are briefly discussed below:

1. Develops new method for process-oriented location modelling. An innovative fuzzy logic-based modelling method is developed for the location search process. The search model accounts for households' continual stress at different life-domains by addressing interdependencies between push and pull factors within the fuzzy logic modelling process. Constraint regarding household affordability is imposed through introducing constraint sets of household income and average property value within the fuzzy model.
2. Offers new behavioural insights regarding lead and lagged effects. This study confirms hypothesis regarding the effects of life-cycle events on longer-term decisions. For example, residential location model results suggest the effects of first time vehicle purchase as a 2-year lead event, and vehicle acquisition as a 1-year lead event. This result reveals that households require longer adjustment period to relocate following first time vehicle purchase than that of a vehicle acquisition. Similarly, for vehicle transactions, households require a longer adjustment period to purchase first vehicle than making a vehicle acquisition following an addition of job in the household.
3. Develops advanced econometric models to address the correlated sequence of repeated choices, and capture unobserved heterogeneity among the sample households. In the case of vehicle transaction, a LSL model is developed to capture unobserved heterogeneity that allocates households into flexible discrete latent segments. The model results reveal that vehicle transaction varies by life-history attributes among households in different segments. For example, addition of a job could trigger first time vehicle purchase for larger-sized suburban dwellers in one segment and deter for smaller-sized urban dwellers in another segment.
4. Implements a new longer-term decision simulator, known as the iTLE. The simulator includes following components: population synthesis,

vehicle ownership level synthesis, life-stage transition, residential location, and vehicle transaction. The model microsimulates for a 15-year period at a yearly time-step, starting from the base year 2006 to 2021. A validation of the iTLE model results is performed. In addition, microsimulation results regarding the predicted spatio-temporal evolution of an urban region, including demographic distribution of the population, housing pattern, neighbourhood configuration, and vehicle ownership and transaction pattern are presented.

9.3 Future Directions

This research presents the development of a state-of-the-art life-oriented proto-type integrated Transport, Land Use, and Energy (iTLE) model. Particularly, this study focuses on modelling and microsimulating long-term and medium-term decisions such as residential location, vehicle transaction, and mode transition. The 15-year simulation results provide promising insights towards the long-range evolution of population in the Halifax region at the micro-level. However, the simulation results are validated for a single year. One of the immediate future researches should focus on performing a historical validation. For example, as the 2016 census information becomes available, a validation of the results should be in the agenda. Another future direction should be the development of the other longer-term components of the iTLE model, which are not implemented in this study. For instance, implementation of the job transition element. Job transition is conceptualized as an important longer-term component of iTLE as it updates employment status of the individuals. Future research should also focus to implement the longer-term commute mode transition model, which will add another layer of validation for the mode choice model within the travel activity module. The incorporation of the mode transition model will be beneficial to further advance the iTLE towards a dynamic, longitudinal, and evolutionary-based integrated

urban modelling system. A parallel research agenda should be the implementation of vehicle type choice component. Further, this study develops a novel two-tier modelling process for location search and location choice. However, the stress-based search model is not implemented within the iTLE simulation model, since microsimulating stress/reasons for relocation is challenging. Future research should emphasize on developing methods to accommodate such stress and process orientation within the simulation environment of the iTLE, which holds the potential to improve the forecasting accuracy.

This research presents the microsimulation results within a proto-type version of the iTLE model, which deals with 10% population of the Halifax region. Future effort should focus on the simulation of 100% population. One of the reasons for the proto-type implementation is the long run time of the model. Further research is required to update the programming code through incorporating parallel computing. In this proto-type iTLE, some simpler version of the advanced econometric models are implemented. Further effort is necessary to investigate how the developed state-of-the-art empirical models such as latent segmentation-based logit model can be implemented within the iTLE framework. The current version of the life-stage module follows heuristic modelling methods. One of the important areas to contribute is to develop micro-behavioural models for advancing the life-stage transition module.

In terms of modelling residential location, vehicle transaction, and mode transition, the historical evolution of transportation system could not be accommodated. As a result, the effects of certain variables including transit availability, transit level of service (LOS), travel time, and travel cost, among others could not be addressed in the model. Future research should focus on developing and maintaining multi-year travel models, which offer information regarding the historical evolution of transportation system measures. Additionally, a GIS database needs to be built to maintain historical record of

urban form. The location choice model only includes owner households. Further investigation should focus to investigate renters' location choice. One of the major challenges during the model estimation process was the small sample size. In fact, the mode specific mode transition model could not employ a LSL modelling technique due to the small sample size hindrance. Since analyzing different domains of contrasts with respect to multiple choice dimensions and latent segmentation are challenging with a small sample size. Hence, more effort is required to collect larger datasets with longitudinal information.

9.4 Concluding Remarks

Integrated urban models are complex large-scale modelling systems, involving the influence of a wide array of decisions of the population. The major challenge in integrated urban modelling is the balance of how much complexity is practical and comprehensive enough for valid implementation. This research advances the integrated urban modelling literature towards a dynamic, longitudinal, and evolutionary-based modelling framework. The iTLE model developed in this study represents greater behaviour by accommodating multi-domain feedback mechanism among a wide range of decisions along the life-course of the population, and offers insights towards the evolution of the urban population by providing micro-scale demographic distribution, housing pattern, neighbourhood configuration, and vehicle ownership pattern. The micro-level land use and vehicle information generated in this study will directly feed the activity-based travel model, and enhance its capacity to support substantial intra-household interactions, and improve activity generation, scheduling, and destination choice procedures. Finally, this study is a significant step forward towards adding the capacity in integrated urban models to test the response of population at different life-stages under alternative land use and transport scenarios.

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Appendix A: Historical Rates

Table A-1: Historical Birth Rates

Year	Birth Rate*
1997	13.58083
1998	11.89293
1999	11.78685
2000	11.68171
2001	11.57751
2002	11.45662
2003	10.77708
2004	10.68095
2005	10.58568
2006	10.49126
2007	10.47819
2008	10.27037
2009	10.17876
2010	10.08797
2011	9.99799

*Number of birth per 1000 population

Table A-2: Historical Death Rates

Year	Death Rate*
1997	6.4862
1998	6.957921
1999	6.895858
2000	6.834349
2001	6.773389
2002	6.702663
2003	7.106526
2004	7.043138
2005	6.980315
2006	6.918053
2007	6.909431
2008	7.252021
2009	7.187335
2010	7.123226
2011	7.059689

*Number of death per 1000 population

Table A-3: Historical Marriage Rates

Year	Marriage Rate*
1981	7.8
1986	7.2
1991	6.4
1996	5.8
2001	5.3
2006	5.1

*Number of marriage per 1000 population

Table A-4: Historical In-migration Rates

Year	In-migration Rate*
2001	42.43813
2002	42.0596
2003	41.68444
2004	41.31262
2005	40.94412
2006	42.65065
2007	42.27021
2008	41.89318
2009	41.5195
2010	41.14916
2011	40.74638

*Number of in-migration per 1000 households

Table A-5: Historical Out-migration Rates

Year	Out-migration Rate*
2001	40.37749
2002	40.01733
2003	39.66039
2004	39.30663
2005	38.95602
2006	39.44413
2007	39.0923
2008	38.74361
2009	38.39803
2010	38.05553
2011	37.68303

*Number of out-migration per 1000 households

Appendix B: Parameter Estimation Results of the Reduced Version of the Micro-behavioural Models

Table B-1 Parameter Estimation Results of the Residential Mobility Model

Explanatory Variables	Variable Description	Discrete Time Binomial Logit Model <i>co-efficient (t-stat)</i>
Constant		-2.09539 (-7.10)
Birth of a Child_Same Year	Birth of a child occurring in the same year of residential mobility	1.39920 (5.47)
Death of a Member_Same Year	Death of a household member occurring in the same year of residential mobility	2.17776 (1.68)
Age below 40 Years	Age of the head of the household below 40 years	0.29203 (2.17)
Age above 55 Years	Age of the head of the household above 55 years	-0.34465 (-2.09)
Income below 50K	Household income below \$50,000 (CAD)	0.28516 (2.29)
Own Vehicle	Household own vehicle	-0.62974 (-4.27)
Dist to CBD above 10km	Distance from home to the Central Business District (CBD) above 10 km	-0.52684 (-2.67)
Dist to nearest Bus Stop below 1km	Distance from home to the nearest bus stop below 1km	0.45825 (2.08)
<i>Goodness-of-fit Measures</i>		
Log-likelihood (at convergence)		-1261.314
Log-likelihood (at constant)		-1351.317
Adjusted Pseudo R-squared		0.067

Table B-2 Parameter Estimation Results of the Residential Location Choice Model

Explanatory Variables	Variable Description	Multinomial Logit Model
		<i>co-efficient (t-stat)</i>
Parcel Size x Birth of a Child_Same Year	Size of the property (acres) interacted with birth of a child occurring at the same year of residential relocation	0.07882 (1.93)
Dist to CBD x Birth of a Child_Same Year	Distance from home to the Central Business District (CBD) in km interacted with birth of a child occurring at the same year of residential relocation	-0.02511 (-2.38)
Dist to CBD x No Car Ownership	Distance from home to the Central Business District (CBD) in km interacted with household not owning vehicle	-0.17151 (-2.34)
Dist to nearest Business Center	Distance from home to the nearest regional business center in km	-0.13655 (-3.64)
Dist to nearest Business Center x Single-detached	Distance from home to the nearest regional business center in km interacted with household residing in single-detached dwelling	0.16206 (4.14)
Dist to nearest School x Presence of Children	Distance from home to the nearest school in km interacted with presence of children in the household	-0.11315 (-1.90)
Dist to nearest Bus Stop	Distance from home to the nearest bus stop in km	-0.02395 (-2.07)
Dist to nearest Park Area	Distance from home to the nearest park area in km	-0.10128 (-1.47)
Population Density	Population per acre area in the home dissemination area	0.00013 (5.34)

Table B-2 Parameter Estimation Results of the Residential Location Choice Model (Continued)

Explanatory Variables	Variable Description	Multinomial Logit Model
		<i>co-efficient (t-stat)</i>
% of Owned Property	Percentage of owned dwelling in the home dissemination area	0.00441 (1.60)
Avg. Property Value X Income above 100K	Average property value (CAD X 1000) in the home dissemination area interacted with household income above 100,000 (CAD)	0.00204 (3.14)
<i>Goodness-of-fit Measures</i>		
Log-likelihood (at convergence)		-773.474
Log-likelihood (at constant)		-886.495
Adjusted Pseudo R-squared		0.134

Table B-3 Parameter Estimation Results of the First Time Vehicle Purchase Model

Explanatory Variables	Variable Description	Discrete Time Binomial Logit Model
		<i>co-efficient (t-stat)</i>
Constant	Constant	-3.44912 (-8.71)
Household Formation_Same Year	First time vehicle purchase and household formation occurring in the same calendar year	-1.43051 (-1.31)
Residential Move_Same Year	First time vehicle purchase and residential relocation occurring in the same calendar year	0.29572 (1.00)
Age below 30 Years	Age of the head of the household below 30 years	1.09653 (3.09)
Age between 30 to 40 Years	Age of the head of the household between 30 to 40 years	1.10918 (3.33)
Income above 100k	Household income above \$100,000(CAD)	0.72391 (3.12)
Household Size less than 4	Number of persons in the household less than 4	0.65059 (2.60)
Owned Dwelling	Household residing in owned dwelling	0.98089 (2.96)
Single-detached Dwelling	Household residing in single-detached dwelling	-0.92243 (-3.40)
<i>Goodness-of-fit Measures</i>		
Log-likelihood (at convergence)		-348.908
Log-likelihood (at constant)		-367.336
Adjusted Pseudo R-squared		0.050

