Longitudinal Modelling of Households' Vehicle Transaction and Type Choice Decisions

by

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Dedicated to

My Dad A.B.M. Moudud Khan

&

My Mom Nazmun Nahar

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Abstract

Longitudinal modelling of vehicle ownership is limited in the literature of ownership models. Temporal variation of households' long-term vehicle ownership decisions can be modelled by considering longitudinal information of the households. Utilizing households' longitudinal vehicle history information, this thesis develops ownership state models, where durations of the households' no-car ownership state and subsequent transient ownership states are evaluated. Moreover, this thesis examines the vehicle type choice behaviour of a household purchasing its first vehicle (i.e. first-time vehicle owner) by terminating the no-car ownership state, and vehicle type choice behaviour of the transient vehicle owner households at repeated vehicle ownership events. One of the unique features of this research is that it examines the effects of life-cycle events on the vehicle ownership decisions. Finally, this research evaluates future vehicle type choice behaviour using a comprehensive set of alternative fuel vehicles by anticipating a future policy scenario of hypothetical gas price increase.

List of Symbols and Abbreviations Used

$\chi(t)$	Hazard function
χ_0	Baseline hazard function
∂, γ	Shape parameter of Weibull distribution
ε	Unobserved random error term
σ	Covariance
β	Parameter coefficient
κ	Censoring indicator
Δ	Alternative-specific constant
θ_c	Class membership probability
ν_c	Class membership constant
φ_c	Class membership parameter coefficient
ASC	Alternative-specific constants
AFV	Alternative fuel vehicles
HEV	Hybrid electric vehicle
PHEV	Plug-in hybrid electric vehicle
PEV	Plug-in electric vehicle

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Chapter 1

Introduction

Modelling vehicle ownership at a disaggregate level has been studied for decades as vehicle ownership directly affect transportation system (such as traffic flow, vehicle kilometers travelled) and the environment (such as emissions and energy use). Vehicle ownership is a critical determinant of household short-term travel behaviour and long-term residential location choice. The majority of research on vehicle ownership has been studied as static models using cross-sectional data at a single temporal point (*Cao et al., 2006; Karlaftis & Golias, 2002*). However, it is obvious that people are more likely to re-evaluate their various household decisions over time. Longitudinal data can provide household information within their lifetime by which the temporal variation of the household vehicle ownership decisions can be captured. Lately, to understand household behaviour of long-term vehicle ownership, researchers have started to focus on the dynamic vehicle ownership models with a growing interest in capturing the impact of significant life occasions (e.g. birth and household formation).

The majority of previous studies concentrated on modelling vehicle ownership level (i.e. number of vehicles) in the households using cross-sectional travel data, which can estimate household behaviour with the change of the number of vehicles in the household (*Anowar et al., 2014; Cirillo & Liu, 2013*). Other types of studies developed household vehicle type choice models (*Choo & Mokhtarian, 2004; Zhao & Kockelman, 2002*) that account for the choice of vehicles at transaction events. Recent studies have started to focus on longitudinal vehicle ownership modelling, such as, vehicle transactions (*Rashidi et al., 2011; Mohammadian & Rashidi, 2007*), vehicle holdings (*Yamamoto et al., 2004*). However, it is not evident from the studies what causes the termination of no-car ownership state of a household, and after termination, how the vehicle choice behaviour of first-time vehicle owners evolves. Also, it is equally important to examine how the life-cycle events along with socio-demographic and neighbourhood variables influence the occurrence of vehicle transaction events, which has not been widely investigated. Using longitudinal information from a retrospective survey, Household Mobility and Travel Survey (HMTS), this research tries to fill these gaps by developing vehicle ownership state models and vehicle type choice models at different ownership states.

This thesis takes a life-oriented approach in modelling household vehicle ownership. In general, vehicle ownership models are estimated by examining various socio-demographic, household characteristics, neighbourhood characteristics, land-use measures, vehicle attributes, accessibility etc. at a single temporal point. However, biographical research that focuses on the impact of life-cycle events and life stages to model vehicle ownership is limited. Life course-oriented biographical studies using longitudinal information help to understand the influence of households' life-cycle events and life stages on vehicle ownership over their lifetime, which is a key contribution of this thesis.

This research also examines a future policy scenario by exploring choice behaviour for alternative fuel vehicles in Halifax, Canada. The future vehicle type choice behaviour is modelled by using a stated response component of the retrospective HMTS data. The stated response component of the survey presented a scenario of sudden 100% gas price hike. Households' alternative fuel vehicle type choice from a comprehensive set of alternative fuel vehicles (i.e. diesel powered vehicle, hybrid electric vehicle, plug-in hybrid electric vehicle, plug-in electric vehicle, and regular gasoline vehicle), is estimated to understand how households will behave in the event of a sudden rise in gas price. The research will essentially explore the determinants of alternative fuel vehicle choice and offer directions for policy making.

1.1 Research Objective

The main purpose of the research presented in this thesis is to develop vehicle ownership models using longitudinal information for use in the development of an integrated Transportation, Land-use and Energy (iTLE) modelling system for Halifax, Canada. Specific technical objectives include:

1) To develop a conceptual framework for modelling vehicle ownership elements of an integrated urban system model;

2) To estimate micro-models of vehicle ownership, specifically households' vehicle ownership states and vehicle type choice in Halifax, Canada;

3) To examine future vehicle choice behaviour given a policy scenario for the Halifax households.

This thesis takes a longitudinal, life course-oriented approach to modelling households' vehicle ownership decision processes. Households make a decision on ownership at different points in time. For instance, a household at some point decides to purchase the first car, and continuously re-evaluates its decision to add, remove or trade vehicles from the vehicle fleet. Therefore, this thesis will first focus on developing models that represent "*no-car state*" (i.e. the episode when the household does not own a vehicle). Then, it will develop models to understand the transaction behaviour throughout the lifetime of sampled households. The thesis will subsequently explore the choice behaviour of vehicle types by both first-time owners and transient owners. Literature review suggests that there is a considerable gap in understanding how households first own a vehicle and what are the differences in terms of the determinants that terminate no-car ownership states for the first-time owners and transient states of subsequent vehicle ownerships. There is also a gap in the understanding of the predictors of vehicle type choices by the first-time owners and transient owners. This research will attempt to fill these gaps by investigating the duration of ownership states and choice modelling of vehicle types at different stages of life. Finally, choice behaviour of alternative fuel vehicles will offer valuable insights on how households respond to sudden rise in gas prices in Halifax.

1.2 Outline of the Thesis

This thesis consists of five chapters. The second chapter offers a conceptual framework developed for modelling vehicle ownership, which includes a theoretical framework and discussion on the data used in this research. In the third chapter, empirical analysis of the vehicle ownership states and the vehicle type choice behaviour are presented. This chapter discusses the relevant literature reviews of the vehicle ownership models, data used during modelling process, and model results of ownership states and type choice behaviour. A future alternative fuel vehicle type choice model of the households is presented in chapter four, where background of that study, data used in response to the stated preference component of the survey, and an empirical model of alternative fuel vehicle type choice behaviour is discussed. The last chapter, chapter five, summarizes the main findings and contributions of the thesis, and suggest some relevant future works.

Chapter 2

Conceptual Framework

2.1 Theoretical Framework

Modelling vehicle ownership is a prominent topic in the field of transportation and travel behaviour analysis. Vehicle ownership has impact on several household decisions, for instance, residential mobility and relocation decisions, employment locations and travel choices. A substantial amount of literature exists on vehicle ownership modelling, such as, vehicle ownership level, types of vehicles, vehicle holding model and vehicle transaction decision. Vehicle ownership level models are developed to understand households' behaviour due to the change in the number of vehicles (*Anowar et al., 2015; Clark et al., 2015*). Type choice models estimate the likelihood of households' vehicle choice behaviour during transaction events (*Cao et al., 2006*). The probability of a household having a set of vehicles at a single point of time can be estimated by vehicle holding models, whereas vehicle transaction models deal with the change in household vehicle fleet by vehicle acquisition, replacement and disposal decisions (*de Jong & Kitamura, 2009*). The details on several forms of vehicle ownership models, along with modelling type, variables used and contribution of the studies is tabulated in Table 2-1. Literature review suggests that, households' status of vehicle ownership, such as, duration of households to sustain a no-car or transaction events and the major factors affecting the occurrence of the no-car or transaction events are absent. Most importantly, the factors that lead to the purchase of first vehicle, and behavioural dissimilarities between first-time and transient owners with multiple transaction events are not well explained in the literature in the case of vehicle type choice.

Table 2-1 Existing Literature on Vehicle Ownership Models

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Anowar et al. (2015)	Montreal, Quebec	Repeated cross-sectional data (O-D surveys of 1998, 2003, 2008 (pseudo panel))	Mixed generalized ordered logit model	Vehicle ownership level	Household and socio-demographics, transit accessibility measures, land-use measures	Socio-demographics vary with time; increased environmental consciousness and inclination to transit lowers current auto ownership than previous
Oakil (2015)	Utrecht, Netherlands	Panel data (Research for individual choices regarding home and car ownership, 1990-2010)	Mixed logit model	Car accessibility	Life events, socio-demographics	Influence of life events on gender differentiated car accessibility
Clark et al. (2015)	England	Panel data (UK household Longitudinal Study, 2009-2011)	Binary multinomial logistic model	Car ownership level	Life events, household structure and life stage, household socio-demographic, neighbourhood context	Various life events are related with different level of car ownership I household
Angueira et al. (2015)	New York, Los Angeles, Washington DC	Cross-sectional data (Travel survey, NHTS 2009)	Latent class segmentation model	Vehicle type choice	Socio-economic and Demographics, activity-travel characteristics,	Short-term vehicle type choice behaviour and distance travelled

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Oakil et al. (2014)	Utrecht, Netherlands	Panel data (Research for individual choices regarding home and car ownership, 1990-2010)	Mixed logit model	Vehicle ownership level	Socio-demographics, life-cycle events	Stressors due to different life-cycle events cause long-term car ownership decision, such as, changes of car ownership level
Clark et al. (2014)	England	Panel data (UK household Longitudinal Study, 2009-2011)	Binary logistic regression model	Vehicle ownership level	Life transitions, household structure and life stage, household socio-demographics, neighbourhood context	Travel behaviour changes during several life transitions. Employment changes, residential relocations, retirement, child birth and changes in household structure strongly affect household car ownership level change and commute mode
Anowar et al. (2014)	Quebec City	Cross-sectional data (O-D survey, Quebec City 2011)	Latent segmentation based ordered logit model, latent segmentation based multinomial logit model	Vehicle ownership level	Household demographics, transit accessibility, land use characteristics	Unordered models have been found better than ordered, in case of car ownership modelling

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Ritter and Vance (2013)	Germany	Panel data (German Mobility panel 2011)	MNL (micro-modelling), simulation of population and household structure	Car ownership level	Household characteristics	If total population is constant over time, larger households gradually decrease the simulated estimates of total cars in households
Cirillo and Liu (2013)	Maryland, USA	Cross-sectional data (2001 and 2009 NHTS data)	Multinomial logit model	Vehicle ownership level and vehicle usage model	Socio-demographics and Neighbourhood characteristics	Household income has greater impact on vehicle usage than ownership level. Increased unemployment rate affects the household vehicle ownership very little
Zegras and Hannan (2012)	Santiago, Chile	Cross-sectional data (Household O-D survey 1991 and 2001)	Traditional multinomial logit model	Vehicle ownership level	Socio-economics, demographics and land-use	Preference of vehicle ownership is dynamic, land-use mix influences the vehicle ownership level negatively, whereas distance to the CBD has a positive impact
Anastasopoulos et al. (2012)	Athens, Greece	Cross-sectional data (Greater Athens metropolitan travel survey 2005)	Random Parameters Bivariate Ordered Probit Model	Automobile and motorcycle ownership level	Socio-demographic, neighbourhood and trip characteristics	Application of bivariate method where the estimated variables can vary across the observations

Table 2-1 **Existing Literature on Vehicle Ownership Models (continued)**

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Caulfiled (2012)	Dublin, Ireland	Cross-sectional data (The place of work census of anonymised records dataset (POWCAR))	Multinomial logit model	Vehicle ownership level	Socio-demographics, trip characteristics, neighbourhood characteristics	Exploring impacts of socio-demographics and household characteristics on multiple car ownership
Rashidi et al. (2011)	Seattle Metropolitan Area and surrounding counties	Panel data (Puget Sound Transportation Study, 1989-2009, 10 waves)	Proportional hazard model (Dynamic joint formulation)	Vehicle transaction timing model conditional on residential and job relocation (both husband and wife) timing	Socio-demographic, built environment, activity characteristics, macroeconomic variables	Implementing a dynamic framework for residential and job relation timing and vehicle transaction timing, which are three critical decisions in households
Urban (2011)	Czech Republic	Panel data (Longitudinal study, household budget survey (1993-2009), EU statistics on income and living conditions (2005-2009))	Multinomial logit model	Vehicle ownership level	Socio-demographics, life-cycle effect, household structural variables, neighbourhood characteristics	Income, larger household, male household head, living in detached or terraced house increases the probability to own a car. Mid-age household have more cars than younger and old. More children decreases the likelihood to afford a car

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Rashidi and Mohammadian (2011)	Seattle Metropolitan Area and surrounding counties	Panel data (Puget Sound Transportation Study, 1989-2002, 10 waves)	Proportional hazard model (Dynamic joint formulation)	Integrated vehicle transaction, residential and employment relocation timing model	Socio-demographic, household structure, neighbourhood characteristics	Husband influences the household and wife influences the vehicle transaction timing decisions most (group-decision making factor influence)
Nolan (2010)	Ireland	Panel data (Living in Ireland (LIS) survey, 1995-2001)	Dynamic random effect probit model	Car ownership level	Socio-demographic, household characteristics	During rapid economic growth and social change, permanent income rather than current income, previous car ownership, presence of young child, lifestyle are the vital factors behind the change in number of cars in household
Li et al. (2010)	Beijing and Chengdu, China	Cross-sectional data (2006 Beijing household survey, 2005 Chengdu household survey)	Ordinary Least Square linear regression (aggregate analysis), Binary logit model (disaggregate analysis)	Car ownership decision/car ownership level	Urban form (neighbourhood characteristics), household characteristics, household head characteristics	Higher population density lowers the car ownership level at sub district level; households having car ownership choose to stay near to the urban center in the megacities

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Cirillo (2010)	Maryland, USA	Cross-sectional data (2001 NHTS)	Multinomial logit model	Automobile ownership level	Household income, household structure, neighbourhood characteristic, land use	Car ownership level is lower in higher dwelling density areas; income has significant and number of worker in household has small effect on household car ownership
Woldeamanuel et al (2009)	Germany	Panel data (German Mobility Panel survey 1996-2006)	Least Square Dummy Variable model (LSDV)	Car ownership level	Socio-economic, household characteristics, accessibility, parking difficulties, accessibility satisfaction	Over time, household car ownership change is insignificant, however, the variation is significant among households in neighbourhood
Yamamoto (2008)	France; Japan (Kofu city urban area, Yamanashi prefecture)	Panel and retrospective data (Parc-Auto survey in France 1984-1998; Retrospective survey in Kofu city 2005-2006)	Competing-risks hazard-based duration model (French case), Multinomial logit model (Japanese case)	Vehicle transaction model (French case), vehicle ownership level (Japanese case)	Life-course events, socio-demographics, neighbourhood characteristics, accessibility	Life-course events are not that much influential for vehicle transaction. Number of adults and residential relocation over lifetime are most significant among life-course events
Potoglou (2008)	Hamilton, Canada	Retrospective data (Choice Internet Based Experiment for Research on CARs)	Random parameter logit model (both normal and log-normal distribution)	Vehicle type choice	Socio-demographic, travel-to-work attitudes, urban form characteristics	Investigating the relationship between vehicle type choice and neighbourhood characteristics

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Potoglou and Kanaroglou (2008)	Central Metropolitan Area of Hamilton, Canada	Retrospective data (Choice Internet Based Experiment for Research on CARs (CIBER-CARS), 2005)	Multinomial logit model, Ordered logit model	Car ownership level	Household structure, socio-economic characteristics, accessibility, neighbourhood characteristics, land use	Evaluates the relationship of car ownership level and Canadian urban form by controlling socio-economic and demographic characteristics
Potoglou and Susilo (2008)	Baltimore, Maryland; Netherlands; Osaka, Japan	Cross-sectional data (2001 NHTS for Baltimore Metropolitan area, Maryland; 2005 Dutch National Travel Survey; 2000 Osaka Metropolitan Area Dataset)	Multinomial Logit, Ordered Logit, Ordered Probit	Car ownership level	Household life-cycle, neighbourhood characteristics, socio-economic and demographics	Unordered models (MNL) are better to explain and predict households' number of vehicle decrease or increase
Mohammadian and Rashidi (2007)	Toronto, Canada	Panel data (1990-1998) "Toronto Area Car Ownership Study: A Retrospective Interview and Its Applications"	Competing risk hazard-based duration approach	Vehicle transaction model	Vehicle attributes, main driver's attributes, attributes of decision making units (DMU, one household could consist one or more DMU)	Competing-risk hazard model is most suitable to estimate vehicle transaction behaviour. Various dynamic variables and time varying covariates have significant role in households' vehicle transaction