Table B-4 Parameter Estimation Results of the Transaction or Do Nothing Model

Explanatory Variables	Variable Description	Discrete Time Binomial Logit Model
		<i>co-efficient (t-stat)</i>
Constant	Constant	-1.97879 (-9.96)
Household Formation_Same Year	Vehicle transaction and household formation occurring in the same calendar year	-1.19280 (-1.60)
Residential Move_Same Year	Vehicle transaction and residential relocation occurring in the same calendar year	0.23221 (1.20)
Age below 30 Years	Age of the head of the household below 30 years	0.18306 (1.74)
Age above 50 Years	Age of the head of the household above 50 years	0.33636 (1.61)
Income above 100k	Household income above \$100,000(CAD)	0.34737 (3.31)
Household Size less than 4	Number of persons in the household less than 4	0.25415 (2.33)
Dist to nearest Bus Stop less than 1km	Distance from home to the nearest bus stop less than 1 Km	0.21895 (1.91)
Dist to nearest School less than 3 km	Distance from home to the nearest school less than 3 km	-0.34588 (-1.86)
<i>Goodness-of-fit Measures</i>		
Log-likelihood (at convergence)		-1445.404
Log-likelihood (at constant)		-1460.900
Adjusted Pseudo R-squared		0.011

Table B-5 Parameter Estimation Results of the Vehicle Transaction Type Model

Explanatory Variables	Variable Description	Multinomial Logit Model <i>co-efficient (t-stat)</i>
<i>Acquisition</i>		
Constant	Constant	0.68757 (1.41)
Age below 30 Years	Age of the head of the household below 30 years	0.55453 (1.56)
Income below 50k	Household income below \$50,000(CAD)	0.79447 (2.66)
Number of Adults	Number of adults in the household	0.22424 (1.63)
Vehicle Fleet Size 1	Household owns one vehicle	-0.84867 (-3.83)
Dist to CBD less than 10 km	Distance from home to CBD less than 10 Km	0.59233 (2.92)
<i>Trade</i>		
Constant		0.75031 (2.13)
Residential Move_1 Year Lead	Residential relocation occurring 1 year prior vehicle transaction	1.27835 (2.58)
Age above 65 Years	Age of the head of the household above 65 years	0.88865 (1.98)
Income above 100k	Household income above \$100,000(CAD)	0.43413 (2.19)
<i>Disposal (Constant = Reference)</i>		
Residential Move_2 Year Lead	Residential relocation occurring 2 years prior vehicle transaction	0.96537 (2.05)
Gender (Female)	Gender of the head of the household is female	0.50058 (1.71)
Vehicle Fleet Size above 1	Household owns more than one vehicle	-0.00190 (-1.88)
<i>Goodness-of-fit Measures</i>		
Log-likelihood (at convergence)		-467.189
Log-likelihood (at constant)		-497.751
Adjusted Pseudo R-squared		0.050

Appendix C: Predicted Spatial Distribution of the Halifax Population

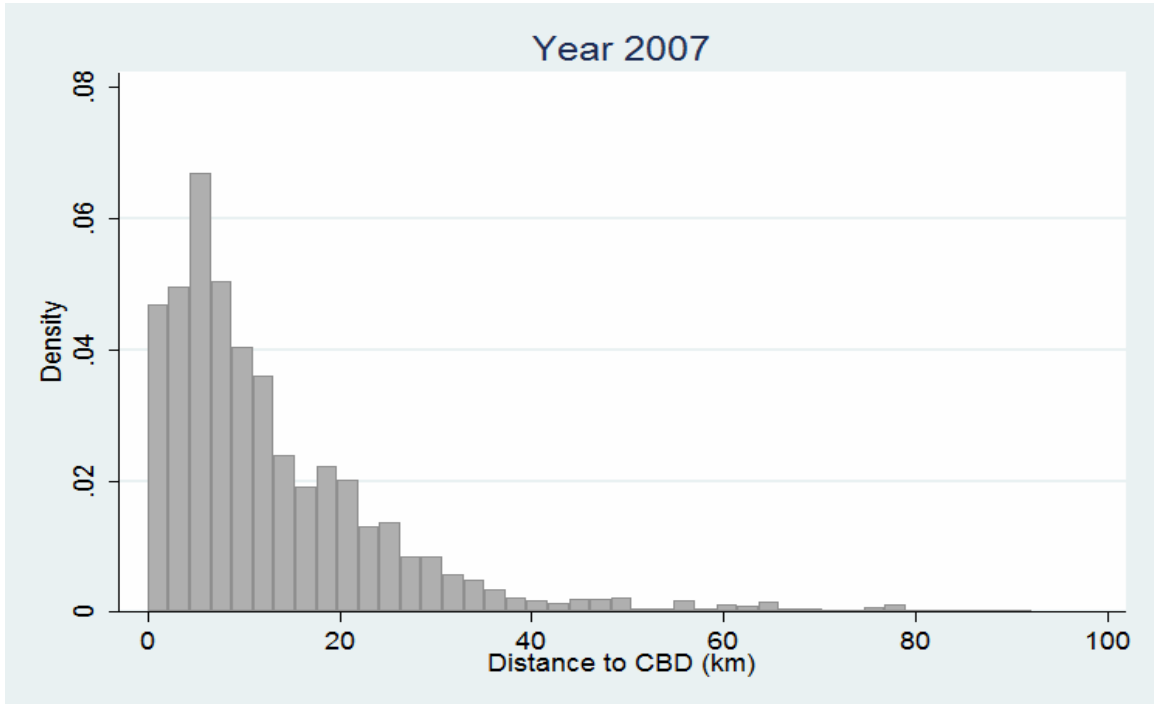


Figure C-1 Predicted Spatial Distribution of the Halifax Population for the Year 2007

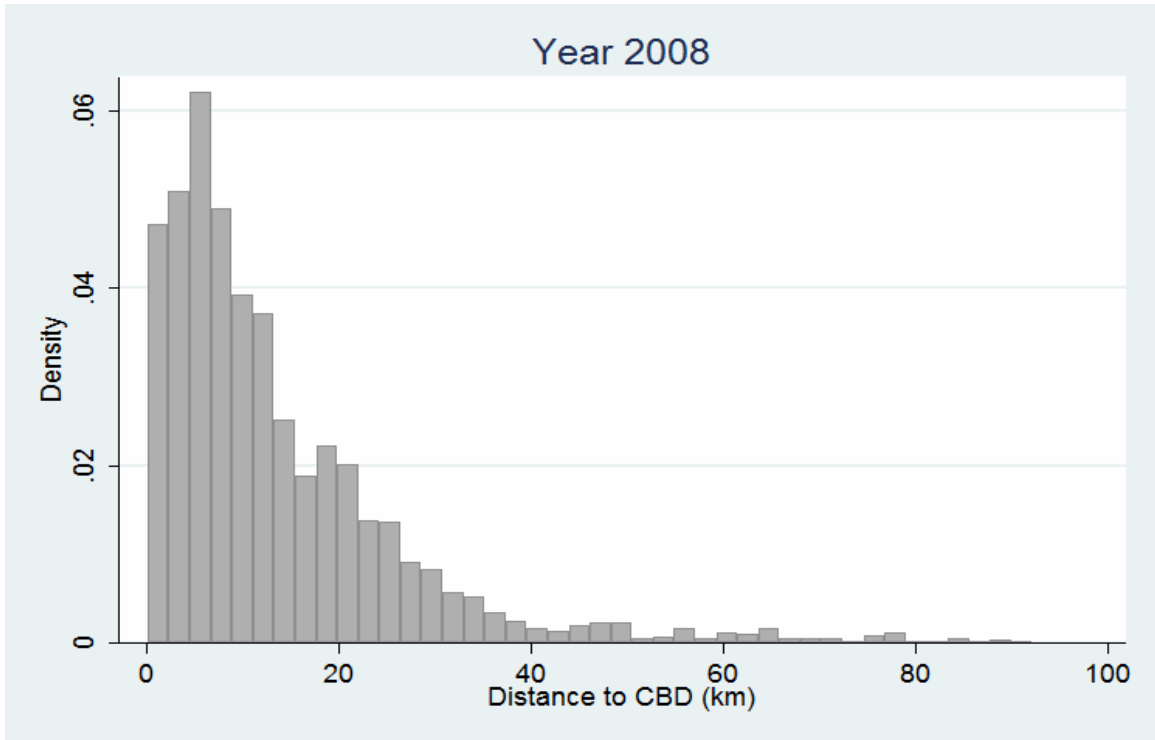


Figure C-2 Predicted Spatial Distribution of the Halifax Population for the Year 2008

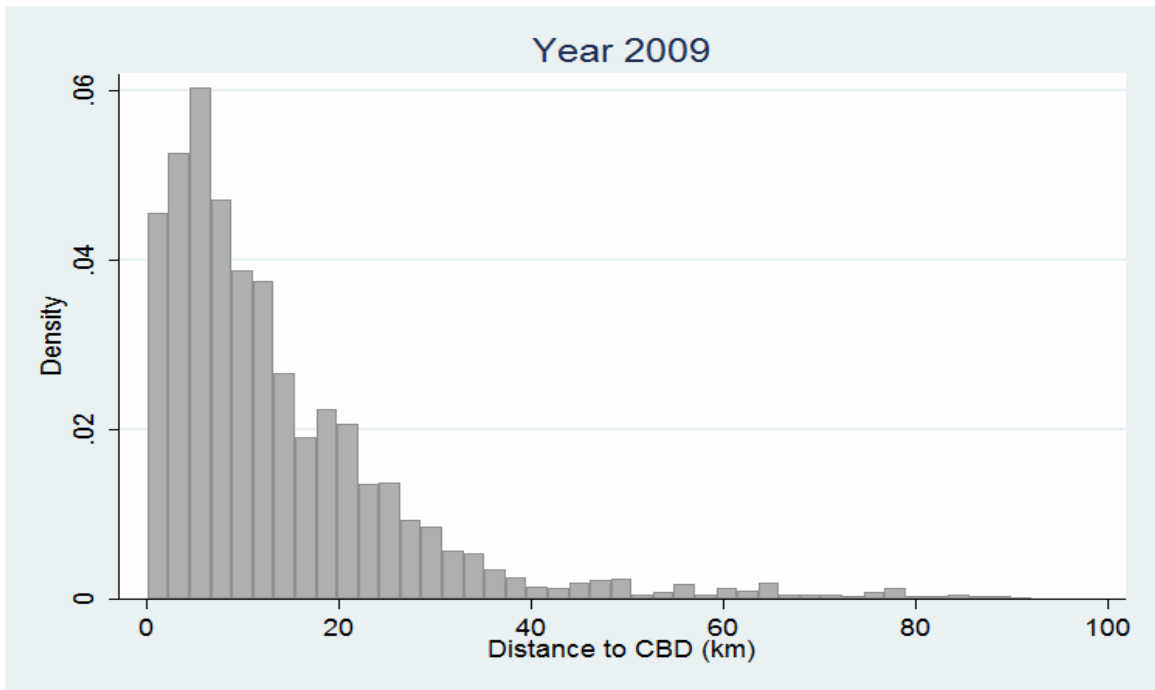


Figure C-3 Predicted Spatial Distribution of the Halifax Population for the Year 2009