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Rubite and Tiglao (2004)	Manila, Philippines	Cross-sectional data (Home-Interview Survey (HIS))	Binary logit model	Vehicle ownership level	Household characteristics, relative location of the household, cost and service level	Household income and number of adult workers are most significant for the change in number of cars in household
Yamamoto et al. (2004)	France	Panel data (Parc-Auto panel survey)	Competing risk duration model	Vehicle transaction model	Vehicle attributes, main driver's attributes, household attributes, macro-economic indicators, policy measure variables	Vehicle inspection programs keep households' vehicles at desirable state with longer holding period. Vehicle scrappage programs expedite vehicle disposal process with lower holding duration of old vehicles
Choo and Mokhtarian (2004)	San Francisco Bay Area	Cross-sectional data (San Francisco Bay Area survey)	Multinomial logit model	Vehicle type choice	Travel attitudes, personality and attitudinal variable, lifestyle, mobility, demographics	Attitudinal, personal and lifestyle factors have much influential on individual vehicle type choice

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Cao et al. (2004)	Northern California	Cross-sectional data (A self-administrated mail survey, 2003)	Nested logit model	Vehicle type choice	Socio-demographics, neighbourhood preferences and characteristics, travel attitudes	Investigating the impact of neighbourhood design on vehicle type choice
Mohammadian and Miller (2003)	Greater Toronto Area (GTA)	Longitudinal panel data, TACOS (Toronto Area Car Ownership, 1990-1998)	Random parameter logit model	Vehicle transaction model	Household attributes, fleet attributes, previous transaction attributes	Exploring effects of heterogeneity and state dependence of a dynamic automobile transaction model
Miller and Mohammadian (2003)	Greater Toronto Area (GTA)	Longitudinal panel data, TACOS (Toronto Area Car Ownership, 1990-1998)	Nested logit model	Vehicle type choice	Household characteristics, household vehicle fleet characteristics, vehicle characteristics	Joint modelling of household vehicle class and vintage choice at disaggregate level, which was used within ILUTE framework for direct forecast of consumers' personal vehicle demand

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Zhao and Kockelman (2002)	USA	Cross-section data (1995 Nationwide Personal Transportation Survey (NPTS))	Multivariate negative binomial model	Vehicle type choice	Household size, population density, income per household	Modelling framework is able to capture underlying vehicle type choice, for both cross-sectional and panel data sets. Household size, income, population density and vehicle prices came out as most influential for households' vehicle type choice
Karlaftis and Golias (2002)	Athens, Greece	Cross-sectional data (roadside interview)	Poisson regression with normal heterogeneity (automobile ownership); binary logit model (autoless)	Vehicle ownership level	Socio-demographics, travel attributes	Higher transit speed, longer commute distance, higher parking search time, and transfer between modes and routes motivate the households to increase their vehicle ownership level

Table 2-1 Existing Literature on Vehicle Ownership Models (continued)

Study	*Study Area*	*Type of Survey*	*Modelling Approach*	*Model Type*	*Variables*	*Major Findings*
Baldwin Hess and Ong (2002)	Portland, Oregon	Cross-sectional data (Oregon and Southwestern Washington 1994 Activity and Travel Behaviour Survey)	Ordered logit model, probit ordered regression	Vehicle ownership level	Household attributes, socio-demographics, neighbourhood characteristics, urban design variables	Households living in mixed land use and dwelling areas, and having better transit accessibility have strong probability of reducing the number of vehicles in household
Chu (2002)	New York City	Cross-sectional data (New York Metropolitan Transportation Council's (NYMTC) Regional Travel Household Interview Survey (RT-HIS), 1997 and 1998)	Ordered probit model	Vehicle ownership level	Socio-economic variables, neighbourhood characteristics	Households living in highly urbanized area, higher number of licensed driver and income have higher probability to increase number of vehicle in household. A balanced land use development has more impact than higher dwelling density on owning less number of cars
Yamamoto and Kitamura (2000)	California (except San Diego)	Panel data (from first two waves of Household Survey in California, 1993 and 1994, 1996)	Hazard-based duration model	Household vehicle holding duration	Vehicle attributes, household attributes, primary user attributes	High income and more vehicle households, and leased, used and company cars have less vehicle holding duration for both actual and intended duration model

The existing literature on vehicle ownership modelling can be broadly categorized as: a) vehicle ownership levels; b) vehicle type choice and c) vehicle transaction behaviour. Most of the discrete choice models of vehicle ownership are based on the number of vehicles or vehicle ownership level in the households at a particular point of time. These models essentially focused on the analysis of the households' likelihood of owning vehicles (i.e. probability of increasing or decreasing the vehicle ownership level) in relation with several socio-demographic, neighbourhood or household characteristics. For instance, presence of younger or old people in household, mixed land use areas, better transit accessibility and mixed housing facilities in the neighbourhood reduce the vehicle ownership level in the households (*Urban, 2011; Baldwin Hess & Ong, 2002*). Also, high population and housing density in the neighbourhood, and presence of children decrease the probability of owning vehicles in the households (*Cirillo, 2010; Li et al., 2010*). On the other hand, highly urbanized areas, high income, living in single-detached houses, and farther commute distance increase the likelihood of the households to own multiple vehicles (*Chu, 2002; Urban, 2011; Caulfield, 2012; Karlaftis & Golias, 2002*). Another type of vehicle ownership models analyzes households' vehicle type choice behaviour. Household characteristics (such as, household size) and vehicle attributes (such as, vehicle price) have significant impact on the choice of vehicle type in a household (*Zhao & Kockelman, 2002*). However, Cao (*2004*) found that, other than vehicle attributes and household characteristics, surrounding neighbourhood design also significantly influences the choice of vehicle in households. Besides, the impact of several attitudinal, personal and lifestyle choices have been found significant in the case of vehicle type choice (*Choo & Mokhtarian, 2004*).

The studies discussed above are based on considering cross-sectional data at a single temporal point for the analysis of vehicle ownership models. There are certain limitations in using a static modelling approach and the cross-sectional travel survey data. For instance, cross-sectional travel data are only an instant snapshot of a single vehicle ownership event, which could be different in another time frame. To avoid this shortcoming, recent studies have started to use longitudinal information of households, which are capable of capturing temporal variation of households' critical decisions by considering observed longitudinal changes across households (*Fatmi et al., 2015).*

However, limited studies focused on life-oriented approach to modelling vehicle ownership utilizing longitudinal information (*Potoglou, 2008; Miller & Mohammadian, 2003*).

Households' composition of vehicles in the fleet does not occur at a single point in time, rather it occurs due to a series of households' decisions about vehicle acquisition, disposal or replacement. A vehicle transaction event in the household can be triggered by various time-varying socio-demographic factors or household composition. For example, Mohammadian & Miller (*2003*) developed a vehicle transaction model that explored the impact of the occurrence of changes in household state (i.e. increase or decrease in number of adults) on observed transaction behaviour. In another study, Mohammadian & Rashidi (*2007*) found that, along with the household state, time-varying covariates (i.e. number of adults, household income) have substantial effect on the vehicle transaction timing.

It is evident that the majority of the previous studies examine vehicle ownership using cross-sectional data at a single temporal point or repeated cross-sectional data (*Anowar et al., 2015*). Therefore this research utilizes a retrospective Household Mobility and Travel Survey (HMTS) in Halifax, which contains households' vehicle ownership information over their lifetime. Using longitudinal information, households' vehicle ownership state and type choice model have been estimated, that are capable of capturing the temporal variation of ownership state and vehicle choice behaviour of the households by considering observed longitudinal changes for Halifax households.

Vehicle ownership models play a critical role in an integrated urban model as it fundamentally interconnects long-term decisions of location choice with the short-term travel activity decisions. As a household vehicle ownership decision is a dynamic and complex behaviour to forecast, a dynamic microsimulation platform is most suitable for such modelling. A microsimulation-based integrated Transportation, Land-use and Energy (iTLE) model is currently under development for Halifax, where vehicle ownership models are expected to be a critical component of the behavioural core. The integrated urban system model will take mathematical implications of vehicle ownership micro-models and provide the practical implications, such as, forecasting vehicle ownership behaviour and its impact on environment. The micro-models use various socio-demographics and household characteristics, life-cycle events and neighbourhood characteristics to determine the households' vehicle ownership state and type choice, and the system will be able to forecast households' behaviour on long-term vehicle ownership decisions by capturing real-world entities within microsimulation platform by testing different transport policies or scenarios. The majority of the integrated urban models do not have a vehicle ownership component. For instance, Waddell *(2002)* developed an integrated urban model, UrbanSim, which essentially incorporates land-use, and residential mobility and location choice sub-modules. However, the only exception that considers vehicle ownership models within the behavioural core is Integrated Land Use, Transportation and Environment (ILUTE) model (*Salvini and Miller, 2005)*, which simulates vehicle ownership behaviour at every simulation time step. ILUTE takes a market-based approach in simulating household and individual level decisions. Recently, there are some emerging integrated urban system models, which use the vehicle ownership component as an exogenous input. For example, Almeida et al. *(2009)* developed an integrated transportation and energy activity-based model (iTEAM), where several behavioural sub-modules, such as, location choice models, activity models and accessibility models are implemented within a microsimulation platform to forecast households' energy and resource consumption. Another integrated model of urban energy system, SynCity, has been developed by Keirstead et al. *(2009)*, which simulates various urban energy related scenarios by simulating layout, activity, and network sub-modules within a microsimulation platform. The integrated Transportation, Land-use and Energy (iTLE) model for Halifax will be developed within a microsimulation platform that consists of comprehensive set of linked sub-modules, such as, residential location choice, vehicle ownership, travel activity model, and dynamic traffic assignment. These sub-modules require estimation of micro-models based on the observed behaviour in Halifax as argued in Fatmi & Habib (*2015*). The iTLE model will take a dynamic life-stage transition-based approach to simulate the evolution of key events and decisions over time and space. Conceptual framework of the iTLE model is shown in Figure 2-1, which identifies vehicle ownership models as a vital component.

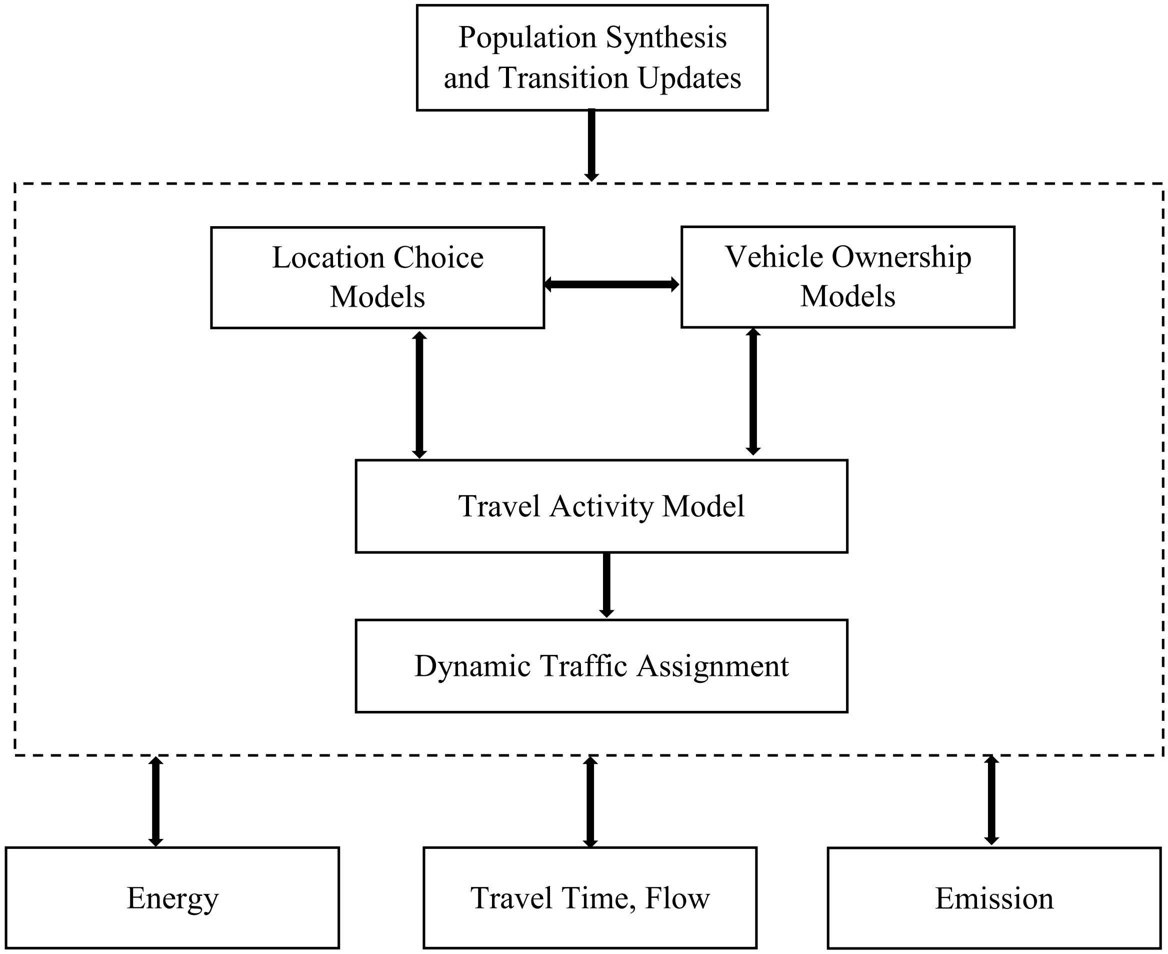


Figure 2-1: Conceptual Framework of integrated Transportation, Land-use and Energy (iTLE) Model

This thesis contributes to the development of micro-models for the proposed integrated urban systems model. The research of this thesis first explores the duration of vehicle ownership states using an event-history analysis process. It also estimates vehicle type choice models to understand the vehicle choice behaviour of the first-time vehicle owner households, which takes place due to the termination of no-car ownership state by purchasing the first vehicle in a household's lifetime, and vehicle choice behaviour of transient vehicle owner households at every transaction event. Figure 2-2 demonstrates the conceptualization of the vehicle ownership state and type choice modelling framework used in this thesis. Vehicle ownership state is conceptualized as no-car ownership state and transient ownership state. A '*no-car ownership state*' refers to the life episode when households do not own a vehicle. This state is assumed to be terminated following the purchase of the first vehicle. No-car ownership state refers to three types of episodes: households' durations of not owning a vehicle until the censoring time (i.e. survey ending time, April 2013), duration of households from moving to Halifax until purchase of the first vehicle, and duration of vehicle free households following the disposal of the last vehicle until the censoring time. '*Transient ownership state*' refers to the duration between two consecutive vehicle ownership events of the households. This state is assumed to be terminated by households' transaction decisions. In addition, this thesis identifies the first time vehicle purchase decisions separately. Households terminating their no-car ownership state following the purchase of their first vehicle are considered as '*First-time Vehicle Owners*'. Subsequently, after the purchase of first vehicle, households having multiple transactions throughout their lifetime referred as '*Transient Vehicle Owners*'.