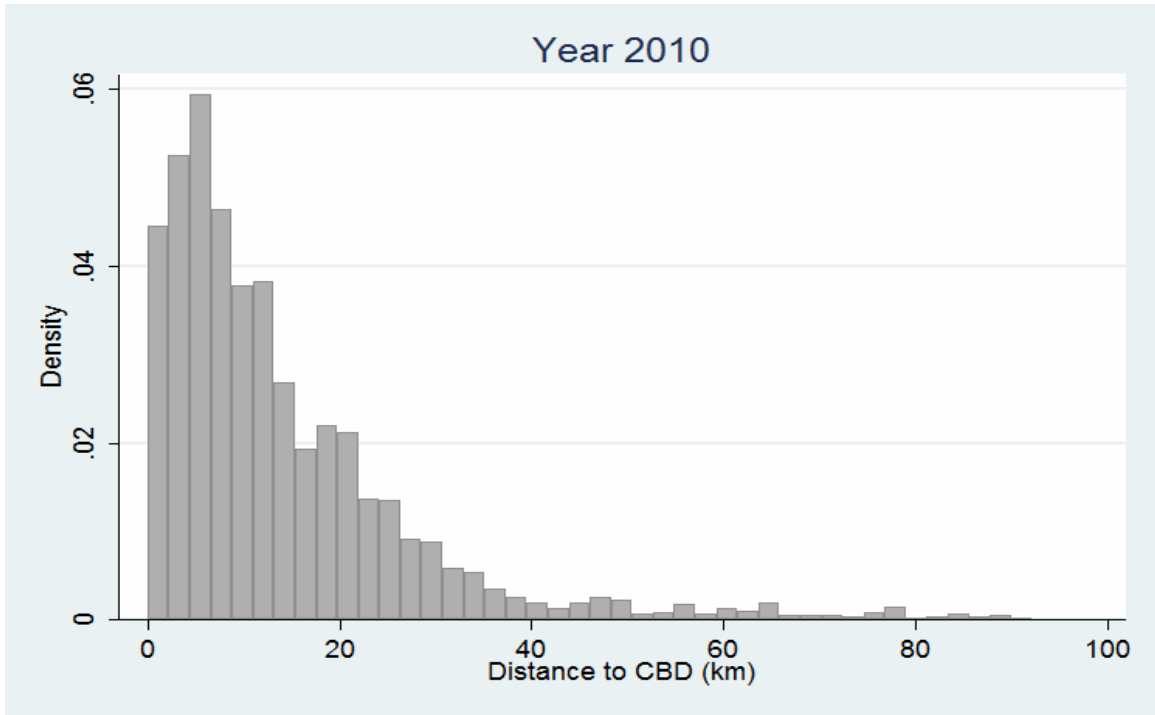


Figure C-4 Predicted Spatial Distribution of the Halifax Population for the Year 2010

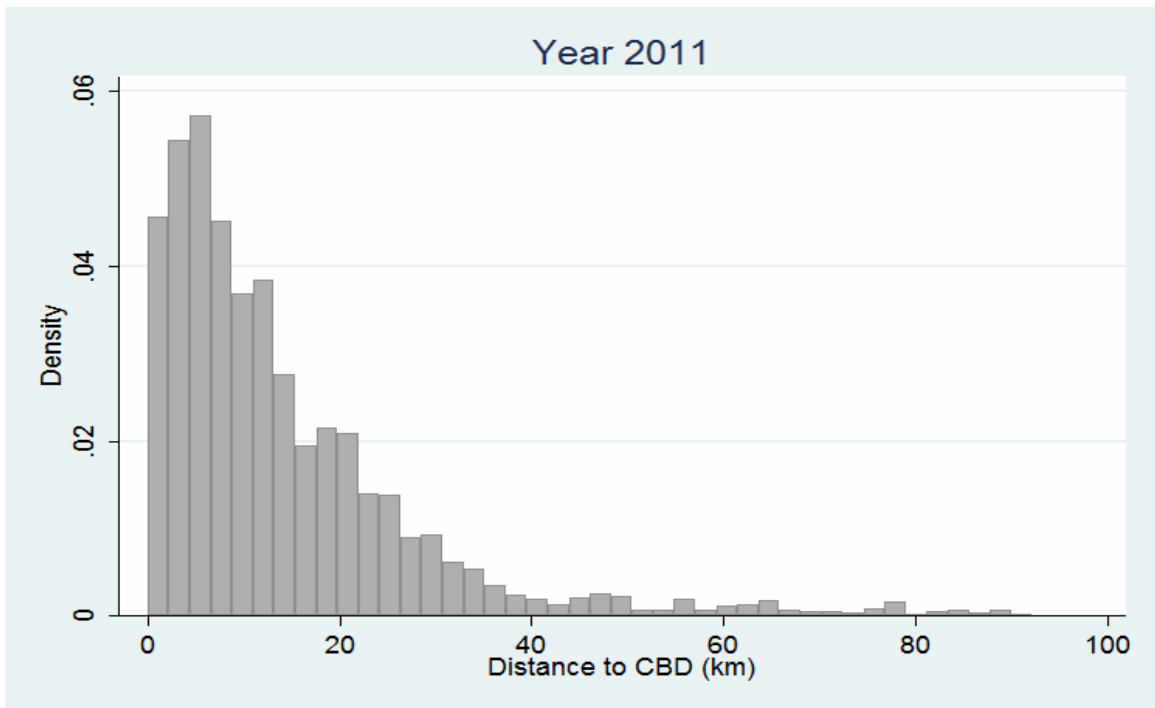


Figure C-5 Predicted Spatial Distribution of the Halifax Population for the Year 2011

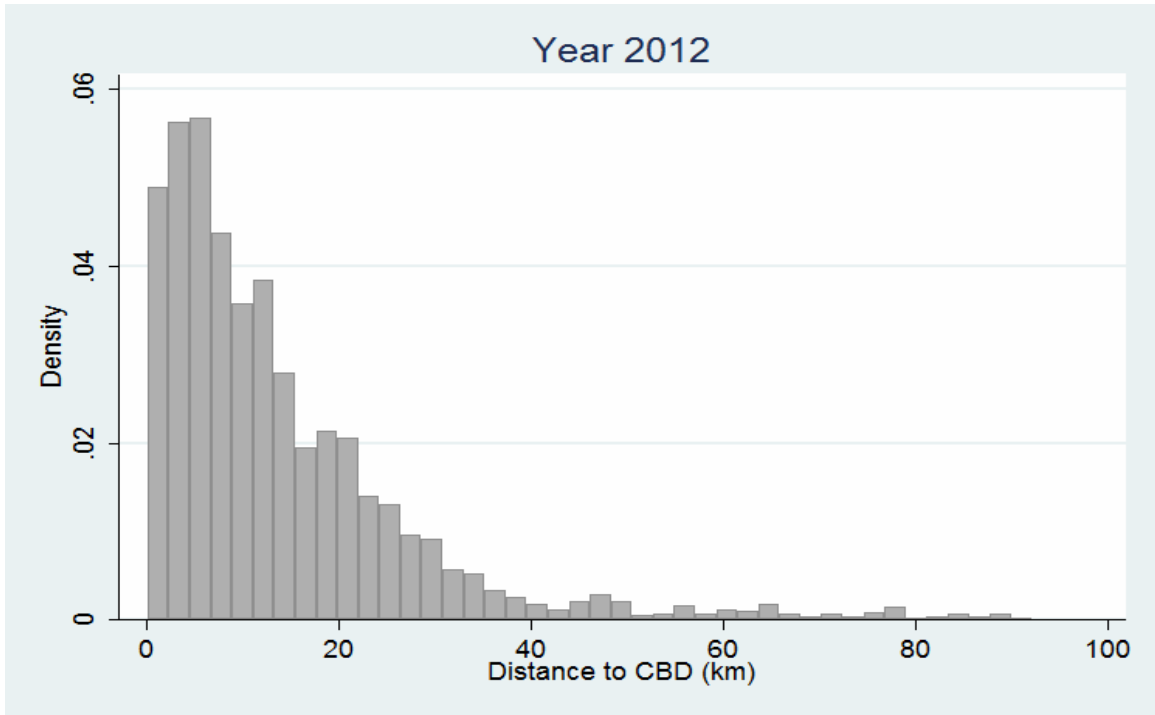


Figure C-6 Predicted Spatial Distribution of the Halifax Population for the Year 2012

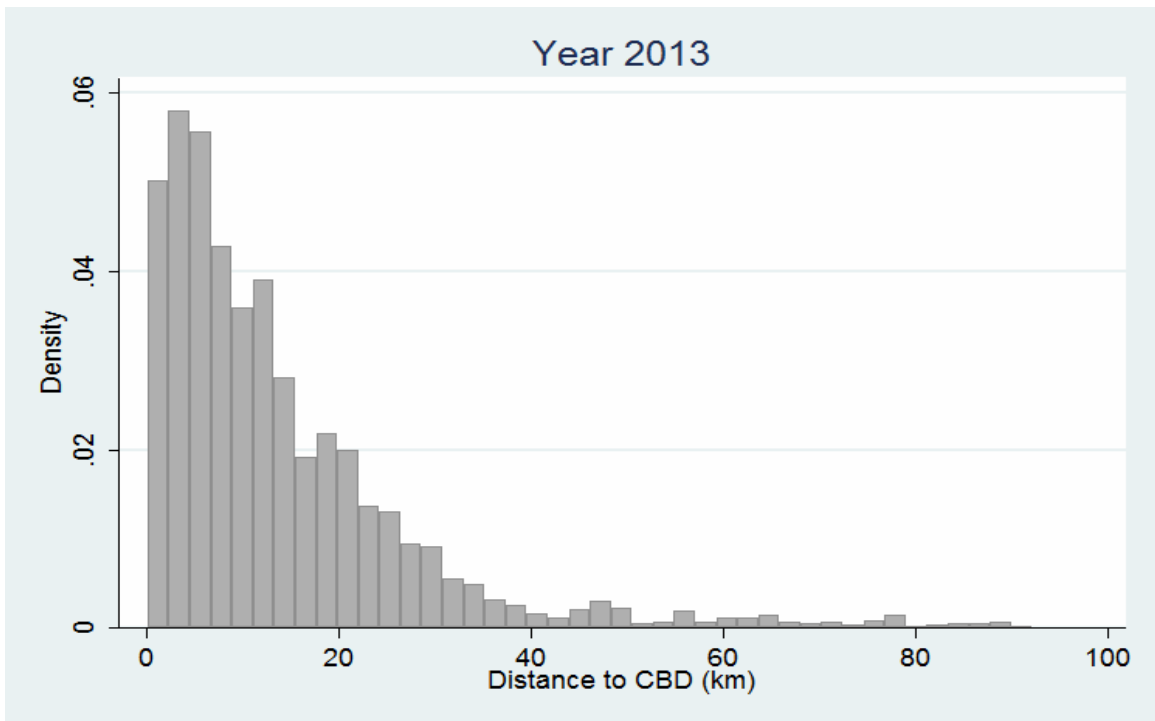


Figure C-7 Predicted Spatial Distribution of the Halifax Population for the Year 2013

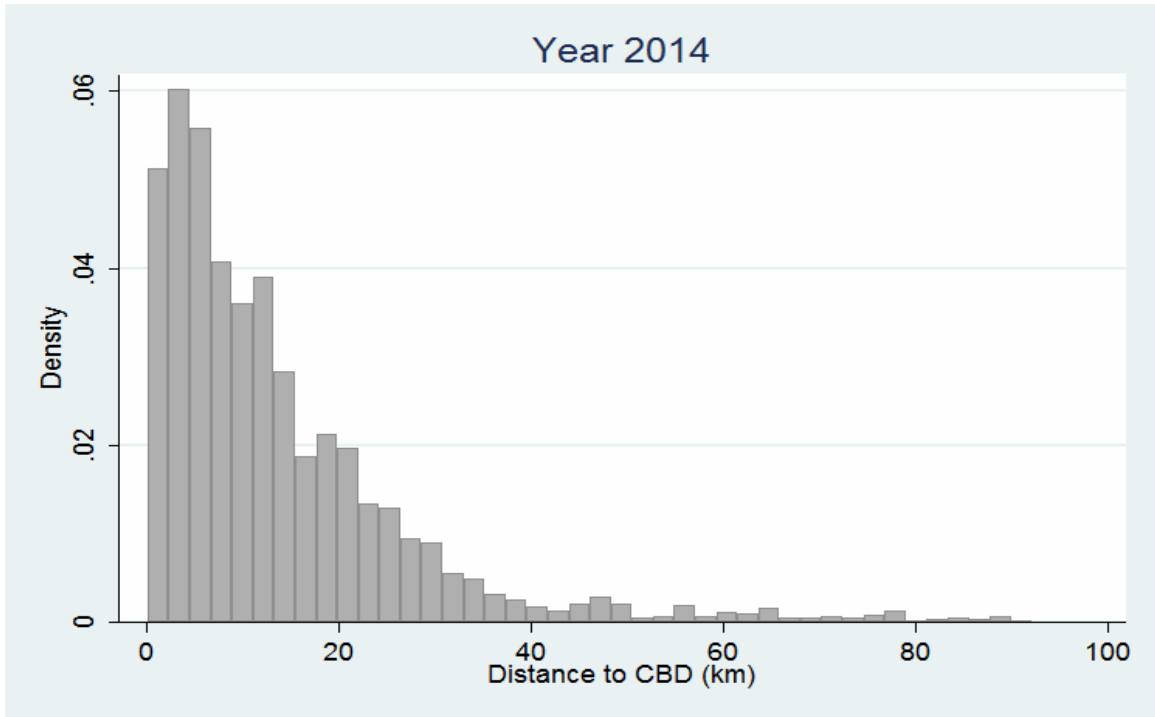


Figure C-8 Predicted Spatial Distribution of the Halifax Population for the Year 2014

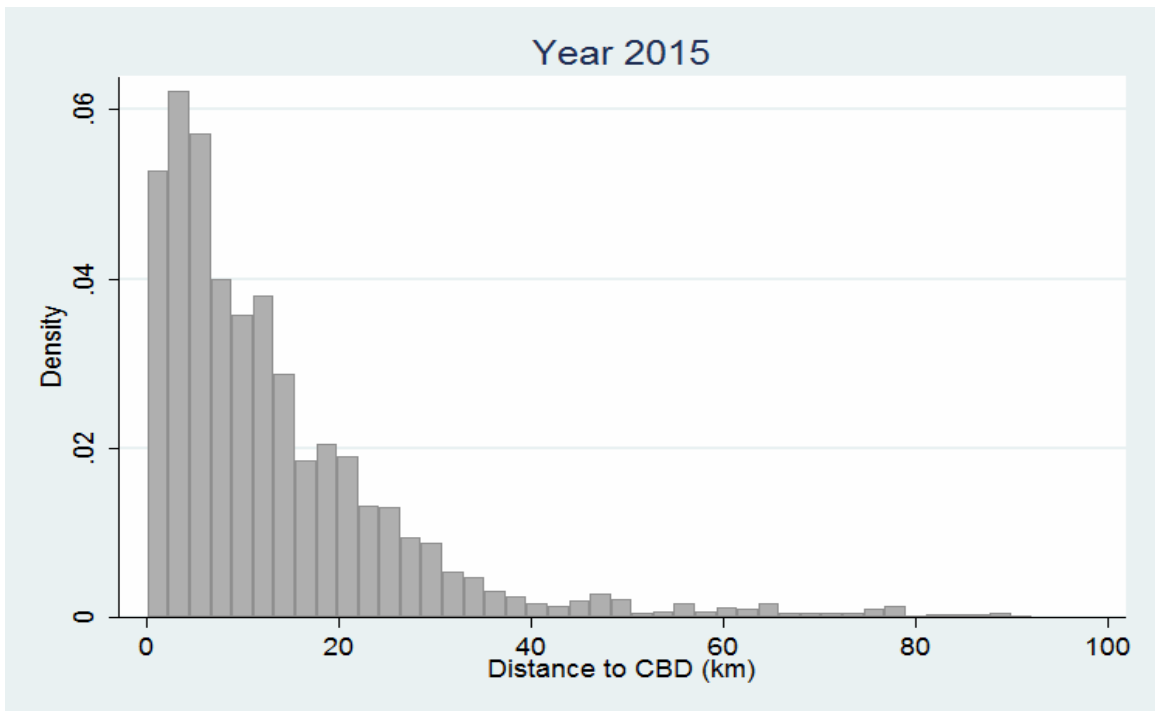


Figure C-9 Predicted Spatial Distribution of the Halifax Population for the Year 2015

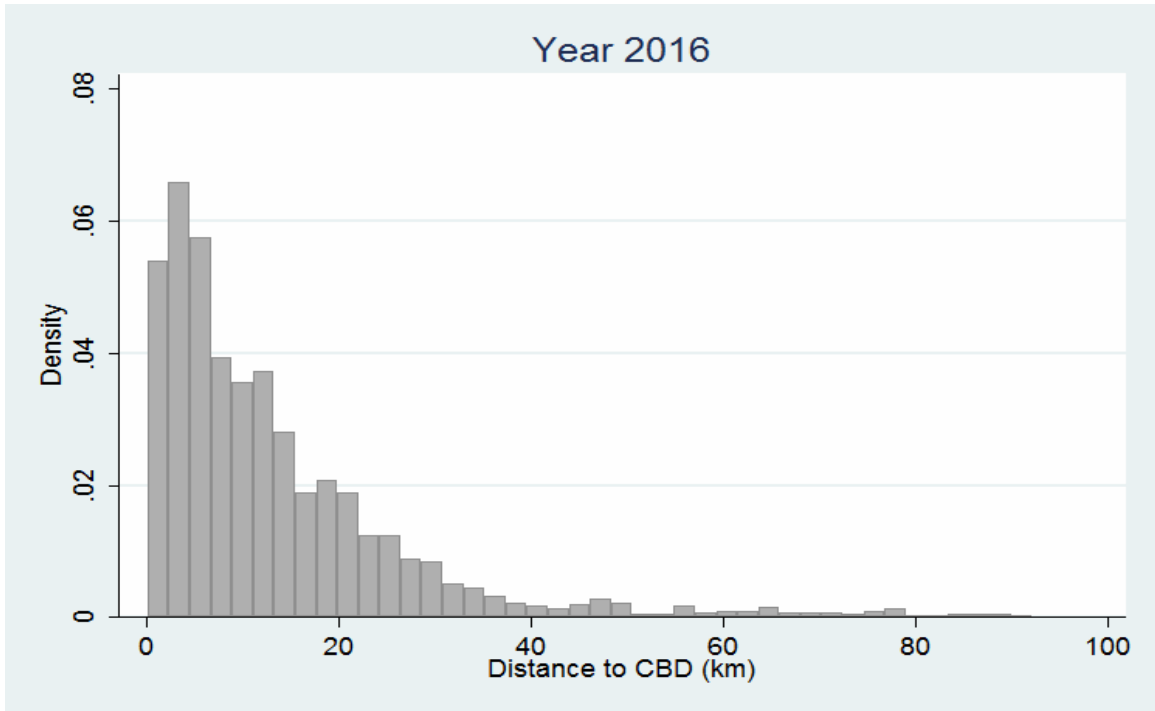


Figure C-10 Predicted Spatial Distribution of the Halifax Population for the Year 2016

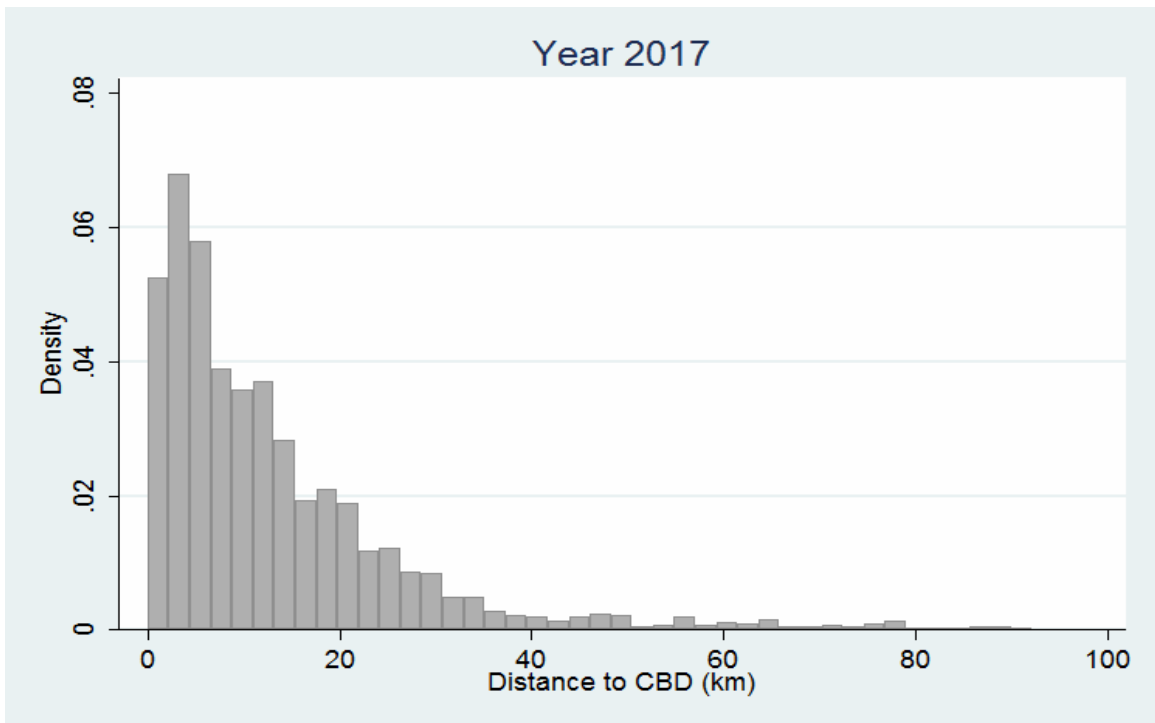


Figure C-11 Predicted Spatial Distribution of the Halifax Population for the Year 2017