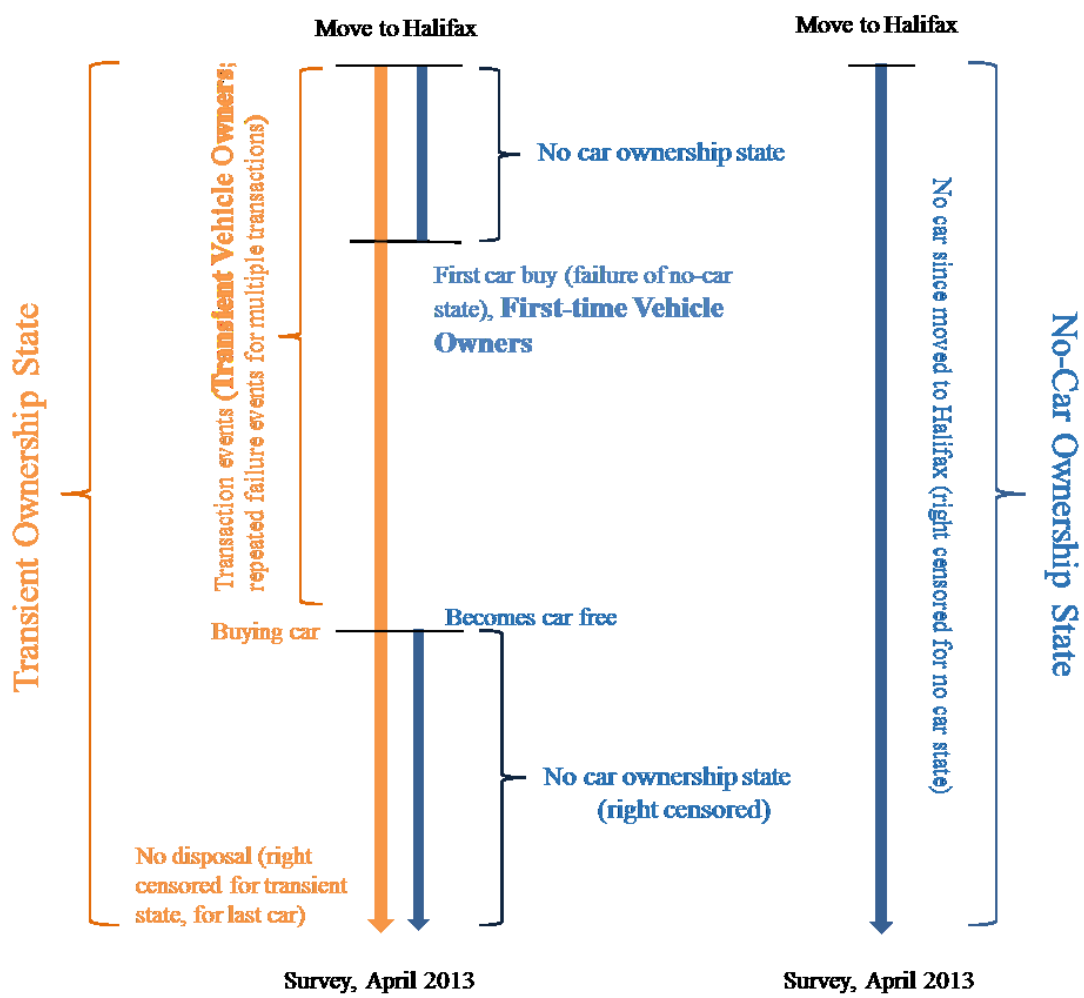


Figure 2-2: Conceptualization of Vehicle Ownership State and Type Choice

2.2 The Longitudinal Survey

The longitudinal survey utilized in this thesis is the Household Mobility and Travel Survey (HMTS), which was conducted in Halifax, Nova Scotia, Canada in 2012-13. This web-based survey contains information on vehicle history, housing career and employment records. Household vehicle history contains information on the current and previous vehicles' manufacturer and model name, manufacturing year, purchase year and purchase price, among others. Previous vehicles' disposal methods and disposal years have also been asked during the survey. The survey collected information on household relocation, household composition changes (i.e. household size, number of children) and several life-cycle events, such as, birth of a child, death, members' move-in etc. Moreover, information about household current and previous jobs (i.e. job location, job type) were collected. Additionally, the survey collected information on socio-demographic characteristics, travel behaviour, mobility tool ownership, and attitudinal and lifestyle preferences. Home and work locations were also collected by the HMTS survey. The survey had two waves with a total of 475 respondents, 324 responses from wave 1 and 151 from wave 2. The findings from wave 1 are reported in an earlier study (*Peterlin & Habib, 2012*). An explanatory analysis is offered in Salloum & Habib *(2015*), which concludes that HMTS can be considered as the representative sample of Halifax as validation results found that socio-demographic characteristics lies within a few percentage points of the total Halifax population. An outline of the longitudinal information collected in HMTS is shown in figure 2-3:

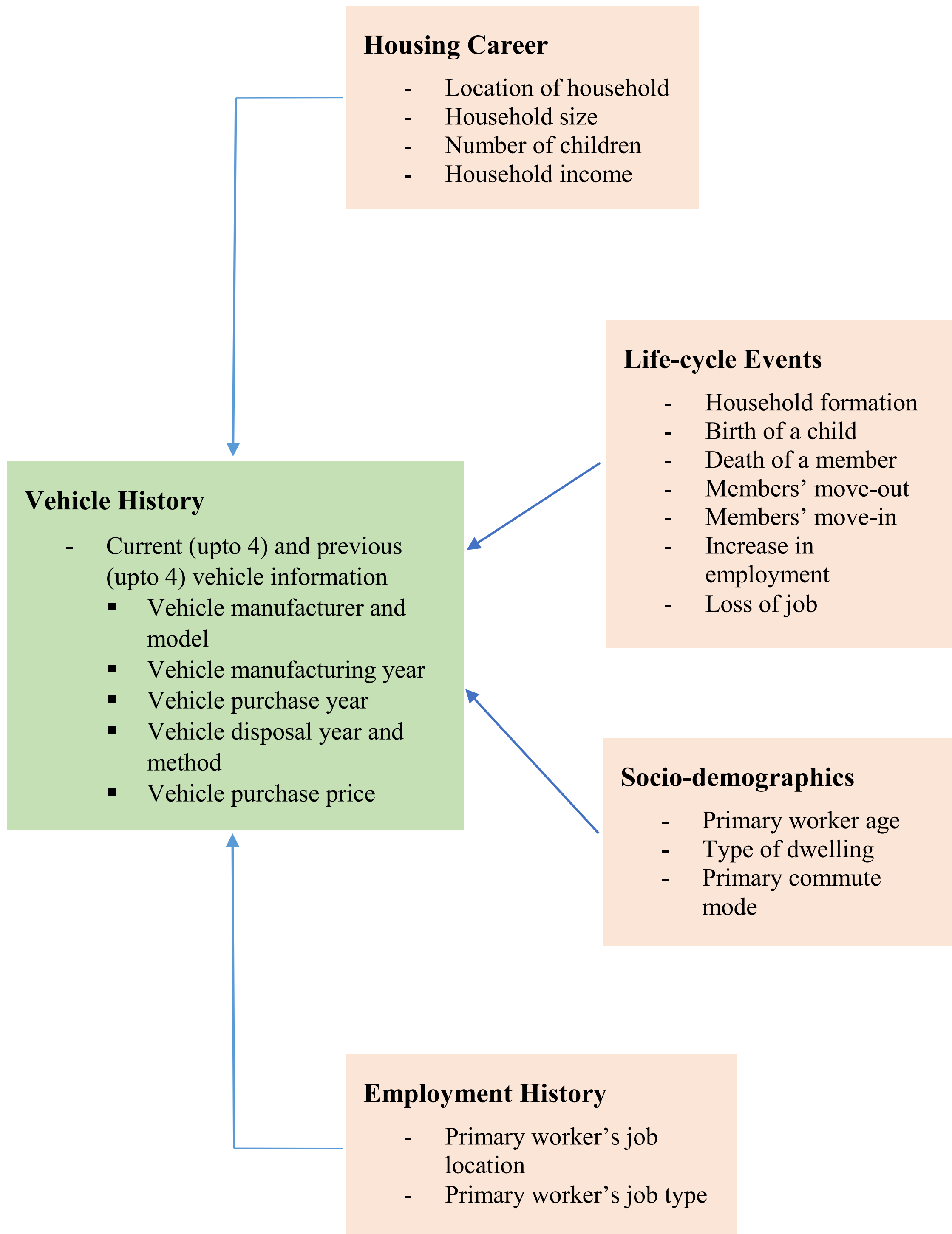


Figure 2-3: Longitudinal Information of HMTS

2.2.1 Sample Characteristics of Data Used in Vehicle Ownership Modelling

Although, the HMTS have total of 475 respondents, 357 households have been obtained with full information of vehicle history over their lifetime. A discussion on the sample 357 respondents' characteristics of the data used in vehicle ownership modelling can be found in this section.

2.2.1.1 *Household Income*

Majority of the respondents (20%) have a high household income of $100,000 to $149,999. A significant number of households (19%) earn a moderate annual household income of $50,000-$74,999. Almost 18% of the households have an annual household income below $25,000 (see Figure 2-4).

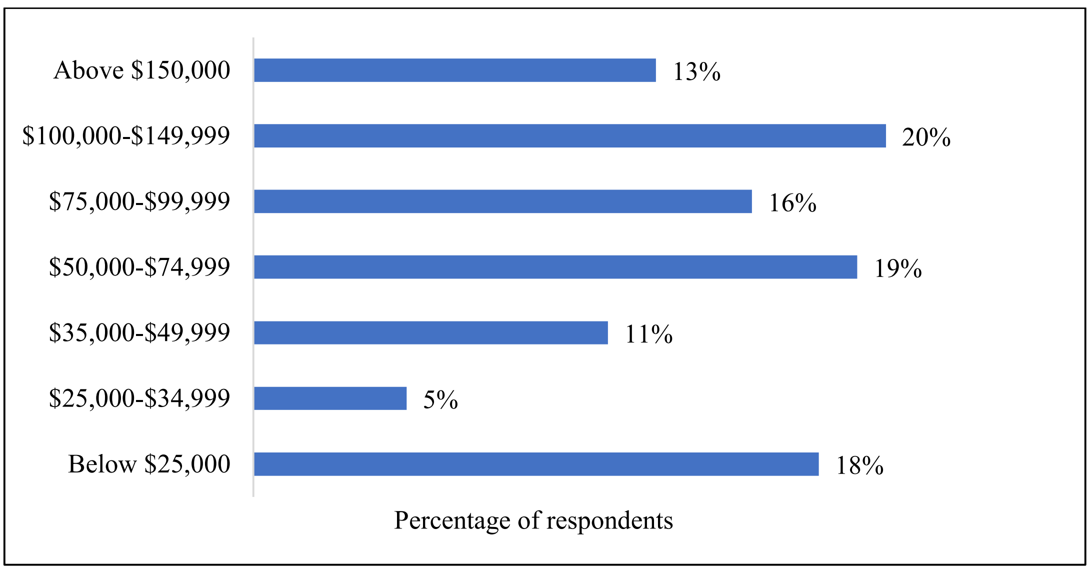


Figure 2-4: Annual Income of the Households

2.2.1.2 *Household Size*

Figure 2-5 shows that the majority of the respondents (34%) live in a household size of 2 persons. Four person households also show a notable percentage (22%) as shown in Figure 2-5.

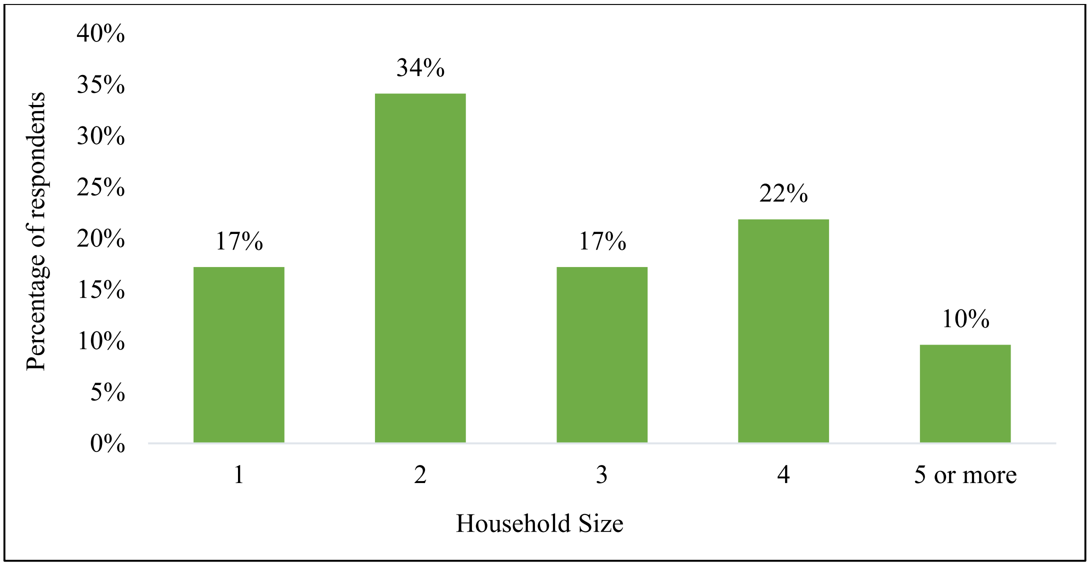


Figure 2-5: Household Size

2.2.1.3 *Primary Worker Age*

Figure 2-6 shows that almost half of the households' primary worker's age is below 40 years. Twenty percent of the primary workers are age 51-60 years and 7% are above 60 years.

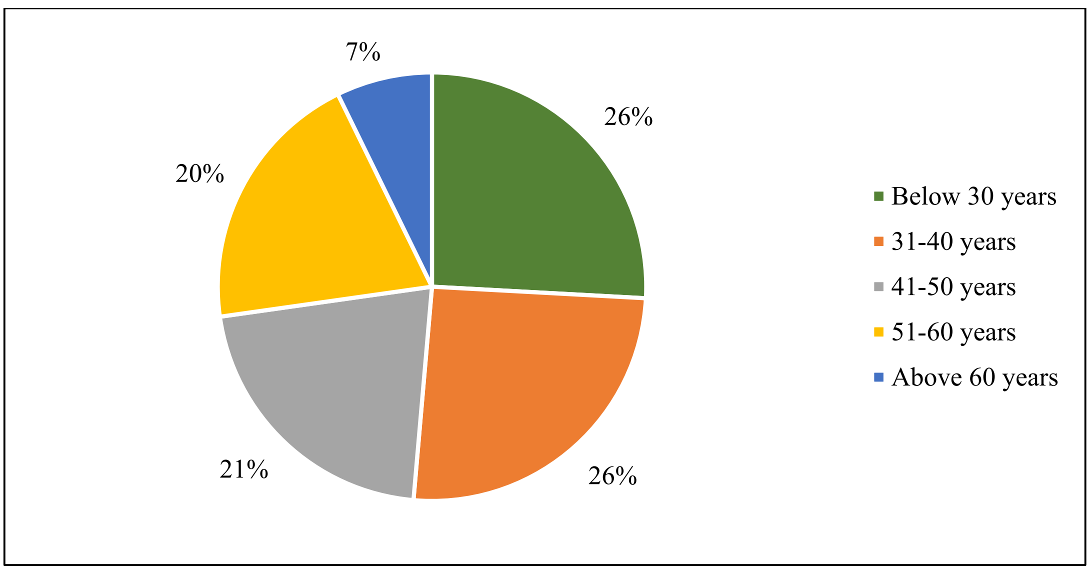


Figure 2-6: Primary Worker Age

2.2.2 Summary Statistics of Vehicle Ownership State and Type Choice

This section presents the summary statistics of the vehicle ownership state and vehicle type choice.

2.2.2.1 *Duration of Ownership States*

According to Figure 2-7, a large number of the households (38%) show a 10 or more years duration in the no-car ownership state. A notable percentage of households (28%) show a no-car ownership state for 0-2 years. In the case of transient state, the majority of the households show a duration of 3-5 years (38%) and 0-2 years (36%).

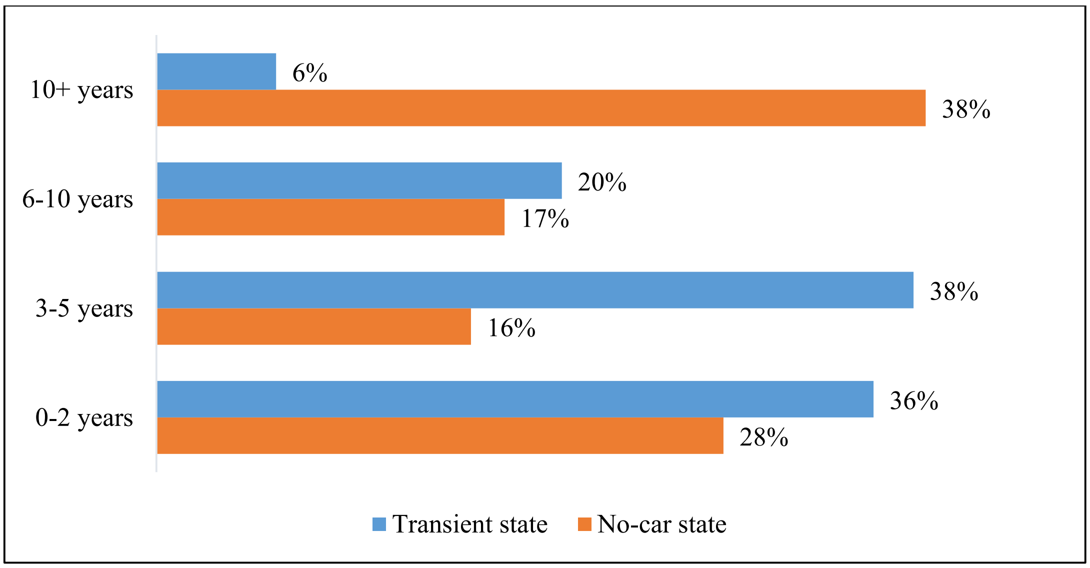


Figure 2-7: Duration of Ownership States

2.2.2.2 *Duration Length According to Household Income*

Table 2-2 shows that a higher percentage of households (all income groups below annual household income of $100,000) falls within the no-car ownership duration of 10 years and more. A higher percentage of high income groups (annual income $100,000-$149,000 and above $150,000) show a 0-2 year duration of no-car ownership.

Table 2-2 Duration of No-car State According to Household Annual Income

Duration	Below $25,000	$25,000-$34,999	$35,000-$49,999	$50,000-$74,999	$75,000-$99,999	$100,000-$149,999	Above $150,000
0-2 years	35.8%	32.0%	33.3%	25.4%	26.0%	45.7%	63.3%
3-5 years	11.9%	24.0%	16.7%	17.5%	22.0%	23.9%	13.3%
6-10 years	9.0%	12.0%	7.1%	23.8%	24.0%	21.7%	16.7%
10+ years	43.3%	32.0%	42.9%	33.3%	28.0%	8.7%	6.7%

In the case of transient ownership state, all income groups show a higher percentage of 0-2 years of transient duration, except income groups $35,000-$49,999 and $75,000-$99,999 (Table 2-3).

Table 2-3 Duration of Transient State According to Household Annual Income

Duration	Below $25,000	$25,000-$34,999	$35,000-$49,999	$50,000-$74,999	$75,000-$99,999	$100,000-$149,999	Above $150,000
0-2 years	44%	33%	33%	42%	29%	38%	43%
3-5 years	33%	28%	41%	30%	43%	37%	33%
6-10 years	11%	33%	20%	19%	22%	21%	16%
10+ years	11%	6%	6%	8%	5%	4%	7%

2.2.2.3 *Duration Length According to Primary Worker Age*

From Table 2-4, it is apparent that the majority of the high aged primary worker households (age groups 41-50, 51-60 and above 60 years) show no-car state duration lengths of 6-10 years. However, a higher percentage of age groups 31-40 and below 30 years exhibit a 0-2 year duration length.