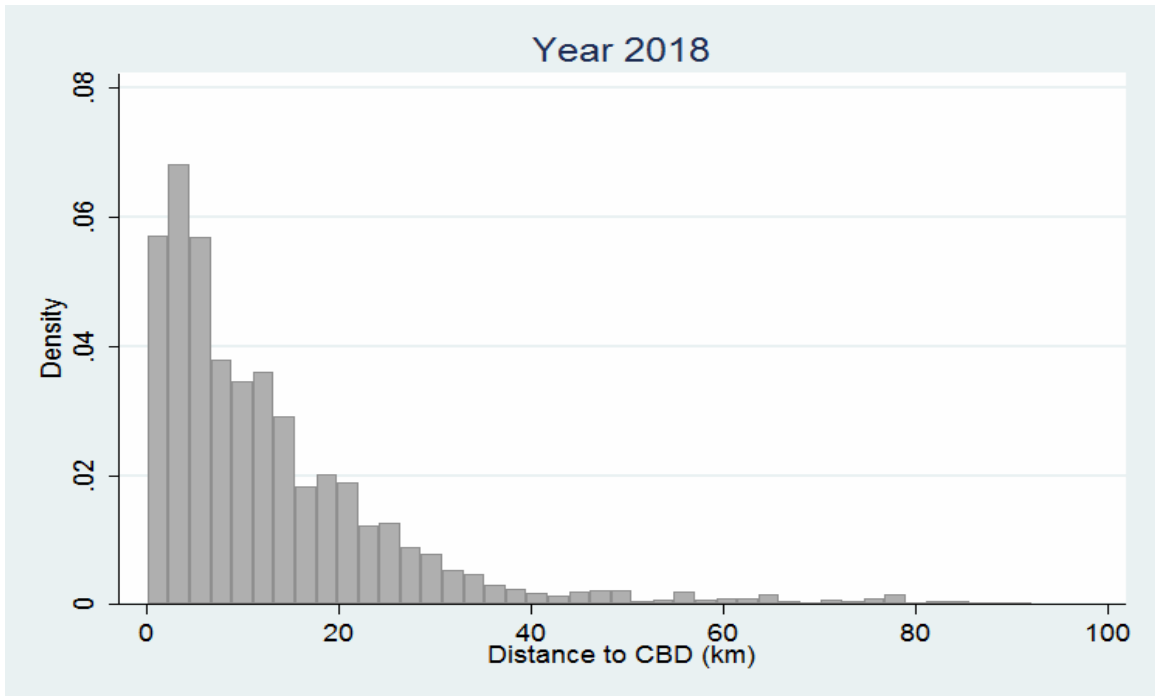


Figure C-12 Predicted Spatial Distribution of the Halifax Population for the Year 2018

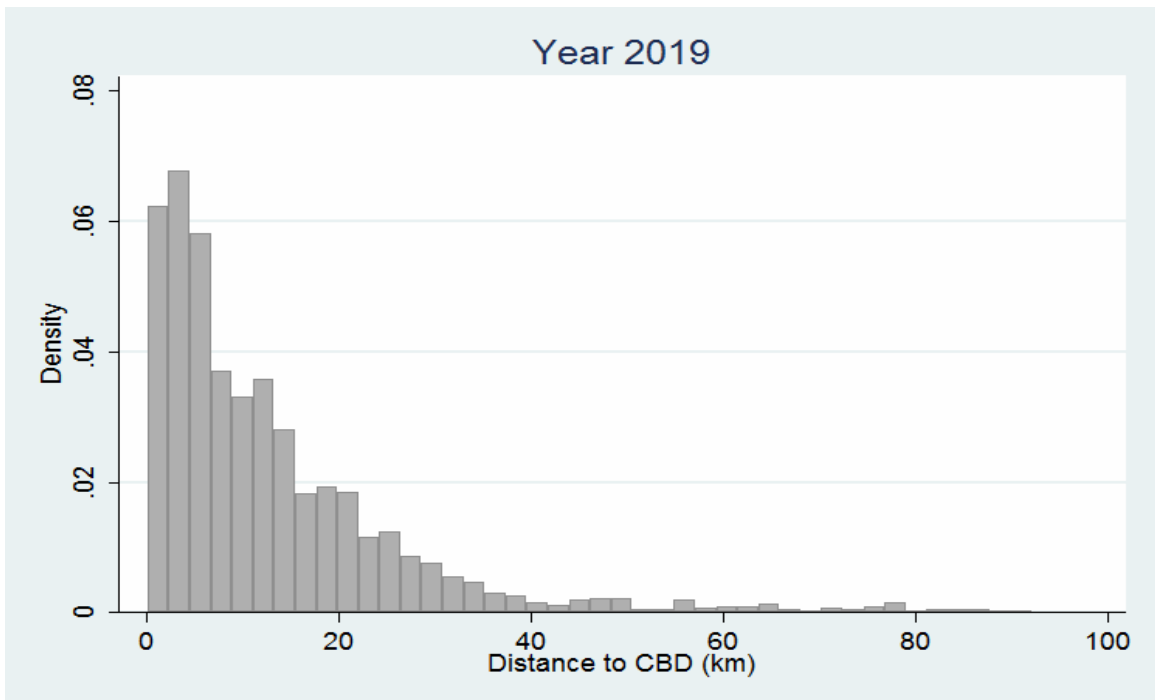


Figure C-13 Predicted Spatial Distribution of the Halifax Population for the Year 2019

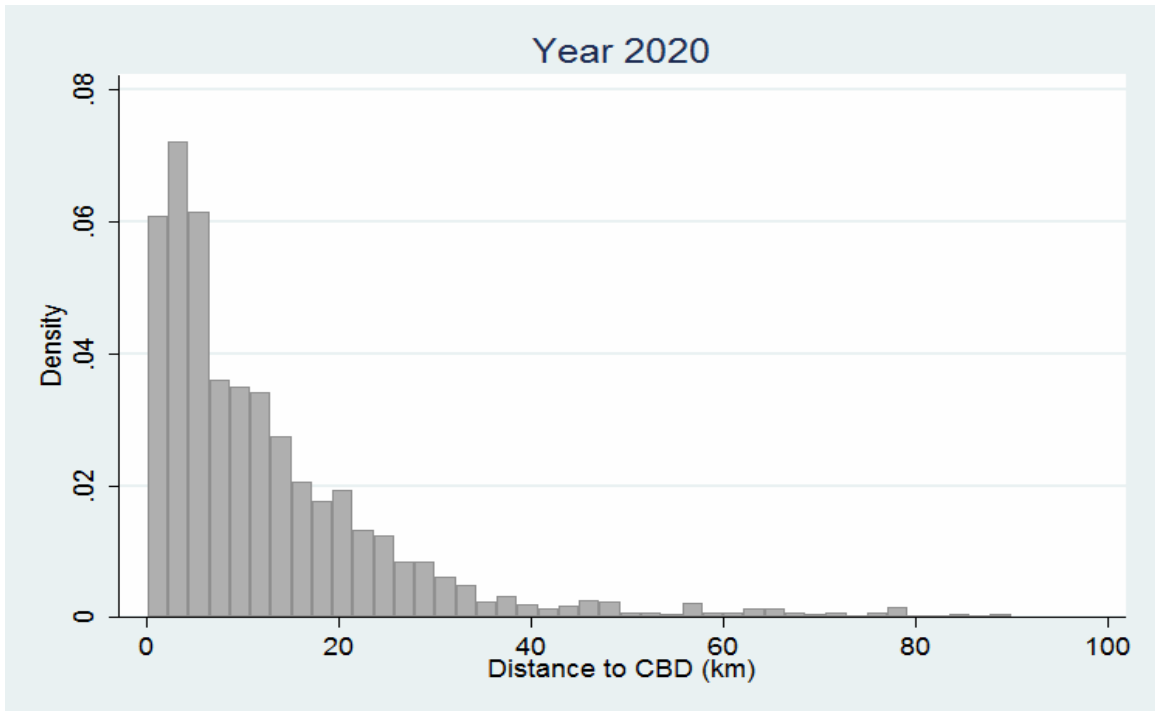


Figure C-14 Predicted Spatial Distribution of the Halifax Population for the Year 2020