Table 2-4 Duration of No-car State According to Primary Worker Age

Duration	Below 30 years	31-40 years	41-50 years	51-60 years	Above 60 years
0-2 years	41%	36%	25%	26%	9%
3-5 years	17%	22%	14%	18%	0%
6-10 years	14%	18%	33%	47%	73%
10+ years	28%	24%	28%	9%	18%

From Table 2-5, in the case of transient state, the majority of the 31-40 and below 30 years of age primary worker households exhibit 0-2 years transient state duration lengths, whereas, a higher percentage of 41-50, 51-60 and above 60 years age groups show 3-5 years duration (Table 2-5). However, 41-50, 51-60 and above 60 years aged primary worker households have a notable percentage of transient duration lengths 0-2 years, and 31-40 and below 30 years aged primary worker households show significant percentages for 3-5 years transaction durations.

Table 2-5 Duration of Transient State According to Primary Worker Age

Duration	Below 30 years	31-40 years	41-50 years	51-60 years	Above 60 years
0-2 years	79%	44%	30%	31%	32%
3-5 years	21%	39%	44%	32%	38%
6-10 years	0%	13%	20%	26%	28%
10+ years	0%	4%	6%	11%	2%

2.2.2.4 *Vehicle Type Choice of First-time and Transient Owners*

Figure 2-8 exhibits the vehicle type choice preference percentage of first-time and transient vehicle owner households. As a first-time vehicle, households prefer compact vehicles (37.9%), followed by midsize (20.2%) and subcompact vehicles (18.6%). Some households reveal their fondness for vans (van/minivan/truck, 10.5%) and SUVs (9.7%), while only a few prefer Luxury vehicles (3.2%) for first time vehicle ownership. Transient owner households prefer compact vehicles (30.3%), followed by midsize vehicles (18.7%).

Some households prefer SUV and subcompact vehicles (both 15.8%), succeeded by van (14.2%) and luxury vehicles (5.2%).

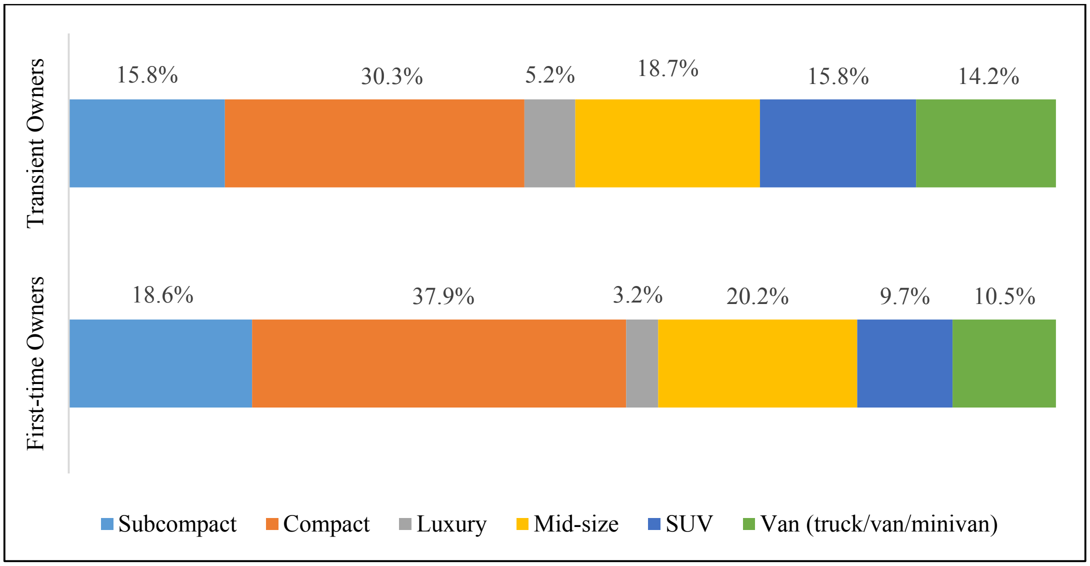
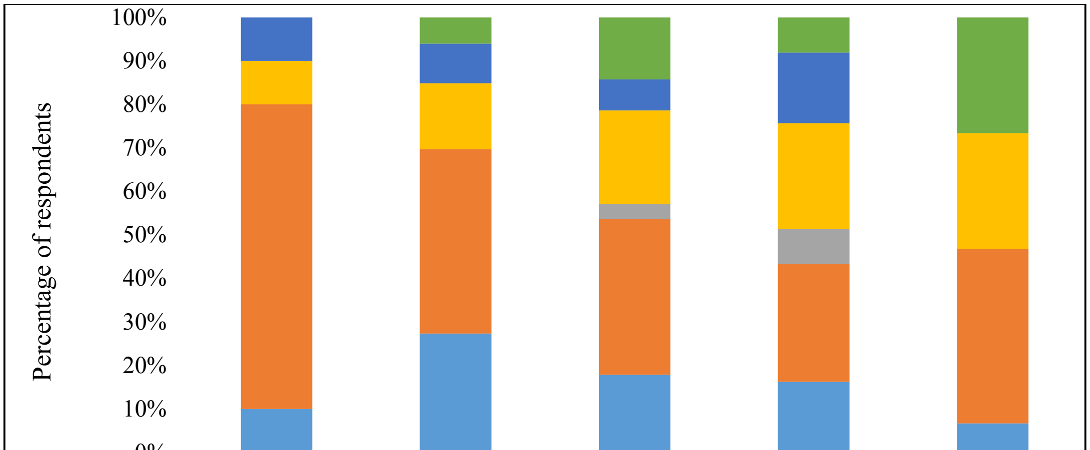


Figure 2-8: Vehicle Type Choice

2.2.2.5 *Vehicle Type Choice According to Primary Worker Age*

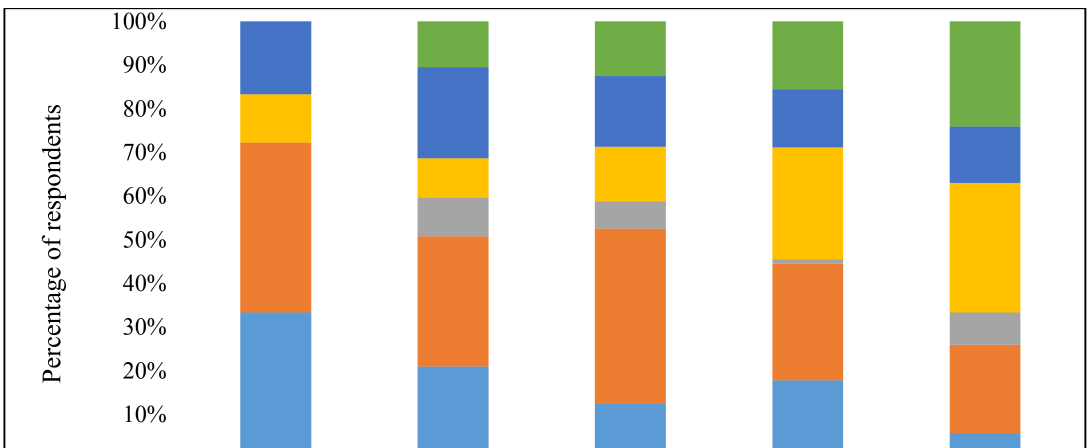
All age groups have a preference for compact vehicles, as evident in the high percentage for the choice of compact vehicles as the first-time vehicle (Figure 2-9). A notable percentage of the respondents within the age range of 41-60 years, show preference for luxury vehicles.



	Below 30	31-40	41-50	51-60	Above 60
Van	0%	6%	14%	8%	27%
SUV	10%	9%	7%	16%	0%
Mid-size	10%	15%	21%	24%	27%
Luxury	0%	0%	4%	8%	0%
Compact	70%	42%	36%	27%	40%
Subcompact	10%	27%	18%	16%	7%

Figure 2-9: Vehicle Type Choice According to Primary Worker Age (First-Time Owners)

Similar to first-time vehicle owners, transient owners' preference of compact vehicles is highest in all age groups (except above 60 years). Thirty percent of the transient owners whose age is more than 60 years, prefer midsize vehicles (see Figure 2-10).

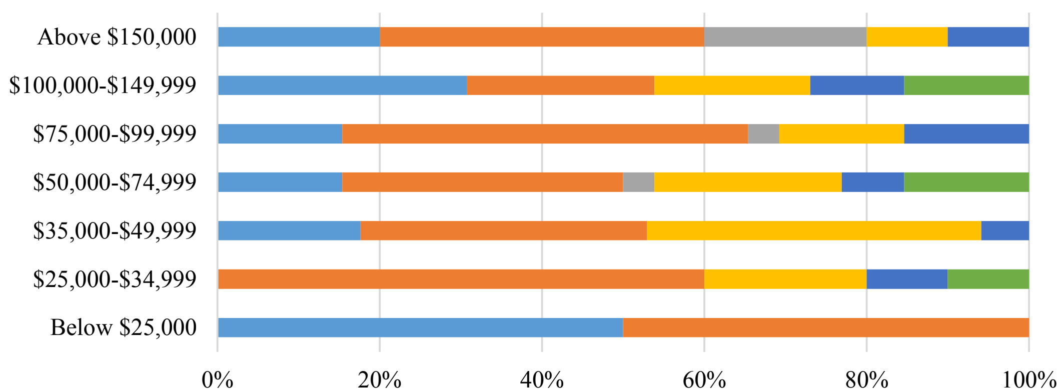


	Below 30	31-40	41-50	51-60	Above 60
Van	0%	10%	13%	16%	24%
SUV	17%	21%	16%	13%	13%
Mid-size	11%	9%	13%	26%	30%
Luxury	0%	9%	6%	1%	7%
Compact	39%	30%	40%	27%	20%
Subcompact	33%	21%	13%	18%	6%

Figure 2-10: Vehicle Type Choice According to Primary Worker Age (Transient Owners)

2.2.2.6 *Vehicle Type Choice According to Household Income*

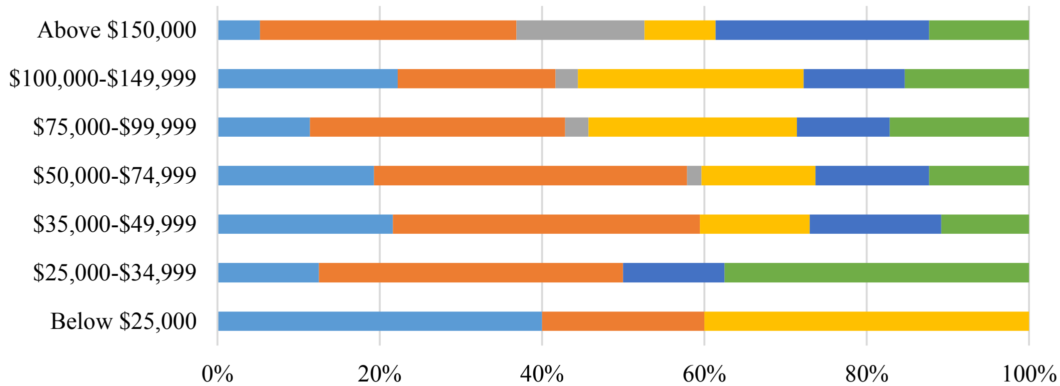
Figure 2-11 shows that, the majority of the first-time owner households prefer compact vehicles. However, 41% of households earning $35,000-$49,999 tend to have midsize vehicles as their first-time ownership. Moreover, the percentage of high income first-time owners ($100,000-$149,999) is highest (31%) for subcompact vehicles.



	Below $25,000	$25,000-$34,999	$35,000-$49,999	$50,000-$74,999	$75,000-$99,999	$100,000-$149,999	Above $150,000
Subcompact	50%	0%	18%	15%	15%	31%	20%
Compact	50%	60%	35%	35%	50%	23%	40%
Luxury	0%	0%	0%	4%	4%	0%	20%
Mid-size	0%	20%	41%	23%	15%	19%	10%
SUV	0%	10%	6%	8%	15%	12%	10%
Van	0%	10%	0%	15%	0%	15%	0%

Figure 2-11: Vehicle Type Choice According to Household Annual Income (First-Time Owners)

A significant percentage of transient owners in all income groups prefer compact vehicles, except the income groups below $25,000 and $100,000-$149,999. These transient owner households show their higher preference for midsize vehicle as shown in Figure 2-12.



	Below $25,000	$25,000-$34,999	$35,000-$49,999	$50,000-$74,999	$75,000-$99,999	$100,000-$149,999	Above $150,000
Subcompact	40%	13%	22%	19%	11%	22%	5%
Compact	20%	38%	38%	39%	31%	19%	32%
Luxury	0%	0%	0%	2%	3%	3%	16%
Mid-size	40%	0%	14%	14%	26%	28%	9%
SUV	0%	13%	16%	14%	11%	13%	26%
Van	0%	38%	11%	12%	17%	15%	12%

Figure 2-12: Vehicle Type Choice According to Household Annual Income (Transient Owners)

Chapter 3

Modelling of Vehicle Ownership State and Vehicle Type Choice Behaviour [1]

Chapter Overview

This chapter presents a biographical research approach of modelling households' vehicle ownership states and vehicle type choice behaviour, using data from a retrospective survey. A random parameter accelerated hazard-based model is developed to investigate vehicle ownership states. One of the unique features of this research is that it evaluates the determinants of termination probability of 'no-car ownership states' and subsequent 'transient states', by explicitly examining the effects of life-cycle events. Model results suggest that a birth, member move-in, and addition of a job in the household accelerate the termination of 'no-car state', leading to the first car ownership. In contrast, those life-cycle events delay transaction events for the transient owners. The research also examines vehicle type choice for both types of households using a random parameter logit model that accounts for the panel effects due to repeated choices. The results reveal that vehicle attributes, including space and performance factors identified by a principal component analysis, are strong predictors for vehicle type choice. However, life stages and life-cycle events also significantly influence the choice of vehicle. For example, the formation of a new household substantially increases the probability of choosing compact and midsize cars by the first-time owners. A birth of a child increases the preference for SUVs and vans among transient vehicle owners. The research also confirms considerable preference differences among first-time owners and transient owners with respect to other variables. Therefore, a longitudinal approach of modelling vehicle ownership is necessary to

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[1] This chapter is adapted from:
Khan, N. A. & Habib, M. A. "Life Course-oriented Approach of Modeling Vehicle Ownership State and Vehicle Type Choice Using Retrospective Data", peer-reviewed proceedings of Transportation Research Board 95th Annual Meeting. Washington, D.C., U.S.A., January 10-14, 2016.

comprehensively assess behavioural dynamics, and adopt policies to influence behavioural changes on a longer-term basis.

3.1 Introduction

Investigation of households' vehicle ownership is vital to the understanding of its impact on transportation networks, energy systems and the environment. Vehicle ownership has become a critical component of an integrated transportation, land-use, and energy modelling system due to its direct influence on different household decision making processes (e.g., residential relocation) and mobility decision (e.g., mode choice, destination choice). The majority of the earlier studies investigate vehicle ownership by taking a cross-sectional approach that relies on single temporal point (*Zhao & Kockelman, 2002*). However, households re-evaluate vehicle choice decisions at multiple temporal points throughout their lifetime. There is a growing interest in longitudinal vehicle ownership modelling, including the investigation of vehicle transactions (*Rashidi et al., 2011; Mohammadian & Rashidi, 2007*) and vehicle holding (*Yamamoto et al., 2004*). However, life course-oriented investigation of vehicle ownership that helps to understand the influence of life-cycle events and life stages is limited. Moreover, it is not evident in the existing literature how households first own a vehicle and what are the differences in terms of the determinants that terminate no-car ownership states for the first-time vehicle owners and transient states of subsequent vehicle ownerships. There is also a gap in the understanding of the predictors of vehicle type choices by the first-time owners and transient owners. This research attempts to fill these gaps by investigating the duration of ownership states and vehicle type choice at different states of ownership using vehicle history information obtained from a retrospective survey conducted in Halifax, Canada.

Biographical research, anticipating life oriented influences, has the ability to capture the temporal variability aspects of vehicle ownership, as well as the effects of life-cycle events and transitions over households' lifetime. The panel or biographical modelling approach could examine the effects of state-dependent behavioural changes (*Clark et al., 2014*). The occurrence of life-cycle events in a household, which could trigger the re-evaluation of routine works and instigate longer-term and short-term travel behaviour changes (*Bamberg et al., 2003*), could also be examined if a biographical modelling framework is considered. Traditional studies on vehicle ownership have predominantly dealt with various aspects of vehicle ownership behaviour, such as vehicle ownership level, vehicle type choice, and vehicle holding using cross-sectional travel data. The biographical approach taken in this research, however, offers flexibility in analyzing different temporal state of vehicle ownership and choice dynamics at different states.

This research first develops an '*ownership state*' model in which the duration of no-car ownership and transient ownership have been evaluated using event-history modelling techniques. '*No-car ownership state*' refers to the life episode of households who do not have any vehicle ownership history. The state could terminate with the purchase of the first car. On the other hand, '*transient ownership state*' refers to life episode of households with a vehicle ownership history, which may terminate with a transaction event, particularly which changes the size of the fleet. A panel random parameter accelerated hazard-based model is developed for analyzing vehicle ownership states. Then, vehicle type choice models are estimated for the '*first-time owners*' and '*transient owners*'. A random parameter logit model is used to examine the determinants of vehicle types, including vehicle attributes, life-cycle events, socio-demographics, and neighbourhood characteristics.

3.2 Literature Review

A substantial amount of literature exists on modelling vehicle ownership behaviour, such as vehicle ownership level (*Potoglou & Kanaroglou, 2008; Clark, 2007*), and vehicle type choice (*Potoglou, 2008; Choo & Mokhtarian, 2004*). The majority of the studies on vehicle ownership are based on the analysis of single temporal point that use cross-sectional travel surveys (*Cirillo & Liu, 2013*), which does not have the ability to capture temporal dynamics inherent in vehicle ownership behaviour (*Anowar et al., 2015*). Detailed reviews of earlier cross-sectional studies are well documented in the literature (*Potoglou & Kanaroglou, 2008; Potoglou, 2008; Cirillo & Liu, 2013, de Jong et al., 2004; Anowar et al., 2014*). Moreover, comparison of methodological approaches can also be found in Bhat & Pulugurta (*1998*) and Potoglou & Susilo (*2008*).

However, to understand the vehicle ownership decision of households over their lifetime, transportation researchers have started examining longitudinal approaches of modelling vehicle ownership (e.g., vehicle transaction studies) over the last two decades. Most of the studies in this paradigm investigated households' vehicle transaction behaviour utilizing hazard-based duration models (e.g. *Gilbert, 1992; Yamamoto et al., 1999*). Gilbert (*1992*) was one of the first studies that assessed the length of household vehicle ownership using duration modelling. The study identified that household characteristics, vehicle attributes, and macroeconomic variables affect the transaction timing of vehicle ownership. Later, Yamamoto et al. (*1999*) developed a household vehicle transaction model utilizing a competing risk duration modelling framework, in which changes in household attributes were found to be strong predictors of vehicle transaction events. Mohammadian & Rashidi (*2007*) used a similar approach to examine household vehicle transaction decision, and revealed that dynamic variables that represent household state, household location characteristics and time-varying covariates influence the timing of a change in vehicle ownership. A mixed logit model, developed in Mohammadian & Miller (*2003*) also confirmed that the effects of time-varying variables (such as, number of adults and household income), vehicle attributes, and recent purchasing or trading are the strong predictors of household transaction decisions over time. In another study, Miller & Mohammadian (*2003*) developed a hierarchical vehicle transaction and type choice model using a nested logit formulation, in which vehicle attributes & socio-demographic attributes were found to be significant in explaining households' vehicle type choices. Moreover, a further comprehensive review on household dynamic vehicle ownership models can be found in de Jong & Kitamura *(2009).*

In case of the absence of panel/retrospective vehicle history dataset, pseudo-panel approaches were utilized by researchers taking an advantage of multi-year repeated cross-sectional surveys. Dargay & Vythoulkas (*1999*) first demonstrated a pseudo-panel approach for dynamic car ownership modelling. The study highlighted the effects of socio-demographics, car ownership cost, and vehicle use on car ownership decisions. Another study conducted by Dargay (*2002*) examined the factors affecting car ownership in rural and urban areas using a similar-type of pseudo-panel approach. The research found that vehicle purchase cost is less influential in the rural areas than urban areas. Recently, Anowar et al. (*2015*) applied a pseudo-panel approach to investigate the temporal variation of household vehicle ownership in Montreal, which found that socio-demographics, land-use measures and transit accessibility were vital predictors of vehicle ownership levels. They however concluded that the effects of some socio-demographic variables were changing with time. For instance, the impact of full time workers on vehicle ownership levels is reducing in 2008 compared to 2003. Nevertheless, the effects of temporal variations and dynamics can only effectively be captured when a biographical panel modelling approach is considered.

Biographical or life course-oriented research, could explicitly consider the effects of life-cycle events and life stages documented in retrospective surveys. Although life course-oriented transportation research is limited, several studies concluded that critical life-cycle events and transitions, for example, birth, death, and employment change, have substantial influence on travel behaviour (*Goodwin, 1989; Flamm et al., 2008*). Clark et al. (*2015*) argues that triggering life events for a household not only causes change in travel behaviour, but also results in changes in vehicle ownership levels. Few other studies suggested that vehicle ownership levels are associated with the changes in life-cycle events and life stages. For instance, changes in household composition over time (i.e. increase or decrease of number of adults) have significant impact on vehicle ownership levels (*Clark et al., 2015; Prillwitz et al., 2006*). Additionally, the birth of a child (*Clark et al., 2015; Prillwitz et al., 2006; Oakil et al., 2014*) and employment status change (*Prillwitz et al., 2006; Dargay & Hanly, 2007*) were found to be strong predictors of levels of vehicle ownership. On the other hand, Yamamoto (*2008*) found strong evidence of improved model fit by utilizing life-course events in household vehicle transaction behaviour. Furthermore, Oakil (*2015*) explored gender differentiated impacts of life occasions on the access to car. The study found that the birth of a first child, residential relocation, and employer change all have greater impacts, regarding getting full access to a car, for female individuals over their male counterparts.

Although life course-oriented vehicle ownership models are growing, it is found that majority of those studies focus on modelling ownership levels or vehicle holding (*Clark et al., 2015; Prillwitzet al., 2006; Oakil et al., 2014; Oakil, 2015)*, and transaction behaviour (such as acquisition, trades and disposal) among existing owners (*Mohammadian &*

Rashidi, 2007; Mohammadian & Miller, 2003; Yamamoto, 2008). Life course models could, however, shed light on first-time ownership and how it differentiates from the transaction events of transient episodes of the existing owners. It is not at all evident what the main causes of termination of no-car state are or how the major life-cycle events and other socio-demographic, accessibility and neighbourhood attributes influence the transition to a first car ownership. Moreover, no research has been conducted regarding the type of differences that exist in cases of determinants for vehicle type choice at those states. This research aims to fill these gaps, and offer an understanding of the effects of life-cycle events and life stages that cause households to re-evaluate their vehicle ownership states and vehicle type choices over their lifetime.

Longitudinal models essentially involve a sequence of choice occasions. However, the majority of the existing studies of vehicle ownership assumes single episode models (e.g. *Cirillo & Liu, 2013; Potoglou & Susilo, 2008*), ignoring the sequence of observations that exists within a longitudinal study. By nature, biographical research requires a flexible form modelling framework that is able to account for the longitudinal nature of repeated choices. Therefore, the research considers a panel-based random parameter accelerated hazard model for the ownership state modelling. To the authors' knowledge, this is the first attempt at accounting for repeated events in a random parameter accelerated hazard-based modelling framework to analyze the duration of vehicle ownership states. Similarly, a panel random parameter logit model is used for vehicle type choice to account for panel effects. The research focuses on modelling vehicle type choice decisions for both first-time and transient owner households.

3.3 Data Used For Empirical Application

3.3.1 Household Mobility and Travel Survey (HMTS)

The dataset utilized in this research was obtained through a retrospective survey known as Household Mobility and Travel Survey (HMTS), which was conducted in 2012-13. The survey collected detailed vehicle ownership history of 357 households in Halifax, Canada. Vehicle ownership data includes the make, type, model, purchase year, manufacturing year, condition (new or used), and purchase price of the vehicles. The HMTS dataset provides additional information about households, including life-cycle events of the respondents, housing career, job history of primary and secondary workers, and travel patterns. For each vehicle, vehicle attribute data was collected from the Canadian Vehicle Specifications (CVS) Database (*Canadian Vehicle Specification System, Version 2015.1)*, which contains data on various vehicles from 1971 to 2012 model year *(see Appendix for sample CVS database)***.** Fuel consumption data was extracted from the Fuel Economy Guide Database (*Fuel Economy Guide database Files (various years)*), which consists of vehicle mileage data by vehicle brand, model and year *(see Appendix for sample fuel economy guide database)*. Data of neighbourhood characteristics and land-use measures were obtained from the 2011 Canadian Census at the Dissemination Area (DA) level *(see Appendix for a sample DA list with neighbourhood characteristics used in this research)* and Desktop Mapping Technologies Inc. (DMTI), respectively.

3.3.2 Vehicle Ownership State

In this research, vehicle ownership state is characterised by two categories: 1) no-car ownership state, 2) transient vehicle ownership state. The transient state episodes are identified as the duration between two consecutive transaction events, specifically new acquisition and/or disposal of a vehicle. On an average, 3 transaction events occur in the lifetime of the households. Trade (meaning acquisition and disposal at the same time, total 90 events) is not considered in this analysis since there is no change in fleet size for the household in this case. The survey end date, April 2013 is considered as the right censoring event. On the other hand, no-car ownership state considers three types of episodes: a) duration of households not owning a vehicle until censoring time, b) duration of households from moving to Halifax until the ownership of the first vehicle, c) duration of vehicle free households from last vehicle disposal until censoring time.

3.3.3 Vehicle Type Choice

Vehicle type choice model includes all vehicle purchases by households over their lifetime. Two separate models are estimated for a) first-time vehicle owner households, and b) transient vehicle owner households. The first-time owners' vehicle choice model analyzes the vehicle type choice behaviour of each household that purchases a vehicle for the first-time. Transient owners' vehicle choice model includes the type choice behaviour of each household's purchase of a new vehicle at multiple temporal points. For both first-time and transient vehicle owners, six types of vehicles are considered: 1) subcompact, 2) compact, 3) midsize, 4) luxury, 5) sport utility vehicle (SUV), and 6) vans (van/ minivan/truck). Example list of vehicle types can be found in Appendix.

In both models, in addition to life-cycle events, socio-demographics characteristics, neighbourhood/land-use variables and vehicle attributes are examined as explanatory variables. Several vehicle attribute variables, such as, vehicle price, horsepower, turning cycle, vehicle weight, length, interior size, headroom, legroom, breaking distance, etc. are considered. Utilizing the CVS Database, this research initially attempts to test hypotheses regarding each aspect of vehicle attributes (e.g. exterior and interior size, engine size, fuel economy, curb weight, various dimensions of vehicle, and overall capacity). However, a correlation test of the variables shows high correlations among them *(see Appendix for the full correlation test)*. For instance, in case of the first time vehicle owners, the variable "overall length" has a positive 68% and 59% correlation with overall capacity and curb weight. Additionally, a positive correlation of 80% is found between overall capacity and curb weight, and a negative correlation of 78% exist between engine size and fuel economy. On the other hand, in case of transient vehicle owners, engine size exhibits positive 53% and 55% correlation with overall length and capacity. Overall capacity also has a positive 64% correlation with overall length. However, a negative 70% correlation has been observed between engine size and fuel economy. Assuming greater impact of vehicle attributes to the vehicle type choice utility, the high multi-collinearities might exhibit erroneous model estimation. To address this issue, Principal Component Analysis (PCA) *(see Appendix for more details)* is conducted with selected variables. It is mainly a variance-focused approach which tries to reproduce the total variable variance. Investigation through the sample data is carried out in the PCA to discover the factors or components which might reduce the number of variables and retain the original variables' variance as much as possible. For both vehicle type choice models, engine size, fuel economy, curb weight, overall length, and capacity are chosen to include in the principal component analysis using Varimax rotation method *(see Appendix for more details)*. Two principal components are identified, vehicle performance factor and space factor. The components in the first time owner vehicle type choice model exhibits total explainable variance of 83% in the sample, while in case of transient owner vehicle type choice model, explain 73% of the total variance in the sample. Vehicle performance factor includes engine size, fuel economy and curb weight, whereas, vehicle space factor includes overall length and capacity of the vehicle. The PCA analysis of both models is shown in Table 3-1.

Table 3-1 Principal Component Analysis of Vehicle Attributes

Variables	First-time Vehicle Owner		Transient Vehicle Owner	
	Factor Loading			
	Factor 1 (Performance Factor)	*Factor 2 (Space Factor)*	*Factor 1 (Performance Factor)*	*Factor 2 (Space Factor)*
Engine Size	0.7049	-0.0500	0.5695	-0.0748
Fuel Economy	0.7086	-0.0650	0.5221	-0.1700
Curb Weight	0.5789	-0.0122	0.4566	-0.0115
Overall Length	-0.0172	0.5430	-0.1507	0.4444
Capacity	-0.0252	0.6082	-0.1664	0.4532
% Variance Explained	**47.66%**	**35.74%**	**51%**	**22%**

3.4 Modelling Approach

As stated earlier, two models, panel random parameter accelerated hazard-based model for vehicle ownership state, and panel random parameter logit model for vehicle type choice have been developed in this research. The modelling approach of both models is described in the following section.

3.4.1 Vehicle Ownership State: Panel Random Parameter Accelerated Hazard-based Model

A parametric hazard-based duration model of household vehicle ownership states is developed in this research to examine the determinants of the termination of households' ownership states. A retrospective dataset is used to test hypotheses regarding the effects of life-cycle events, along with other factors affecting the duration of vehicle ownership states. As stated earlier, household vehicle ownership states is evaluated in two categories: 1) no-car ownership state, and 2) transient ownership state.

Suppose, the duration of staying in a certain ownership state of a household *j* is *T*, which is a non-negative random variable. A specified period in the continuous time scale is *t*. The probability density function can be described as:

$$u(t) = \lim_{k \to 0} \frac{P(t \le T < t+k)}{k} \quad , \quad t \ge 0 \tag{1}$$

Where, k is a very small time period in which a household's ownership state ends after time *t;* meaning that the ownership state lasts till time *t*. Thus, the cumulative distribution function is expressed as:

$$U(t) = P(T < t) = \int_0^t u(v)dv \,, \quad t \ge 0 \tag{2}$$

And the probability that the duration of the household's ownership state does not expire before time *t* can be expressed as the survival function:

$$P(T \ge t) = S(t) = 1 - U(t) = \int_t^{-\alpha} u(v)dv \,, \quad t \ge 0 \tag{3}$$

Thus, the hazard function of a household *j* at time *t* is defined as:

$$\chi(t) = \frac{dU/dt}{S(t)} = \frac{u(t)}{S(t)} = \frac{-dS(t)/dt}{S(t)} = \frac{-d\log S(t)}{dt} = \lim_{k \to 0} \frac{P(t+k > T \ge t \mid T \ge t)}{k} \,, t \ge 0 \tag{4}$$

For direct interpretation of the effects of the explanatory variables on the households' vehicle ownership duration, this research considers an accelerated failure time hazard-based duration model. Accelerated hazard-based models measure the direct impact of explanatory variables over time rather than hazard. In other words, the explanatory variables rescale the time directly over a baseline hazard function. Moreover, to incorporate the unobserved heterogeneity among the households in both models, random parameters have been introduced in the duration model.

Let, X_j *is* the covariate vector, β' is the estimable parameter coefficient and χ_0 is the baseline hazard distribution. The hazard function of the parametric accelerated failure time model can be written as:

$$\chi_j(t \mid X_j) = \chi_0[te^{\beta' X_j}]e^{\beta' X_j} \tag{5}$$

Here, χ_0 is the baseline hazard distribution. Three specific baseline hazard function, Weibull, Log-normal and Log-logistic are considered in duration modelling. Although, this research estimates log-logistic and log-normal models, the panel model only converges for Weibull distribution. Also, literature suggests that Weibull, a monotonic distribution better suit with vehicle duration modelling (*Yamamoto et al., 1997*). Hence Weibull model is considered for the final model specification. The hazard function for the Weibull distribution is:

$$\chi(t) = \partial\gamma(\partial t)^{\gamma-1} \tag{6}$$

Where ∂, γ are shape parameters of the distribution. The parameter γ indicates the duration effects. With the increase of duration, if γ is greater than 1, hazard monotonically increases, and hazard decreases for a value less than 1.

This research incorporates unobserved heterogeneity within the parametric hazard-based model by introducing random parameters. Let's assume the random parameter duration model for households *j* with repeated ownership events *i* ending at or after a time *t* is given by:

$$\beta'_{jt} = \beta_0 + \sigma\varepsilon_{ji} \tag{7}$$

Where β_0 is the fixed constant term in the means of the distribution, σ is the covariance matrix for the unobserved random term ε_{ji}, which works as scale parameter.