Appendix D: Predicted Evolution of the Vehicle Ownership of Halifax Population

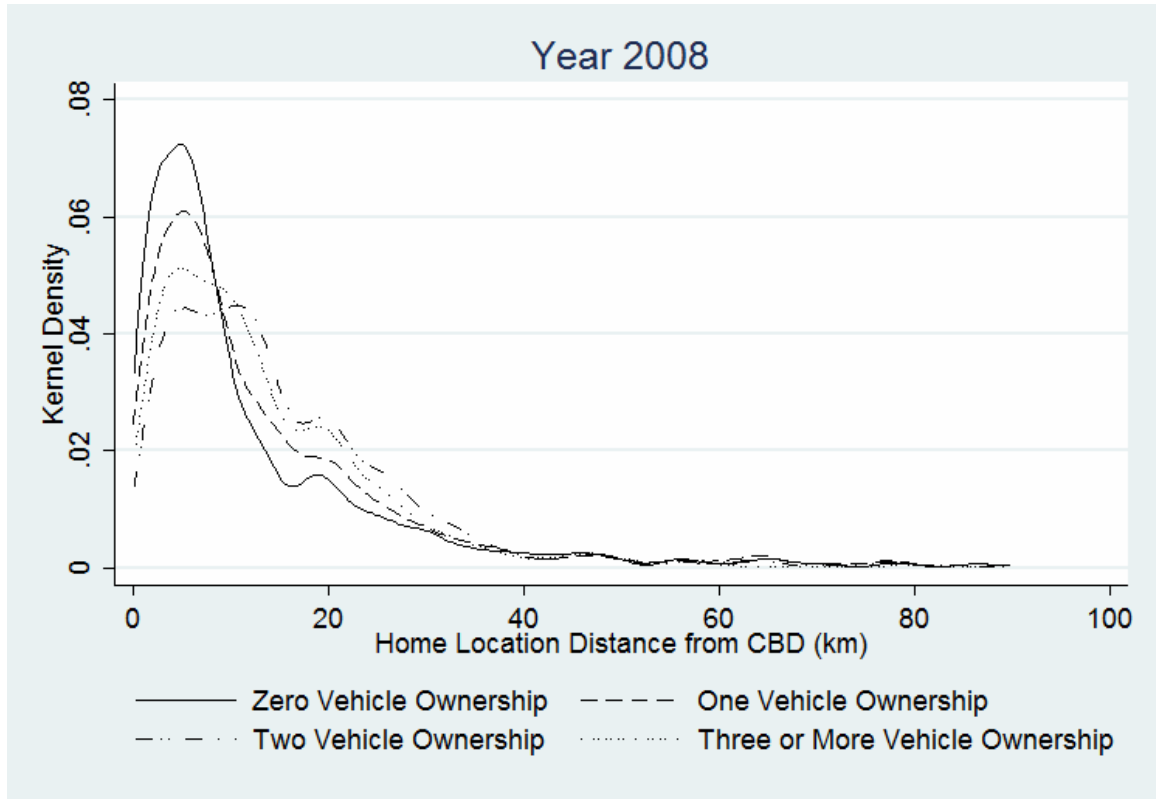


Figure D-1 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2008

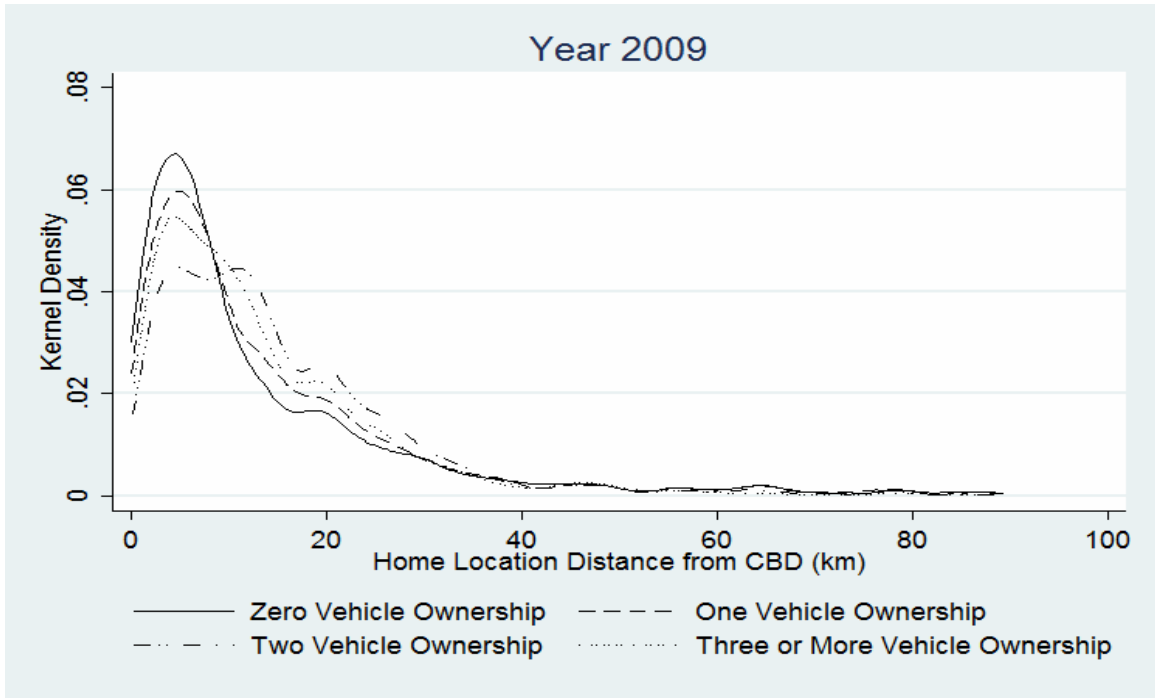


Figure D-2 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2009

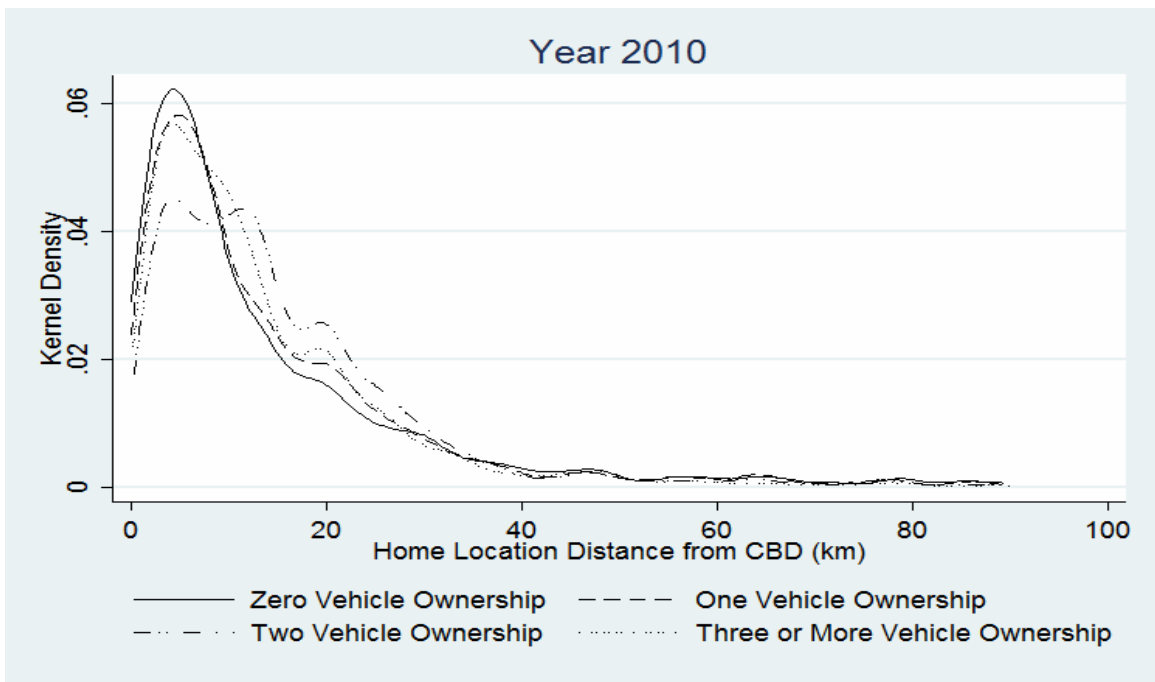


Figure D-3 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2010

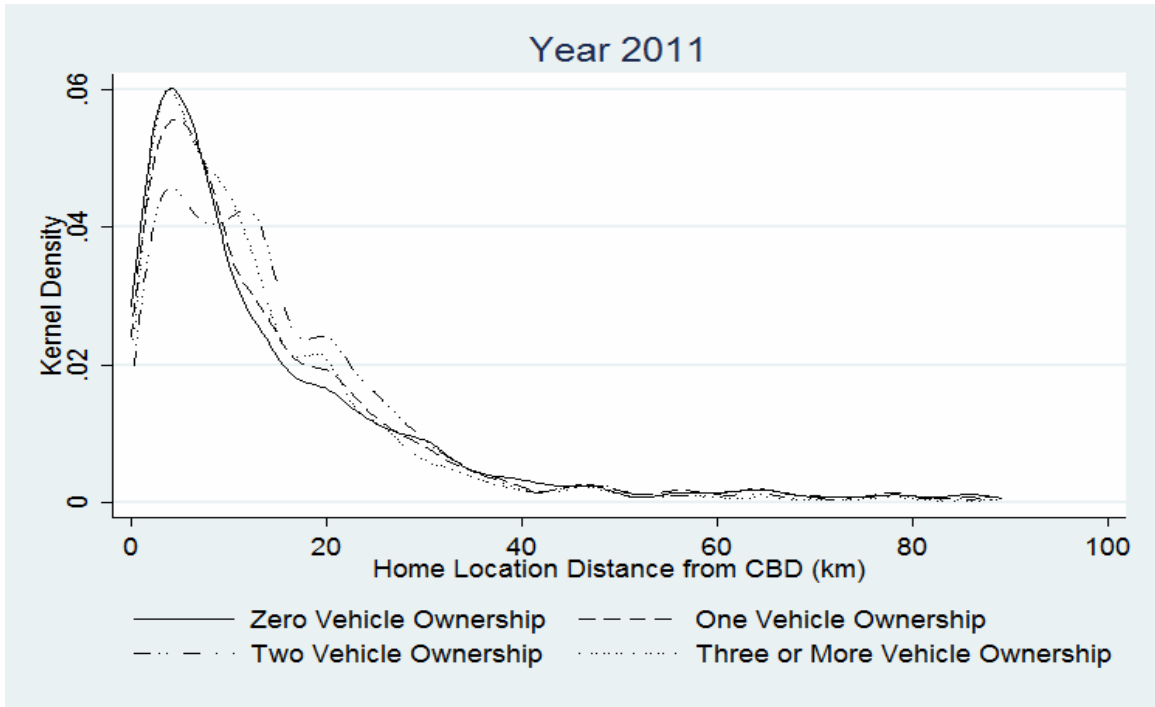


Figure D-4 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2011

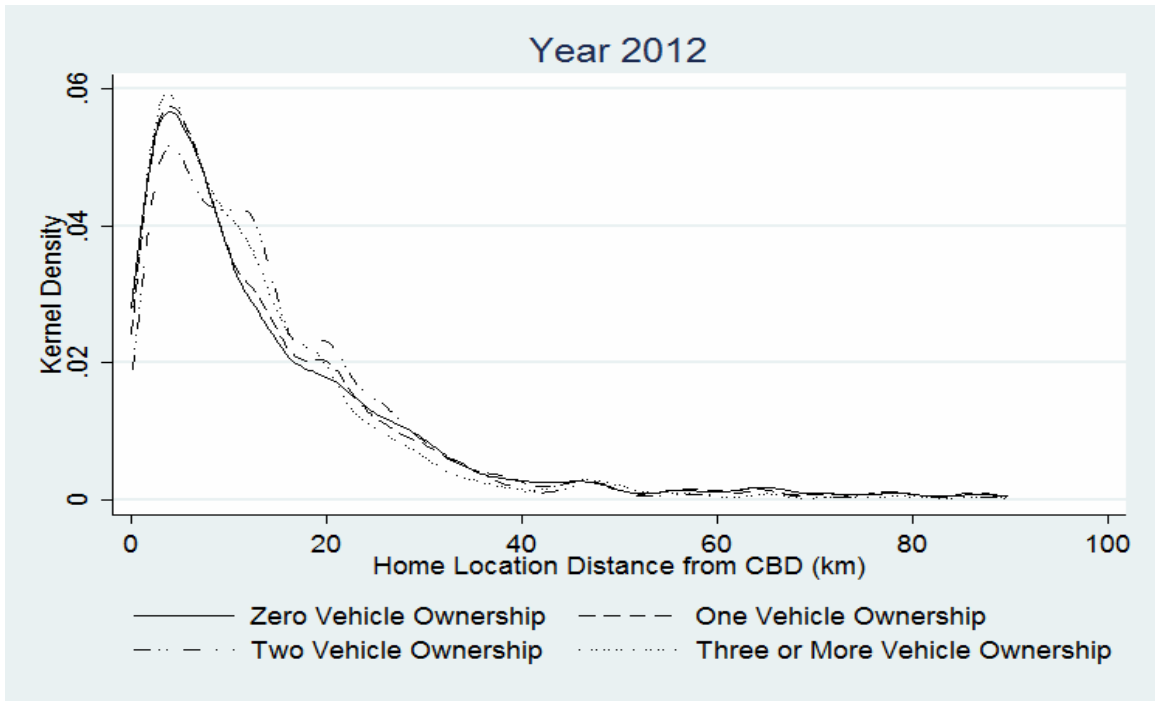