Suppose, a set of observed covariates is denoted by covariate vector X_{jit} and coefficient vector is β'_{jt}, both are specific to time *t*; in which all or some of the covariates are time-varying. The random parameter ε_{ji} is assumed to be normally distributed and independent of X_{jit}, and also have a standard baseline distribution function for the accelerated hazard model. Let us assume the interval starts from zero and ends at t_{ji}. This time interval can be divided into *f* non-overlapping intervals where $t_f = t_{ji}$. Although the time varying parameters are assumed to be constant within each of the intervals, they might change from one interval to another. Suppose, the time period is from t_{n-1} to t_n, then the hazard function within that interval is $\chi_{ji}(t \mid \mathrm{X}_n)$. The relationship between hazard function and survival rate $S_{ji}(t)$ is:

$$\chi_{ji}(t) = \frac{-d \log S_{ji}(t)}{dt} \tag{8}$$

Thus, the cumulative distribution function

$$P[T < t_n \mid T \geq t_{n-1}] = \exp[-\int_{t_{n-1}}^{t_n} \chi_{ji}(\mathrm{s}_{ji} \mid \mathrm{X}_n) ds] \tag{9}$$

Then the survival function for duration of t_f or more can be expressed as:

$$S_{ji}(t_f \mid X_f) = \prod_{n=1}^{f} P[T \geq t_n \mid T \geq t_{n-1}] \tag{10}$$

And the density function at t_f is:

$$u_{ji}(t_f \mid X_f) = \chi_{ji}(t_f) S_{ji}(t_f) \tag{11}$$

Therefore, with Equation 5, the hazard function incorporating random parameter can be written as:

$$\chi_{ji}(t_{ji} \mid X_{jit}, \varepsilon_{ji}) = \chi_0[t_{ji} e^{\beta'_{jt} X_{jit}}] e^{\beta'_{jt} X_{jit}} \tag{12}$$

For household *j* having *i* ownership events, the log-likelihood function is conditional on ε_{ji} for *M* observations and can be expressed as:

$$\log L = \sum_{j=1}^{M} \kappa_{ji} \log u[y_{ji}, \chi_{ji}(t_{ji} \mid X_{jit}, \varepsilon_{ji}), \gamma] + (1 - \kappa_{ji}) \log S[y_{ji}, \chi_{ji}(t_{ji} \mid X_{jit}, \varepsilon_{ji}), \gamma] \tag{13}$$

Where y_{ji} is the log-activity duration of the parametric accelerated hazard-based model, and κ_{ji} is the censoring indicator, that is zero if an event is not terminated (censored) and takes the value 1 if the event is terminated (not censored). Therefore, the maximized unconditional log-likelihood function can be found by integrating the random term (ε_{ji}) out of the conditional log-likelihood:

$$\log L = \sum_{j=1}^{M} \int_{-\infty}^{\infty} \{ \kappa_{ji} \log u[y_{ji}, \chi_{ji}(t_{ji} \mid X_{jit}, \varepsilon_{ji}), \gamma] + (1 - \kappa_{ji}) \log S[y_{ji}, \chi_{ji}(t_{ji} \mid X_{jit}, \varepsilon_{ji}), \gamma] \} u(\varepsilon_{ji}) d\varepsilon_{ji}$$

This integral does not exist in closed form. Therefore, to evaluate the integral Monte Carlo simulation is applied. Halton draws are used in order to minimize run-time. The conditional likelihood function is calculated for each q Halton draws and repeated for Q times for each household. Thus, the simulated log-likelihood function can be described as:

$$LL_s = \sum_{j=1}^{M} \frac{1}{Q} \sum_{q=1}^{Q} \left\{ \kappa_{ji} \log u[y_{ji}, \chi_{ji}(t_{ji} \mid X_{jit}, \varepsilon_{ji}), \gamma] + (1-\kappa_{ji}) \log S[y_{ji}, \chi_{ji}(t_{ji} \mid X_{jit}, \varepsilon_{ji}), \gamma] \right\}$$

Where ε_{ji} is the random sample for Q Halton draws of the households. The model is converged and stable covariates are found at 200 Halton draws. LIMDEP, an econometric modelling tool is used to estimate the parameters. The goodness-of-fit of the models are revealed on the basis of various model fits, such as, Akaike Information Criteria (AIC), and Bayesian Information Criteria (BIC). The random parameter model is found better than the traditional Weibull hazard model as evident in the lower AIC and BIC values, which indicates the better fit of the model.

3.4.2 Vehicle Type Choice: Panel Random Parameter Logit Model

This research investigates vehicle type choice of first-time vehicle owners and transient owners using six types of vehicles: 1) compact, 2) subcompact, 3) midsize, 4) luxury, 5) SUV, and 6) van (van/minivan/truck). This research employs a random utility-based discrete modelling approach, specifically the random parameter logit (RPL) modelling technique.

Let's assume that U_{ijt} is the utility of an alternative (vehicle type) i chosen by a household j, which can be expressed as:

$$U_{ijt} = \Delta_{ij} + \beta X_{ijt} + \varepsilon_{ijt} \tag{14}$$

Where alternative-specific constants (ASCs) for alternative i and household j is denoted by Δ_{ij} at a given choice occasion t, one of which is zero (considered as reference). In this research, "luxury vehicle" is considered as the reference. β is the household's estimated coefficient parameters; X_{ijt} is a column vector of the observed attributes of alternative i for household j at t-th choice occasion. ε_{ijt} is an unobserved random error term that represents the distinctive impact of unobserved variables which are choice occasion specific, rather than household specific.

The traditional multinomial logit is restricted to an IID assumption and does not account for any unobserved heterogeneity across households. Panel models inherently include repeated choices of the same households, which violated the IID assumption. Therefore, an alternative, flexible random parameter logit (RPL) model that relaxes the IID assumption is used in this research. This research assumes a normally distributed density function with mean m and covariance σ (i.e. all random parameters are normally distributed, $\beta = \beta_j \sim N(m, \sigma)$). Hence, conditional on β_j, the probability of households' observed sequence of vehicle type choices can be written as:

$$R_j(t \mid \beta_j) = \prod_t \frac{e^{\theta_{ij} + \beta_j X_{ji(j,t)t}}}{\sum_{i=1}^{I} e^{\theta_{ij} + \beta_j X_{ji(j,t)t}}} \qquad (15)$$

Here, *i(j,t)* is the vehicle type alternative that a household *j* chooses at choice occasion *t*. The unconditional probability of the sequence of choices can be expressed as:

$$G_j(t \mid m, \sigma) = \int R_j(t \mid \beta_j) f(\beta_j \mid m, \sigma) \, \mathrm{d}\sigma \qquad (16)$$

Where, $f(\beta_j \mid m, \sigma)$ is a normally distributed density function. Therefore, the unconditional log-likelihood function for the estimation can be given by:

$$L_j(m, \sigma) = \sum_{j=1}^{J} \ln G_j(t \mid m, \sigma) \qquad (17)$$

Where, parameters m and σ are to be estimated. The Monte Carlo simulation is used in this research as Equation 17 is a multivariate integral that cannot be evaluated in closed form. For each household, the conditional choice probability $R_j(t \mid \beta_j)$ is calculated for every q Halton draws. This process is repeated for Q times. The integration over $f(\beta_j \mid m, \sigma)$ is approximated by averaging Q draws. Finally the simulated log-likelihood function (*SL*) can be obtained as:

$$SL = \sum_{j=1}^{J} \ln \frac{1}{Q} \sum_{q=1}^{Q} G'_j(t \mid m, \sigma) \qquad (18)$$

$G'_j(t \mid m, \sigma)$ is the simulated probability that a household j will choose an alternative i at choice setting *t*. Here, the coefficient vector β_j, and the distribution of the density function (m, σ) are to be estimated *(Train, 2009).*

The Halton sequence is used in this research as it requires a substantially lower number of draws than random draws. 200 Halton draws have been used for estimating the parameters of the models. The goodness-of-fit value for each of the models is evaluated on the basis of adjusted Rho-square, AIC and BIC. The panel RPL model is found better than the traditional multinomial logit model (MNL) as the adjusted Rho-square is higher in RPL. Also, the RPL model has lower AIC and BIC values, indicating a better model than the traditional MNL.

3.5 Result Discussion

This section first presents the descriptive statistics and model results of vehicle ownership state. Then, the descriptive analysis and model results of vehicle type choice are discussed in this section.

3.5.1 Vehicle Ownership State

Analysis of vehicle ownership state using retrospective data offers valuable insights into the behaviour of vehicle owners throughout their lifetime. As stated earlier, the models tested several factors, including life-cycle events, socio-demographic characteristics, neighbourhood characteristics, and land-use measures, to understand the behaviour of the households for both no-car and transient ownership states. Table 3-2 and 3-3 respectively show the descriptive analysis and parameter estimation of the accelerated hazard-based panel random parameter models. Results are briefly discussed below.

Table 3-2 Descriptive Analysis of Vehicle Ownership State Models

Variables	Description	No-car Ownership State		Transient Car Ownership State	
		Mean/ Proportion	*Standard Deviation**	*Mean/ Proportion*	*Standard Deviation**
Life-cycle Events					
Birth	Dummy, if the reason for household size change is birth of a child = 1, 0 otherwise	24.70%	-	33.49%	-
Death	Dummy, if the reason for household size change is death of a member = 1, 0 otherwise	21.69%	-	14.45%	-
Move-in	Dummy, if the reason for household size change is move-in of a member = 1, 0 otherwise	31.33%	-	28.74%	-
Move-out	Dummy, if the reason for household size change is move-out of a member = 1, 0 otherwise	19.88%	-	16.86%	-
Increase in employment	Dummy, if the reason for household employment change is addition of a new job = 1, 0 otherwise	40.78%	-	43.21%	-
Decrease in employment	Dummy, if the reason for household employment change is loss of employment = 1, 0 otherwise	10.68%	-	11.93%	-
Socio-demographic Variables					
Age	Age of the primary worker	41.17	13.398	48.60	11.661
Income > $100,000	Dummy, if households' annual income is more than $100,000 = 1, 0 otherwise	23.46%	-	38.02%	-
Income < $50,000	Dummy, if households' annual income is less than $100,000 = 1, 0 otherwise	41.35%	-	-	-
Single-detached house	Dummy, if household dwelling type is a single-detached house = 1, 0 otherwise	-	-	62.90%	-
Apartment	Dummy, if household dwelling type is an apartment = 1, 0 otherwise	35.96%	-	18.20%	-
Number of people	Total household member	2.56	1.357	2.86	1.245

Table 3-2 Descriptive Analysis of Vehicle Ownership State Models (continued)

Variables	Description	No-car Ownership State		Transient Car Ownership State	
		Mean/ Proportion	*Standard Deviation**	*Mean/ Proportion*	*Standard Deviation**
Socio-demographic Variables					
Transit	Dummy, if household primary mode of commuting is transit = 1, 0 otherwise	21.35%	-	11.98%	-
Auto	Dummy, if household primary mode of commuting is auto (auto driver/passenger) = 1, 0 otherwise	37.64%	-	-	-
Neighbourhood Characteristics					
Index	Land-use Index	0.1778	0.1623	0.1516	0.1650
Dwelling density	Dwelling density in the neighbourhood	3283.12	4911.5	1869.6	2351.54
Participation rate	Labor force participation rate in the neighbourhood	70.07	9.48	71.43	9.97
Employment rate	Employment rate in the neighbourhood	-	-	66.11	10.09
Percentage of rental house	Percentage of rental house in the neighbourhood	46.75	32.03	36.36	33.36
Percentage of own house	Percentage of own house in the neighbourhood	-	-	61.39	32.45

** = standard deviations are not available for dummy variables (proportion reported)*

3.5.1.1 *No-car Ownership State*

Life-cycle events play a crucial role in terminating no-car ownership state, leading to the first-time vehicle ownership. For example, the birth of a child increases the probability of termination of households' no-car ownership state. Similarly, the moving-in of a member in the household causes earlier termination in no-car state. On the other hand, the death of a member prolongs the duration of the no-car ownership. Additionally, the occurrence of a 'move-out' event exhibits a positive parametric relationship with no-car ownership state. Increase in employment within a household enhances the probability of terminating no-car ownership state, whereas, decrease in employment reduces the probability of no-car state termination. In case of socio-demographic variables, age of the primary worker, high income household, and number of people in a household exhibit negative parametric relationships with the no-car ownership state. For example, households earning $100,000 annually show a negative sign (-0.0978) indicating a quicker termination of no-car ownership state. In contrast, lower income households (annual income less than $50,000), households living in apartments, and transit as a primary mode of commuting exhibit a higher probability of prolonging their no-car ownership state. However, households living in apartment have a significant standard deviation at 5% significance level (*t*-statistics 4.062), indicating the heterogeneous nature of the effect across households. Interestingly, in the case of neighbourhood characteristics, the land-use index has a high positive effect on no-car ownership state. The variable, however, also exhibits a large standard deviation. Although households living in mixed land use areas stay longer without a car ownership, some households might show faster termination of the state given that the standard deviation is larger than the mean (mean, 0.33 and standard deviation, 0.69).

Table 3-3 Analysis of Vehicle Ownership State Models

Variables	No-car Ownership State		Transient Car Ownership State	
	Coefficient	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*
Life-cycle Events				
Birth of a child (Dummy)	-0.2895	-3.838 (0.0001)	0.0365	1.763 (0.0787)
Death of a member (Dummy)	0.6332	3.028 (0.0025)	-0.1057	-1.676 (0.0937)
Member move-in (Dummy)	-0.2204	-2.389 (0.0169)	0.0157	1.695 (0.0908)
Member move-out (Dummy)	0.1102	1.305 (0.1919)	-0.0477	-0.931 (0.3520)
Increase in employment (Dummy)	-0.0174	-1.216 (0.2252)	0.0702	1.794 (0.0728)
Decrease in employment (Dummy)	0.2833	1.179 (0.2383)	-0.0143	-2.219 (0.0270)

Table 3-3 Analysis of Vehicle Ownership State Models (continued)

Variables	No-car Ownership State		Transient Car Ownership State	
	Coefficient	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*
Socio-demographic Variables				
Age of the primary worker	-0.0119	-5.503 *(0.0000)*	0.0075	5.207 *(0.0000)*
Household income more than $100,000 (Dummy)	-0.0978	-1.201 *(0.2296)*	0.0468	1.189 *(0.2345)*
Household income less than $50,000 (Dummy)	0.0334	0.834 *(0.4051)*	-	-
Dwelling type - single-detached house (Dummy)	-	-	0.1001	2.073 *(0.0382)*
Dwelling type - apartment (Dummy)	0.1400	2.303 *(0.0213)*	-0.1335	-2.466 *(0.0137)*
Number of people in household	-0.0411	-2.103 *(0.0354)*	0.0216	1.497 *(0.1343)*
Primary mode of commuting – transit (Dummy)	0.0048	2.071 *(0.0394)*	-0.0464	-2.993 *(0.0029)*
Primary mode of commuting – auto (Dummy)	-0.1977	-2.592 *(0.0096)*	-	-
Neighbourhood Characteristics				
Land-use index	0.3253	1.894 *(0.0582)*	-0.2247	-1.844 *(0.0651)*
Dwelling density in neighbourhood	0.0009	1.204 *(0.2287)*	-0.0015	-1.601 *(0.1095)*
Participation rate in neighbourhood	-0.0061	-2.452 *(0.0142)*	0.0064	1.586 *(0.1128)*
Employment rate in neighbourhood	-	-	0.0055	1.388 *(0.1650)*
Percentage of rental house in neighbourhood	0.0004	0.940 *(0.3482)*	-0.0026	-1.012 *(0.3116)*
Percentage of own house in neighbourhood	-	-	0.0026	0.985 *(0.3244)*

Table 3-3 Analysis of Vehicle Ownership State Models (continued)

Variables	No-car Ownership State		Transient Car Ownership State	
	Coefficient	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*
Standard Deviation of Random Parameters				
Primary worker age	-	-	0.0015	2.996 *(0.0027)*
Dwelling type - single-detached house (Dummy)	-	-	0.0660	3.572 *(0.0004)*
Dwelling type - apartment (Dummy)	0.1513	4.062 *(0.0000)*	-	-
Land-use index	0.6879	6.105 *(0.0000)*	-	-
Constant	*2.6017*	*11.803*	*3.0118*	*11.055*
Shape Parameter of the Distribution	0.361301	19.648	0.2796478	25.349

Note: | *t-statistics* | ≥ 1.60 indicates significance level at least at 10%
| *t-statistics* | ≥ 1.96 indicates significance level at least at 5%

	No-car Ownership State		Transient Car Ownership State	
Model Fit	Traditional Weibull	Random Parameter Accelerated Hazard-based Model	Traditional Weibull	Random Parameter Accelerated Hazard-based Model
Log-likelihood	-181.5174	-168.4051	-179.7979	-145.7525
AIC	1.5587	1.0697	0.9421	0.7839
BIC	1.7056	1.3092	1.1672	0.9935

3.5.1.2 *Transient Ownership State*

Life-cycle events also influence transient ownership episodes of existing owners. Interestingly, households terminate the transient ownership state quickly in the event of death, move-out, and loss of employment. This result is opposite to the finding of the 'no-car state' model. Arguably, this result might indicate a downsizing of the vehicle fleet. However, the birth, member move-in, and increase in employment prolong the duration of transient state, which means that households do not immediately add or dispose vehicle in response to these events. In case of socio-demographic variables, primary worker age, high income households, households living in single-detached home, and the number of people exhibit positive parametric relationships. For instance, households living in single-detached houses demonstrate a higher probability of prolonging their transient ownership state. The variables, ‘age of the primary worker’ and ‘single-detached house’ show considerable heterogeneity across households as evident in statistically significant standard deviations. Unlike ‘no-car ownership state’ model, a large number of neighbourhood characteristics are found to be the determinants of the duration of transient state. The model also suggests that the higher the land-use index, the higher is the probability of transient ownership state termination.

Model results reveal some interesting contrasts in terms of the impact of certain variables on no-car and transient car ownership state duration. For example, the birth of a child is more likely to terminate the no-car ownership state quickly; but it increases the probability of longer duration in transient ownership state. Perhaps, households of no-car state might require a vehicle when a child is born, and transient owners might not be interested in any change in the fleet size. The probability of termination of no-car ownership decreases for the event of death. On the other hand, this variable offers an opposite relationship in case of transient car ownership. In both models the ‘death of a member’ shows the highest magnitude among all life-cycle events. The number of people in a household has a positive coefficient value of 0.0215 in case of transient ownership state and a negative value (-0.0412) for no-car ownership state. This may indicate that the higher number of household members necessitates maintaining the vehicle fleet size. On the other hand, larger household requires obtaining the first vehicle as quickly as possible, terminating the no-car state.