Figure D-5 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2012

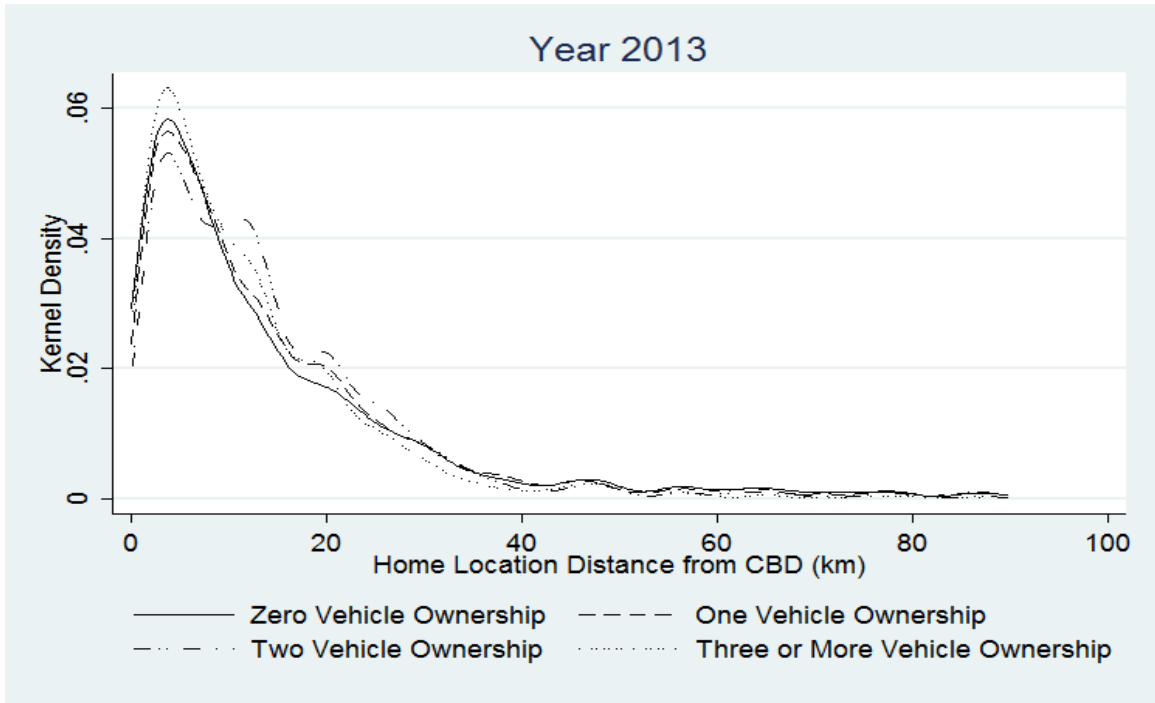


Figure D-6 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2013

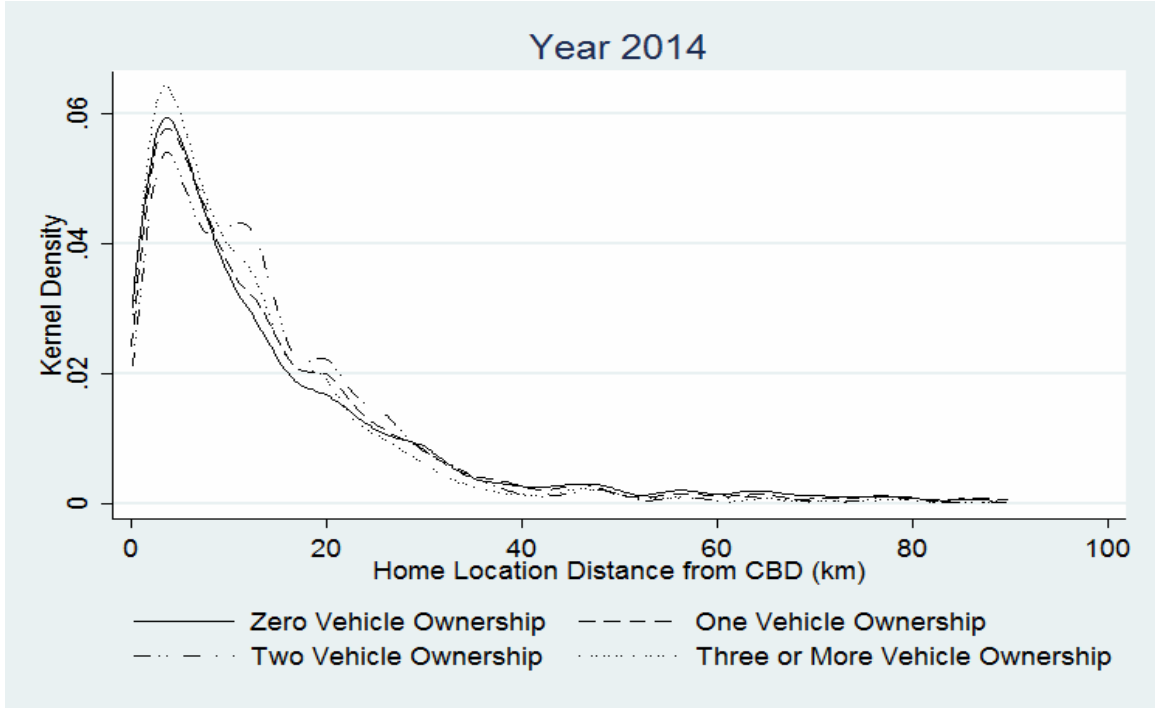


Figure D-7 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2014

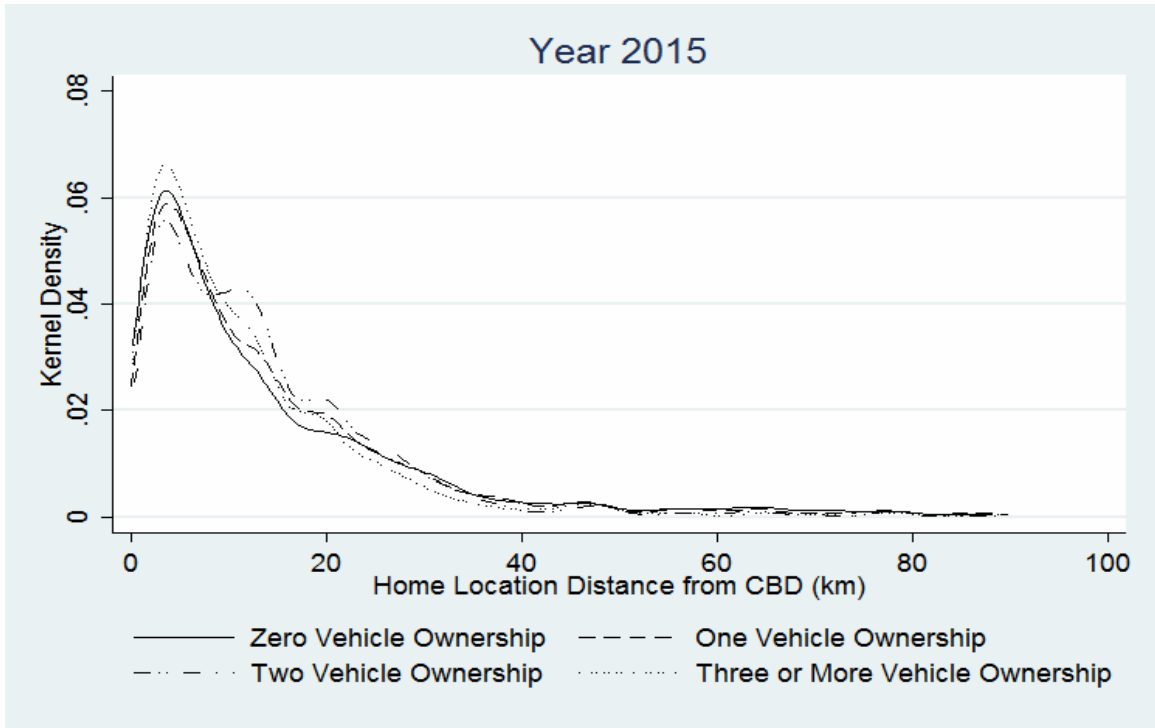


Figure D-8 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2015

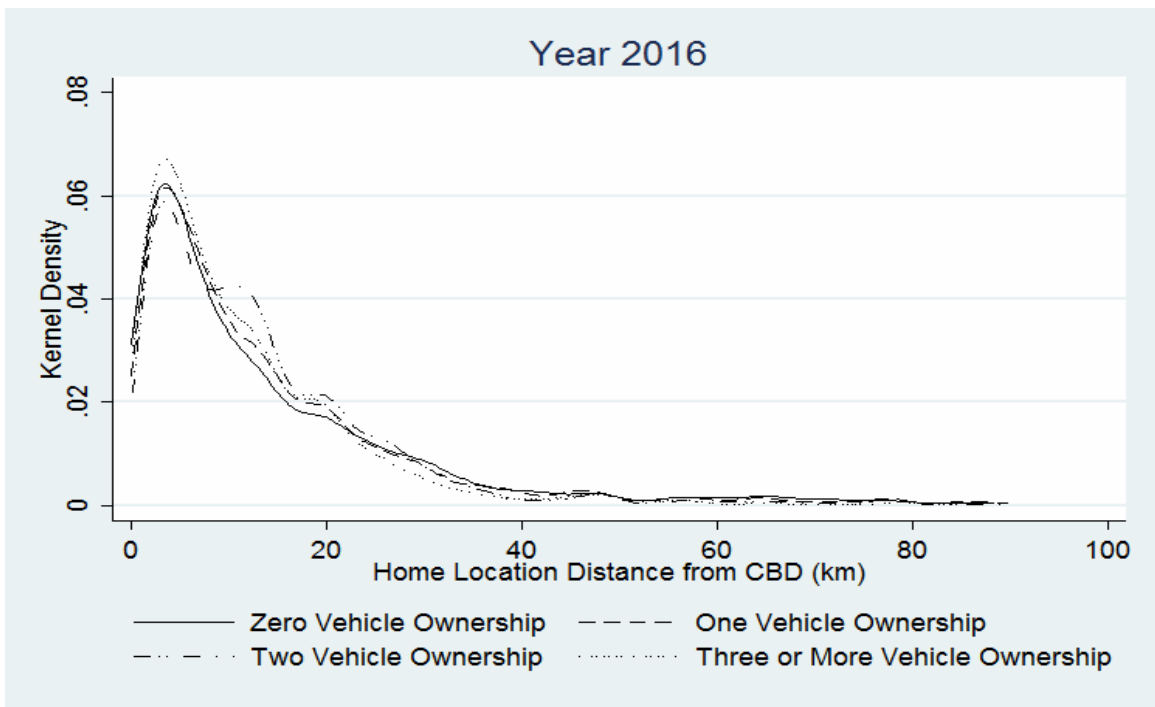


Figure D-9 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2016

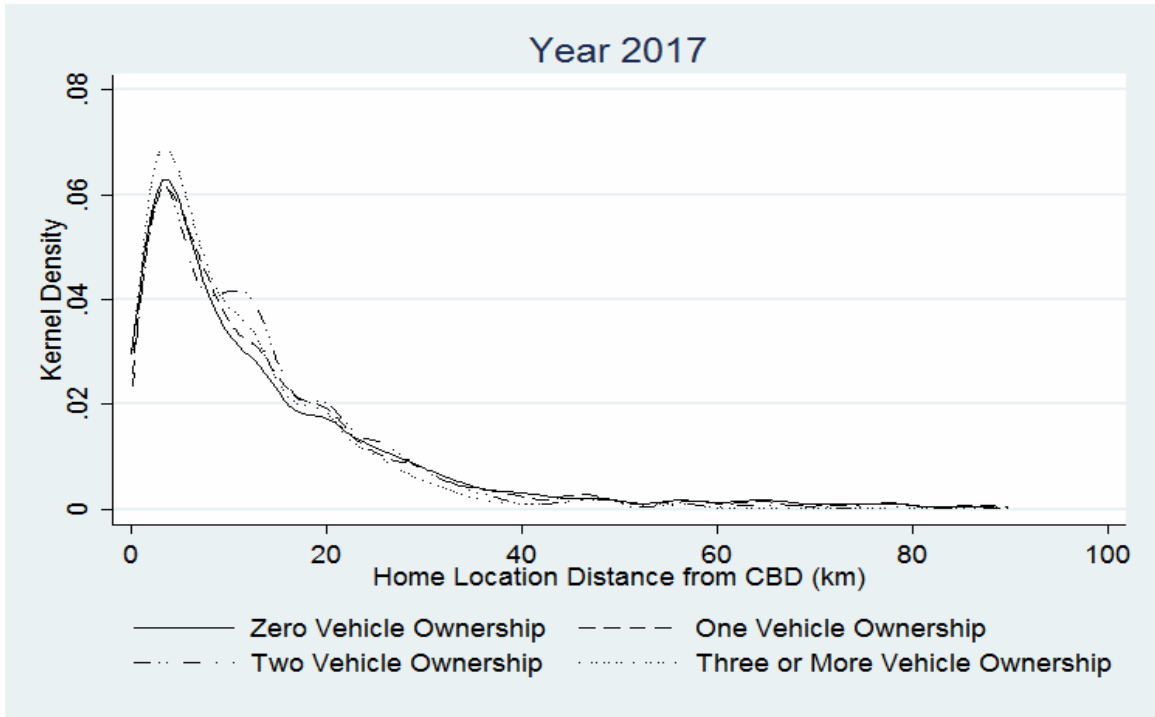