3.5.2 Vehicle Type Choice

A panel random parameter logit model (RPL) is developed to explore the predictors of the vehicle type choices by the first-time and transient owners. Table 3-4 is the descriptive analysis, and Table 3-5 shows the results of vehicle type choice models.

Table 3-4 Descriptive Analysis of Vehicle Type Choice Models

Variables	Description	First-time Vehicle Owner		Transient Vehicle Owner	
		Mean/ Proportion	*Standard Deviation**	*Mean/ Proportion*	*Standard Deviation**
Vehicle Attributes					
Purchase price	Purchase cost of the vehicle (CAD)	14562.10	11779.60	18355.80	11533.10
Space factor	Includes overall length and capacity of vehicles	4.781	1.185	0.788	1.374
Performance factor	Includes engine size, fuel economy and curb weight of the vehicle	22.638	3.546	13.724	2.467
Vehicle age > 5 years	Vehicle age more than 5 years	19.36%	-	15.48%	-
New vehicle	Vehicle age 0 years	37.90%	-	44.84%	-
Life-cycle Events					
New household formation	Dummy, if the reason for residential location change is new household formation = 1, 0 otherwise	14.52%	-	11.61%	-
Birth	Dummy, if the reason for household size change is birth of a child = 1, 0 otherwise	31.45%	-	32.90%	-
Move-out	Dummy, if the reason for household size change is move-out of a member = 1, 0 otherwise	26.61%	-	28.39%	-
Increase in employment	Dummy, if the reason for household employment change is addition of a new job = 1, 0 otherwise	21.77%	-	25.16%	-
Socio-demographic Variables					
Age	Age of the primary worker	47.244	11.803	49.142	11.547
Income > $100,000	Dummy, if households' annual income is more than $100,000 = 1, 0 otherwise	29.50%	-	47.90%	-
Single-detached house	Dummy, if household dwelling type is a single-detached house = 1, 0 otherwise	53.23%	-	66.77%	-
Apartment	Dummy, if household dwelling type is an apartment = 1, 0 otherwise	25.00%	-	15.48%	-
Number of people	Total household member	-	-	2.923	1.250
Number of children	Total number of children in a household	0.746	0.964	0.829	0.996

Table 3-4 Descriptive Analysis of Vehicle Type Choice Models (continued)

Variables	Description	First-time Vehicle Owner		Transient Vehicle Owner	
		Mean/ Proportion	*Standard Deviation**	*Mean/ Proportion*	*Standard Deviation**
Neighbourhood Characteristics					
Population density	Population density in the neighbourhood	3828.33	3512.41	3323.44	3164.29
Dwelling density	Dwelling density in the neighbourhood	2122.54	2553.92	1772.69	2259.17
Percentage of own house	Percentage of own house in the neighbourhood	-	-	62.783	32.807
Participation rate	Labor force participation rate in the neighbourhood	71.145	10.304	71.540	9.823
Index	Land-use index	0.158	0.171	0.149	0.162
Vehicle Type					
Subcompact vehicles		18.55%		15.81%	
Compact vehicles		37.90%		30.32%	
Midsize vehicles		20.16%		18.70%	
Luxury vehicles		3.23%		5.16%	
Sports Utility Vehicles (SUV)		9.67%		15.81%	
Vans (vans/ minivans/ trucks)		10.49%		14.20%	

** = standard deviations are not available for dummy variable (proportion reported)*

3.5.2.1 *First-time Owners' Vehicle Type Choice Model*

Vehicle attributes are strong predictors of the vehicle types in case of first-time owners. The model results suggest that the higher the purchase price, the lower is the probability of choosing subcompact and compact vehicles. However, higher purchase price increases the likelihood of choosing luxury vehicles and SUVs. In contrast, the larger the vehicle (as represented by the space factor), the higher is the probability of choosing SUVs or vans by the first-time owners. In addition, the space factor for subcompact vehicles is found to be negative, but with a statistically significant standard deviation at 5% significance level.

Performance is important in case of choosing luxury vehicles. First-time owners are more likely to choose luxury vehicles with the increase of performance factor. The age of vehicle is also a critical factor for first-time owners' vehicle choice. Vehicle age, of more than five years, lowers the probability of choosing expensive vehicles such as luxury vehicles and SUVs. However, older vehicles are preferable in case of subcompact, compact and midsize vehicles. Perhaps these households that choose these types of cars have budget constraints.

Life stages and life-cycle events also demonstrate significant effects on vehicle type choices by the first-time owners. Newly formed households prefer compact and midsize vehicles. The model results show that the birth of a child increases the probability of choosing a SUV for the first-time vehicle owners. On the other hand, adding an employment in the household increases the likelihood of preferring compact vehicles. The moving out of members from a household gives a higher probability of choosing subcompact and compact vehicles. The coefficient value for subcompact is found to be the highest (8.005). Interestingly, households with an older primary worker are less likely to choose expensive vehicles, such as, luxury vehicles and SUVs. Instead, they would prefer subcompact, compact vehicles and vans as their first vehicle. The number of children in the household also affects vehicle type choice. For example, the higher the number of children the higher will be the probability of choosing midsize cars. On the other hand, high income households (annual income over $100,000) prefer luxury vehicles and vans, which exhibit a positive parametric value of 10.93 and 1.12 respectively. Similarly, the variable 'dwelling type – single-detached house', also show positive parametric relationship with luxury vehicles as first-time owners' choice. However, the variable has a statistically significant standard deviation, indicating heterogeneity across households.

Furthermore, among the neighbourhood characteristics used in this research, the land-use index exhibits a substantial impact on first-time vehicle owners' vehicle choice. Households living in mixed land use areas (higher land-use index) are highly likely to purchase comparatively smaller and economic vehicles (i.e. subcompact and compact vehicles) as their first-time vehicle. The coefficient of subcompact vehicles has a higher magnitude (7.86) for "land-use index", indicating perhaps the advantage of smaller vehicles in congested traffic and parking situation in mixed land use areas.

Table 3-5 Parameter Estimation of Vehicle Type Choice Models

Variables	First-time Vehicle Owner						Transient Vehicle Owner					
	Sub compact	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*	*Sub compact*	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*
	Coefficient (t-statistics) p-value	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*
Vehicle Attributes												
Purchase price	-0.0003 (-1.141) *0.2539*	-0.0008 (-1.071) *0.2840*	-	0.0004 (1.739) *0.0820*	0.0003 (2.521) *0.0117*	-	-	-0.0002 (-2.479) *0.0149*	-0.0030 (-1.027) *0.3043*	0.0019 (1.444) *0.1520*	0.0023 (1.496) *0.1379*	-0.0088 (-1.82) *0.0688*
Space factor	-5.5773 (-1.168) *0.2462*	-7.0276 (-5.146) *0.0000*	-3.6118 (-2.864) *0.0042*	-	1.3034 (1.163) *0.2448*	4.9137 (1.220) *0.2259*	-0.2464 (-1.445) *0.1484*	-0.0319 (-2.496) *0.0143*	0.1170 (0.793) *0.4276*	-0.0741 (-0.998) *0.3208*	0.0326 (2.118) *0.0342*	0.6350 (3.355) *0.0008*
Performance factor	-0.7219 (-4.501) *0.0000*	-0.6466 (-5.158) *0.0000*	-0.3322 (-2.867) *0.0041*	0.0029 (1.599) *0.1135*	-0.1216 (-1.182) *0.2370*	-	-2.2630 (-1.447) *0.1478*	-0.2720 (-1.552) *0.1239*	1.0687 (0.789) *0.4304*	0.6687 (1.600) *0.1152*	-	-5.7815 (-3.335) *0.0009*
Vehicle age more than 5 years (Dummy)	3.6304 (0.954) *0.0127*	5.1148 (1.618) *0.1056*	5.4693 (1.733) *0.0831*	-1.7829 (-1.239) *0.2188*	-7.4415 (-1.885) *0.0594*	-	0.7416 (1.092) *0.2748*	1.2799 (1.410) *0.1585*	-2.0305 (-1.976) *0.0481*	-0.4209 (-2.347) *0.0210*	0.6007 (2.343) *0.0212*	1.8881 (2.111) *0.0347*
Birth event causing household size change (Dummy) x Space factor	-0.0097 (-1.250) *0.2114*	-0.0061 (-1.064) *0.2872*	-0.0056 (-0.977) *0.3285*	-0.3122 (-5.017) *0.3285*	0.0175 (1.592) *0.1152*	-	-0.0063 (-3.546) *0.0006*	-	0.0004 (1.125) *0.2607*	-0.0050 (-2.738) *0.0062*	0.0024 (1.401) *0.1612*	0.0042 (2.257) *0.0240*

Table 3-5 Parameter Estimation of Vehicle Type Choice Models (continued)

Variables	First-time Vehicle Owner						Transient Vehicle Owner					
	Sub compact	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*	*Sub compact*	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*
	Coefficient (t-statistics) p-value	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*
Vehicle Attributes												
Household formation for residential relocation (Dummy) x new car (Dummy)	9.8431 (0.985) *0.3248*	2.8200 (1.227) *0.2196*	-	-	-	-	-	-	-	-	-1.5396 (-1.042) *0.2973*	7.9109 (3.007) *0.0026*
Life-cycle Events												
New household formation (Dummy)	-4.8512 (-1.532) *0.1293*	3.4645 (0.773) *0.4397*	9.3824 (2.301) *0.0214*	-	-	-	0.7173 (0.715) *0.4748*	0.4750 (1.507) *0.1351*	-0.6210 (-3.112) *0.0025*	-	-	-2.1098 (-1.198) *0.2309*
Birth of a child (Dummy)	-	-	-	-	6.3738 (0.721) *0.6738*	-0.0054 (-5.002) *0.0000*	-	-	-	-15.0784 (-2.785) *0.0054*	6.7477 (1.307) *0.1910*	9.3215 (1.876) *0.0607*
Member move-out (Dummy)	8.0053 (2.564) *0.0103*	2.0933 (1.069) *0.2852*	-3.8779 (-1.856) *0.0635*	-	-	-	-1.9378 (-1.639) *0.1012*	0.1166 (3.011) *0.0033*	-0.2949 (-1.349) *0.1805*	-1.1660 (-0.914) *0.3608*	-0.6210 (-3.440) *0.0008*	-

Table 3-5 Parameter Estimation of Vehicle Type Choice Models (continued)

Variables	First-time Vehicle Owner						Transient Vehicle Owner					
	Sub compact	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*	*Sub compact*	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*
	Coefficient (t-statistics) p-value	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*
Life-cycle Events												
Increase in employment (Dummy)	-1.3815 (-0.783) *0.4359*	0.7982 (1.451) *0.1608*	-2.5887 (-1.39) *0.1645*	-17.0092 (-1.367) *0.1716*	-	-	1.7066 (1.998) *0.0457*	1.3396 (1.527) *0.1268*	1.3205 (1.365) *0.1724*	2.6340 (2.602) *0.0093*	-	-
Socio-demographic Variables												
Age of the primary worker	6.2732 (2.493) *0.0127*	0.4046 (3.338) *0.0012*	-	-12.1322 (-1.038) *0.2991*	-4.1525 (-1.872) *0.0612*	0.1377 (1.552) *0.1206*	-1.9039 (-2.057) *0.0397*	-1.4886 (-1.568) *0.1168*	-0.0817 (-2.028) *0.0425*	1.1970 (1.150) *0.2501*	-0.6956 (-2.124) *0.0362*	0.0515 (1.264) *0.2062*
Household income more than $100,000 (Dummy)	-3.6320 (-1.452) 0.1465	-6.5398 (-3.345) *0.0008*	-7.3660 (-3.146) *0.0017*	10.9303 (1.594) *0.1109*	-	1.1191 (0.962) *0.3388*	-0.6235 (-1.710) *0.0905*	-0.5422 (-0.715) *0.4746*	-0.0837 (-3.527) *0.0006*	1.1211 (1.319) *0.1872*	1.0385 (0.788)	-0.8447 (-1.112) *0.2660*
Dwelling type - single-detached house (Dummy)	-2.1397 (-0.909) *0.3633*	-	-3.7580 (-2.388) *0.0169*	27.8319 (3.213) *0.0013*	-	-	-0.5497 (-1.716) *0.0894*	-	-0.6064 (-1.728) *0.0872*	1.8028 (1.970) *0.0488*	-	-
Dwelling type - apartment (Dummy)	-	-2.1898 (-1.636) *0.1019*	-	-	-4.7981 (-2.451) *0.0163*	10.6596 (2.307) *0.0211*	-	0.4716 (0.958) *0.3405*	-	-	-0.8218 (-0.666) *0.5057*	1.4118 (0.980) *0.3256*

Table 3-5 Parameter Estimation of Vehicle Type Choice Models (continued)

Variables	First-time Vehicle Owner						Transient Vehicle Owner					
	Sub compact	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*	*Sub compact*	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*
	Coefficient (t-statistics) p-value	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*
Socio-demographic Variables												
Number of people in household	-	-	-	-	-	-	-	-	-	-	0.6074 (1.138) *0.2552*	0.0745 (3.212) *0.0018*
Number of children in household	-1.1458 (-2.919) *0.0045*	-0.1766 (-2.165) *0.0332*	0.3825 (0.990) *0.3251*	-7.1811 (-2.459) *0.0139*	-2.2080 (-1.662) *0.0966*	-	-0.1741 (-3.545) *0.0006*	-0.6426 (-1.672) *0.0945*	0.4067 (1.002) *0.3161*	-	-	-
Neighbourhood Characteristics												
Land-use index	7.8570 (4.491) *0.0000*	1.1213 (3.035) *0.0032*	-0.1716 (-2.118) *0.0372*	-12.7908 (-2.374) *0.0199*	-5.8758 (-2.433) *0.0171*	-	0.2430 (1.114) *0.2681*	1.4538 (1.600) *0.1160*	3.8187 (1.748) *0.0804*	-10.5043 (-2.183) *0.0290*	-1.8639 (-1.601) *0.1126*	-4.3822 (-1.534) *0.1251*
Population density in neighbourhood	-	0.0002 (2.485) *0.1500*	-	-	-	-0.0007 (-1.305) *0.1919*	-	-0.0008 (-1.960) *0.0536*	-	-0.0002 (-1.595) *0.1107*	-	-0.0001 (-0.755) *0.4504*
Dwelling density in neighbourhood	0.0005 (2.677) *0.0039*	-	0.0005 (1.006) *0.3144*	-	-0.0002 (-1.248) *0.2155*	-	-0.0003 (-1.206) *0.2280*	-	0.0039 (2.300) *0.0236*	-	-0.0001 (-0.988) *0.6330*	-
Percentage of own house in neighbourhood	-	-	-	-	-	-	-	-	-	-	0.0010 (1.092) *0.2747*	-0.0161 (-1.248) *0.2119*

Table 3-5 Parameter Estimation of Vehicle Type Choice Models (continued)

Variables	First-time Vehicle Owner						Transient Vehicle Owner					
	Sub compact	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*	*Sub compact*	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*
	Coefficient (t-statistics) p-value	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*
Neighbourhood Characteristics												
Participation rate in the neighbourhood	-0.0595 (-1.465) *0.1467*	-0.0749 (-0.914) *0.3608*	-0.0780 (-0.948) *0.3432*	0.9957 (3.498) *0.0005*	-0.0049 (-1.128) *0.2626*	-	-0.0905 (-2.511) *0.0120*	-0.0318 (-0.960) *0.3369*	-0.0221 (-1.642) *0.5210*	0.0623 (1.432) *0.1521*	-	-
Constants												
	16.8112 (1.751) *0.0837*	23.4660 (2.535) *0.0131*	-6.7508 (-1.190) *0.2375*	***Reference***	-23.5602 (-0.975) *0.3295*	-32.3625 (-2.903) *0.0047*	-3.1097 (-2.573) *0.0116*	-6.9599 (-1.342) *0.1796*	2.9486 (2.223) *0.0285*	***Reference***	0.2995 (3.344) *0.0012*	-1.4249 (-1.209) *0.2296*
Standard Deviations of Random Parameters												
Space factor	35.5012 (3.198) *0.0014*	-	-	-	-	-	-	-	-	-	0.0239 (2.547) *0.0109*	-
Dwelling type-single-detached house (Dummy)	-	-	-	14.6678 (2.867) *0.0041*	-	-	-	-	-	-	-	-
Number of children	-	-	-	-	-	-	-	0.5303 (1.960) *0.0505*	-	-	-	-

Table 3-5 Parameter Estimation of Vehicle Type Choice Models (continued)

Variables	First-time Vehicle Owner						Transient Vehicle Owner					
	Sub compact	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*	*Sub compact*	*Compact*	*Midsize*	*Luxury*	*SUV*	*Van*
	Coefficient (t-statistics) p-value	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*	*Coefficient (t-statistics) p-value*
Standard Deviations of Random Parameters												
Population density	-	-	-	-	-	-	-	-	-	-	-	0.0002 (2.225) *0.0261*
Land-use index	-	-	-	-	-	-	-	-	-	6.4363 (1.706) *0.0881*	-	-

Note: | *t-statistics* | ≥ 1.60 indicates significance level at least at 10%
| *t-statistics* | ≥ 1.96 indicates significance level at least at 5%

Model Fit	First-time Vehicle Owner		Transient Vehicle Owner	
	Multinomial Logit	Random Parameter Logit	Multinomial Logit	Random Parameter Logit
Log-likelihood	-81.5657	-73.7014	-198.7827	-190.5855
Adjusted Rho-squared	0.428	0.546	0.141	0.190
AIC	3.02	2.91	5.78	5.69
BIC	5.02	4.96	3.86	3.80

3.5.2.2 *Transient Owners' Vehicle Type Choice Model*

Vehicle attributes also play a vital role in case of transient owners' vehicle type choice. Similar to first-time owners, transient owners are price sensitive for compact and midsize vehicles; but would prefer higher priced luxury vehicles and SUVs. As expected, transient owners exhibit a higher probability of choosing larger vehicles (i.e. midsize, SUV and Van), as indicated by the space factor. However, the space factor for SUV exhibits a statistically significant standard deviation at the 5% significance level, indicating the heterogeneous nature of the sampled households. In case of the performance factor, only luxury and midsize vehicles exhibit a positive sign. The higher the comfort and performance of luxury and midsize car, the higher will be the probability of choosing the vehicles by the transient owners. If vehicle age is more than 5 years, transient owners are highly likely to prefer subcompact, compact, SUVs, and vans, rather than luxury and midsize vehicles. Note that, first-time owner households exhibit opposite relationships for midsize vehicles and SUVs.