Figure D-10 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2017

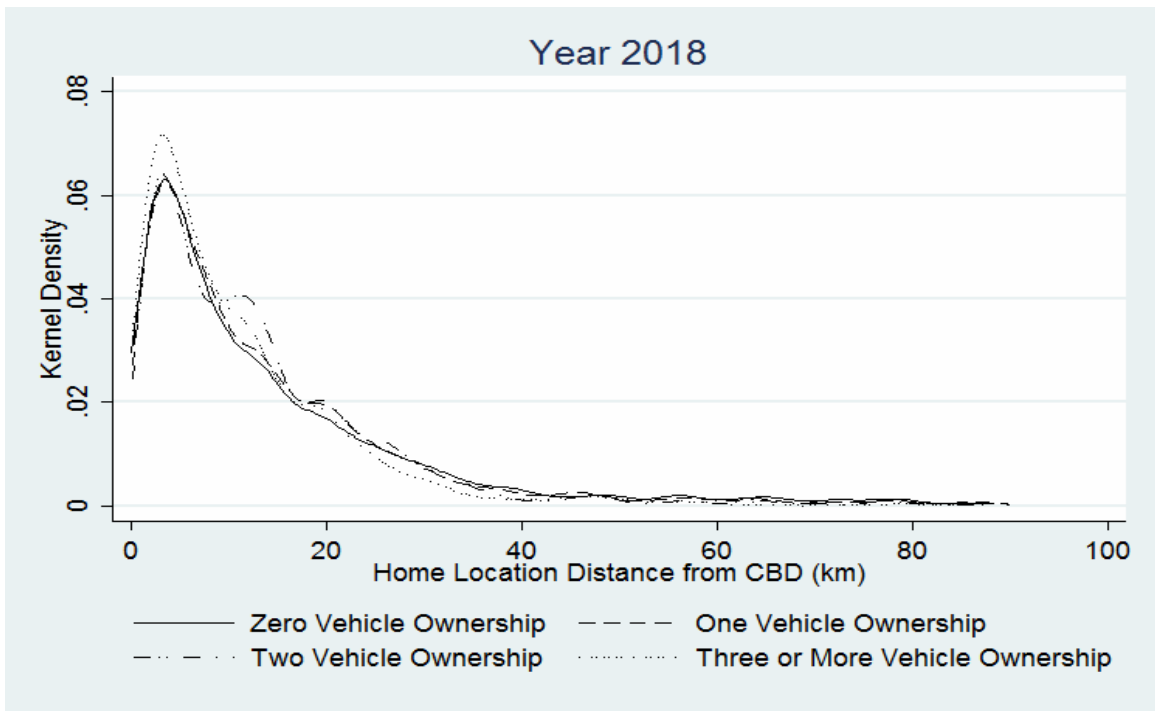


Figure D-11 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2018

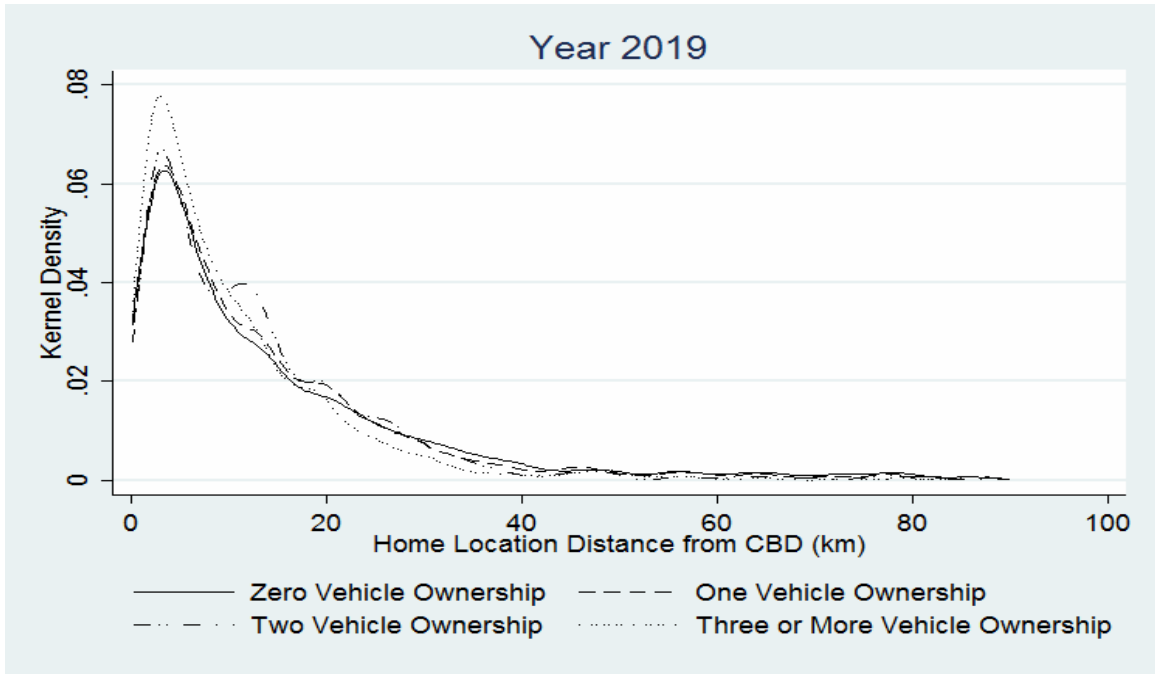


Figure D-12 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2019

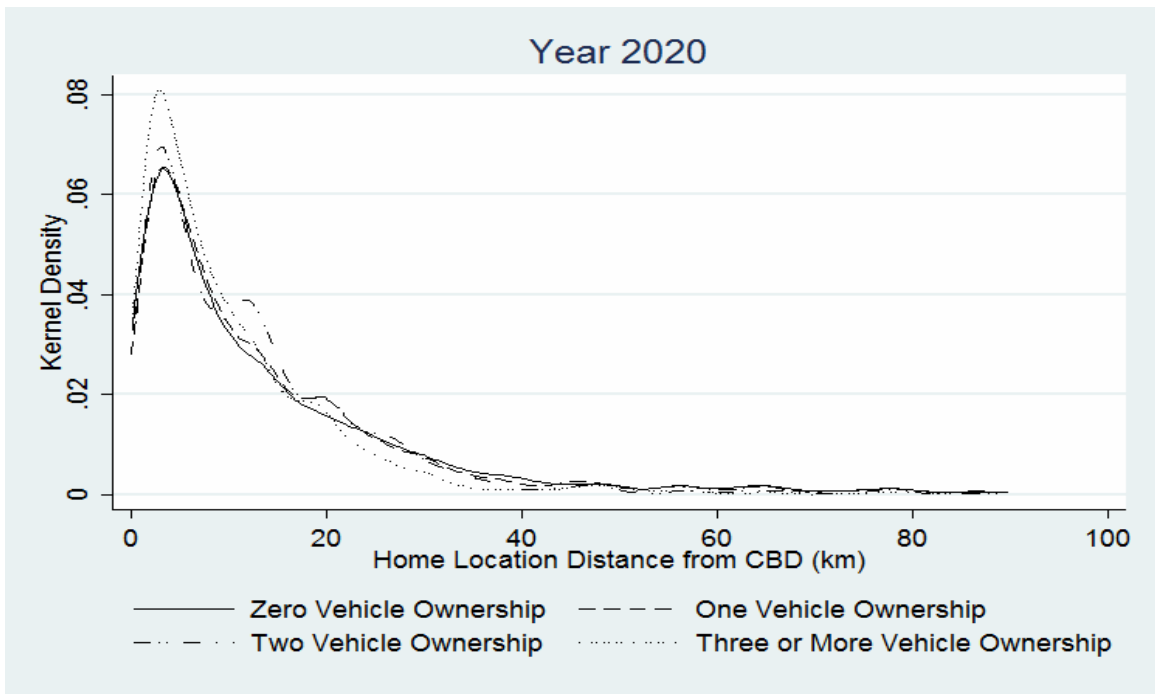


Figure D-13 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2020

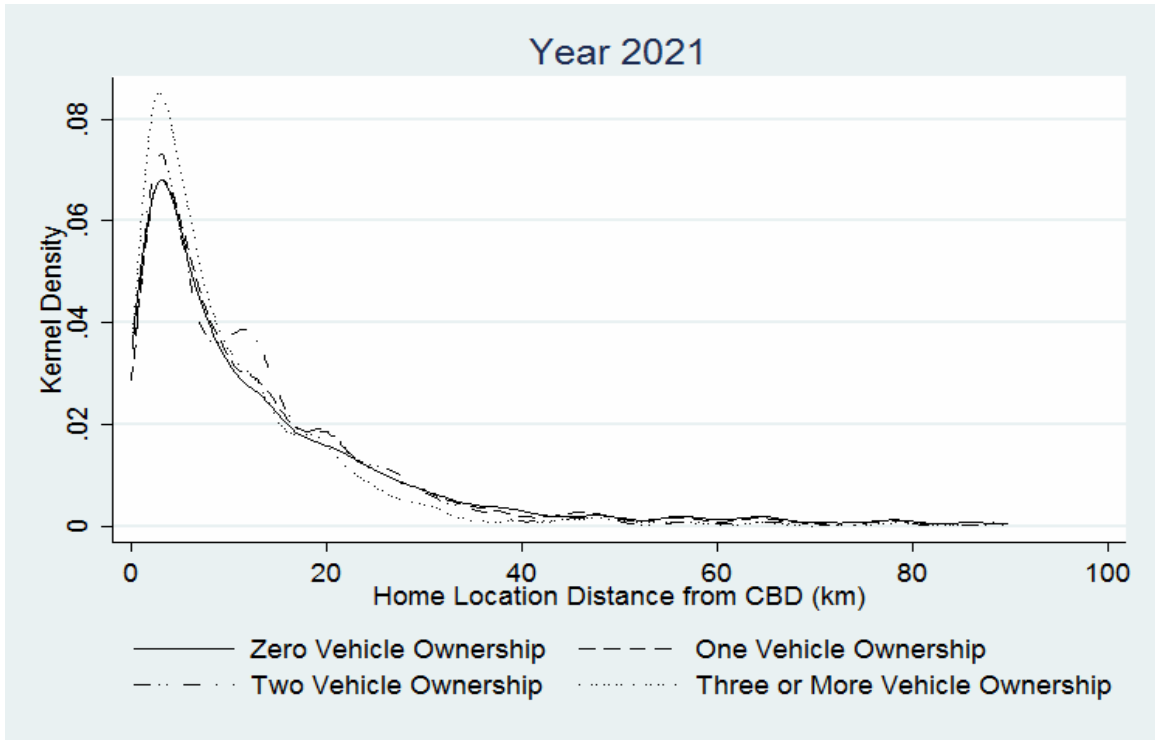


Figure D-14 Predicted Distribution of Vehicle Ownership Level by Home Location for the Year 2021