Newly formed households have high probability to choose compact or subcompact vehicles if they are transient owners. In case of first-time owners, such households exhibit high probability to prefer compact and midsized. Perhaps transient owners already have vehicles in their holding, and add smaller vehicles (e.g. subcompact vehicles) in their fleet. As expected, transient owners are highly likely to buy SUVs and vans due to the occurrence of a birth of a child. The probability of choosing compact vehicles is higher for transient owners if a member of household moves out. Interestingly, adding employment in a household exhibits a higher probability of choosing subcompact, compact, midsize, and luxury vehicles, among which luxury vehicles show the highest parametric value (2.634).

Households with older primary worker are highly likely to make a choice towards luxury vehicles and vans. This behaviour, however, is opposite in first-time owner households. First-time owners have a higher probability of choosing subcompact and compact vehicles and a lower probability of choosing luxury vehicles in this regard. This might suggest that older transient owners reached to certain life-stage of financial stability that allows buying expensive cars. This hypothesis is further reinforced by the positive parametric value for luxury vehicles and SUVs in case of households' income over

$100,000. However, with the higher number of children in the household, transient owners exhibit a higher likelihood of choosing midsize vehicles, which is similar to the choice behaviour of the first-time owners. The 'number of children' for compact vehicles shows a statistically significant standard deviation at 95% confidence interval.

Further, transient owner households living in mixed land uses prefer subcompact, compact and midsize vehicles. In contrast, they do not prefer large, expensive vehicles such as luxury car, SUV and van. The variable exhibits a statistically significant standard deviation at 90% confidence interval in case of luxury vehicle. Additionally, smaller effects are observed for other neighbourhood characteristics. For example, 'population density in neighbourhood', negatively influence the probability of choosing vans, compact, and luxury vehicles. The variable shows a significant standard deviation (*t*-statistics 2.23) for vans, indicating the heterogeneous nature of effects across households.

3.6 Conclusion

This research presents findings of a biographical research that takes a life course-oriented approach in modelling vehicle ownership behaviour using longitudinal information. The research helps to understand the influence of life-cycle events and life stages in explaining vehicle ownership states and type choice, hitherto limited in the existing literature. Particularly, it sheds lights on what triggers the first-time ownership of a vehicle and what are the differences in terms of the determinants that terminate no-car ownership states for the first-time owners and transient states of subsequent vehicle ownerships. The research develops a panel-based random parameter accelerated hazard model for duration modelling. Furthermore, vehicle type choice behaviour of the first-time vehicle owners and transient vehicle owners is investigated by using a panel random parameter logit modelling framework, which takes into account the repeated vehicle choice behaviour of the transient owners during their lifetime. One of the unique features of the research is that it exhaustively evaluates the effects of life-cycle events and life stages in addition to socio-demographic characteristics, vehicle attributes, and neighbourhood characteristics.

Results provide a strong evidence of the impact of life-cycle events on households' vehicle ownership states. For instance, the birth of a child, move-in of members, and increase in employment in the household exhibit high probability of shorter no-car ownership state, leading to the first-time vehicle ownership. On the other hand, these events prolong transient states, essentially reducing the probability of fleet size changes. In contrast, households terminate the transient ownership state quickly in the event of death, move-out, and loss of employment. Other socio-demographic and neighbourhood characteristics also influence the termination of each state. For example, households living in the higher mixed land use areas stay longer without vehicle ownership. This variable however shows statistically significant variation in case of no-car state. In contrast, the higher the land-use index, the higher is the probability of transient ownership state termination.

The research also analyzes the vehicle type choice behaviour of first-time vehicle owners and transient vehicle owners during their lifetime. Model results suggest that vehicle attributes and life-cycle events significantly influence the vehicle type choice behaviour for both first-time and transient owners. While choosing a vehicle, space is vital for the first-time owners. For example, first-time owners and transient owners exhibit high probability of choosing SUVs and vans with the increase of space factor. Performance factor is found to be vital in choosing luxury vehicles. First-time owners and transient owners are both highly likely to choose luxury vehicles as the performance factor increases. In case of first-time owners, newly formed households have higher likelihood to prefer compact and midsize vehicles. On the other hand, transient owners show high probability of choosing subcompact and compact vehicles. The model results show that transient owners are highly likely to buy SUVs and vans due to the occurrence of a birth of a child. The birth of a child increases the probability of choosing a SUV for the first-time vehicle owners. The results also confirm that significant heterogeneity exists in both models.

This research could however, offer empirical evidences of critical aspects of ownership states and vehicle type choice. The research contributes significantly to the existing literature by taking a biographical research approach and comprehensively evaluating the determinants of vehicle ownership states and type choice for first-time owners and transient owners. It provides vital insights on behavioural dynamics of vehicle ownership, which would assist the policy makers to adopt relevant strategies on a longer-term basis.

Chapter 4

Future Vehicle Type Choice Behaviour [2]

Chapter Overview

This chapter presents the findings of modelling alternative fuel vehicle type choice behaviour in the case of a hypothetical scenario of 100% increase in gas prices in Halifax, Canada. A latent class model (LCM) is developed utilizing information from a stated response component of the Household Mobility and Travel Survey. This research considers a comprehensive set of alternative vehicle type choices, including: Diesel Powered Vehicles, Hybrid Electric Vehicles, Plug-In Hybrid Electric Vehicles, Plug-In Electric Vehicles, and regular gasoline vehicles. The LCM model developed in this research captures latent heterogeneity among the sample households by distributing households into discrete latent classes. In this research, the LCM model assumes two latent classes, where the behaviour of households assigned to each class is defined using their socio-demographic, accessibility, and neighbourhood characteristics. The model results suggest that considerable heterogeneity exists, as evident in the parametric values of the two classes. For instance, presence of children in the household shows a higher probability to choose hybrid electric vehicles in class two. On the other hand, households in class one shows a negative relationship. High income households show a lower likelihood of choosing alternative vehicles and exhibit a higher propensity to continue with regular gasoline vehicles. The elasticity effects suggest that significant variation in the magnitude of effects of different variables exist across the two classes, which needs to be addressed within the policies for promoting alternative fuel vehicles as an alternate choice for consumers during a sudden increase in gas price.

[2] This chapter is submitted for:
Khan, N. A., Fatmi, M. R. & Habib, M.A. "Type Choice Behaviour of Alternative Fuel Vehicles: A Latent Class Model Approach", under review in Transportation Research Procedia, a peer-reviewed proceeding of 14th World Conference on Transport Research, Shanghai, China, July 10-15, 2016

4.1 Introduction

Energy security has become a significant concern in recent years. An unstable global oil market might lead consumers to move towards the use of alternative fuel vehicles, to reduce the consumption of regular fuel. An increase in gas prices affects travel behaviour and activities in the short-term and long-term (*Goodwin, 1992*). Due to gas price increases, travelers reduce their vehicle mileage as well as upgrade their existing vehicles to fuel efficient options (*Jeihani & Sibdari, 2010; Pitts et al., 1981*). Although there is a demand for the future vehicles (known as alternative fuel vehicles) due to a rise in gas price (*Jeihani & Sibdari, 2010*), limited research has investigated the choice phenomenon in the travel behaviour research field. Among the few studies, the majority of the researches on alternative fuel vehicles focus on the electric and hybrid-electric vehicles (*Hensher & Greene, 2001; Qian & Soopramanien, 2011*).

This research develops a latent class modelling (LCM) framework to investigate the choice of alternative fuel vehicles due to a hypothetical scenario of 100% increase in gas prices. The data is obtained from a stated response component of the Household Mobility and Travel Survey (HMTS) conducted in Halifax, Canada. The research develops the model considering a comprehensive set of alternative vehicle type choices: (1) diesel powered vehicle, (2) hybrid electric vehicle, (3) plug-in hybrid electric vehicle, (4) plug-in electric vehicle, and (5) regular gasoline vehicle. The effects of socio-demographic, land-use and accessibility measures, and neighbourhood characteristics have been accommodated in this research. One of the key features of this research is to capture unobserved heterogeneity among the sample households. The LCM model developed here uses a flexible class membership model that distributes households into discrete latent classes. The class membership model is defined using households' observed attributes. Additionally, this research develops a conventional multinomial logit model (MNL) to compare with the LCM model.

The next section of this chapter reviews existing literature relevant to future vehicle choice behaviour. Then, the modelling approach is explained, followed by an outline of data sources and preparation. Next is detailed discussion on model results. Finally, the chapter concludes with summary of contributions and direction for future research.

4.2 Literature Review

Alternative fuel vehicles (AFVs) are the most environmental friendly and fuel efficient vehicles. AFV refers to any kind of technology powering an engine that is not completely dependent on gasoline. The development of cleaner fuels and advanced power systems is driven primarily by growing environmental concerns, high gas prices, and the threat of reaching peak oil. This research focuses on the choice behaviour of AFV due to a significant increase in fuel prices.

A significant rise in gas prices can immediately trigger changes in travel behaviour (*Pitts et al., 1981; Dargay & Gately, 1997; Bomberg & Kockelman, 2007*). The innovation of fuel efficient vehicles emerged due to the instability of gasoline prices (*Horne et al., 2005; Sweeney, 1984*). The majority of previous studies have analyzed the elasticity of the short-term and long-term behavioural changes due to increases in gas price. For instance, gas price increases have a low-short-term and high long-term impact on travel behaviour in terms of an impact analysis (Go*odwin, 1992; Puller & Greening, 1999; Caulfield et al., 2010*). Jeihani & Sibdari (*2010*) found an increase in the purchase of fuel-efficient vehicles approximately two years following a gasoline price spike. Fatmi et al. (*2014*) suggested that a considerable and probable percentage of individuals in Halifax, Canada exist who intend to invest in fuel efficient vehicles in long term. In contrast, Caulfield et al. (*2010*) explored the probability of replacing regular gasoline vehicles with hybrid electric vehicles within a short-time range (i.e. ten years timeline).

Promotion of AFV is a fairly new policy concept, which has become more prominent following the peak oil theory *(Peter et al., 2013)*. Identifying energy security as a concern, the majority of previous studies focused on the demand analysis of electric vehicles (*Marfisi et al., 1978; Hensher, 1982*). Some other studies evaluated the potential demand of other particular alternative fuel vehicles. For example, Qian & Soopramanien (*2011*) found increased preference for hybrid electric vehicles over electric and petrol fuel vehicle, which could dominate future demand. Zhu & Liu (*2013*) investigated factors affecting purchase decision of hybrid electric vehicle (HEV) and found that the socio-demographics and neighbourhood characteristics influence the adoption process of HEV most. Li et al. (*2013*) explored the influence of the socio-demographic factors and environmental consciousness, which increases the likelihood of purchasing flexi-fuel and hybrid-electric vehicles. However, limited studies broadened their research parameters to include alternative fuel vehicles altogether, as opposed to a particular focus on a particular alternative fuel vehicle. For example, Koetse & Hoen (*2014*) evaluated a choice experiment of conventional technology, hybrid, plug-in hybrid, fuel cell, electric, and flexi-fuel vehicles, and found that preference for alternative fuel vehicles is lower than the conventional gasoline vehicles. In contrast, van Rijnsoever et al. (*2013*) suggested a higher preferences for alternative fuel vehicles (i.e. battery electric vehicle and fuel cell vehicle) than conventional vehicles. However, Bhavsar et al. (*2014*) developed a network simulation strategy and found that plug-in hybrid vehicles (PHEV) save 30% on electricity consumption, and 65% in travel time optimization; whereas, electric vehicles save 64% for energy consumption and 21% for travel time optimization. Dagsvik et al. (*2002*) employed a probabilistic choice model to understand the potential demand for electric, hybrid, and liquid propane gas (LPG) vehicles, where they explored that men are more reserved than women concerning new technology. Brownstone et al. (*1996*) investigated a transaction choice model for forecasting electric, compressed natural gas (CNG), methanol, and regular gasoline vehicle demand, which revealed a higher preference for alternative fuel vehicles in the high income groups and households with children.

Different modelling approaches are employed to understand the effect of gas price spikes on travel behaviour. The majority of these studies focused on analyzing the demand of alternative fuel vehicles. However, limited research has investigated the choice behaviour. For instance, Chorus et al. (*2013*) employed a utility based model (random utility maximization model) and a regret based model (random regret minimization model) to understand the choice preference of consumers for alternative fuel vehicles. A multinomial logit model was developed by Koetse & Hoen (*2014*), where they explored the preference of alternative fuel vehicles by company drivers. Qian & Soopramanien (*2011*) examined multinomial and nested logit models to explore consumer behaviour when choosing between alternative fuel vehicles and conventional vehicles.

Clearly, in the existing literature it is not evident how the households behave during the event of a sudden rise in gas prices and what their choice of vehicle would be from a comprehensive set of alternative fuel vehicles. This research fills this gap by developing models to test a scenario in which the gasoline price is assumed to be doubled, and how households in Halifax, Canada would choose alternative fuel vehicles in that scenario. Particularly, the research focuses on what will be the determinants concerning the choice of vehicles, if such a scenario occurs. The research develops a flexible-form latent class discrete choice modelling approach that captures the unobserved heterogeneity in the choice behaviour of the alternative fuel vehicles among the sample households. However, the unobserved heterogeneity cannot be captured within a traditional multinomial logit model (MNL) (*Greene & Hensher, 2003; McFadden, 1973*), which might lead to incorrect estimate of parameters. Latent class models (LCM) and random parameter logit (RPL) models have the ability to capture the unobserved heterogeneity across the population. However, the latent class formulation is advantageous as the correlation among the parameters is implicit and it does not require any prior assumptions of parametric distribution (*Greene & Hensher, 2003*). In addition, the LCM captures unobserved heterogeneity by distributing households into discrete latent classes (*Hess et al., 2011*). Households are distributed into different classes by using a latent class membership model within the LCM framework. Most of the previous studies assumed the class membership as constant (*Greene & Hensher, 2003*). However, in this research, a flexible class membership model is developed that relates the probability of households distributed into different classes with several household attributes.

4.3 Data Used for Empirical Application

A brief description of the datasets used and data preparation during modelling the choice behaviour of alternative fuel vehicle is presented in this section.

4.3.1 Halifax Mobility and Travel Survey (HMTS)

This research uses data from a retrospective survey, Household Mobility and Travel Survey (HMTS), conducted in Halifax, Canada, in 2012-13. A stated response component was included in the HMTS, which presented a hypothetical scenario of 100 percent increase in gasoline price to the respondents. The respondents were asked to identify their vehicle preference under this scenario from the following five options: (1) Diesel Powered

Vehicles, (2) Hybrid Electric Vehicles (HEV), (3) Plug-in Hybrid Electric Vehicles (PHEV), (4) Plug-in Electric Vehicles (PEV), and (5) Regular gasoline vehicles (for comparison purposes). In addition, the HMTS collected information regarding home and work locations, socio-demographics, dwelling characteristics, vehicle fleet, and travel patterns, among others. The HMTS survey yields a total response from 475 households. A detailed exploratory analysis of the survey can be found in another study (*Salloum & Habib, 2015*). Additional data used for analysis includes neighbourhood characteristics from the 2011 Canadian Census at the Dissemination Area (DA) level, land-use information from the Halifax Regional Municipality (HRM), and location information of activity points and transportation services from the Desktop Mapping Technologies Inc. (DMTI).

4.3.2 Data Preparation

The first step in data preparation is to clean up the data for missing values. Out of 475 respondents of HMTS, 249 responses were found with complete information of alternative fuel vehicles. The second step is to geocode households' home and work locations. Following the geocoding, the accessibility measures are determined using the Halifax Regional Municipality (HRM) road network in ArcGIS 10.1. The accessibility measures include home to work distance, distance from home to the closest bus stop, food store, shopping center, library, park, health services, and public administration, among others. The fourth step involves determining the land-use index (*Bhat & Gossen, 2004*). The land-use index ranges from 0 to 1, where, perfect land-use heterogeneity is represented by 1 and 0 indicates perfect homogeneity. Finally, a full database is built by joining the survey data with the corresponding accessibility measures, land-use, and neighbourhood characteristics.

4.4 Modelling Approach

This research investigates the choice behaviour of four types of alternative fuel vehicles and one regular gasoline vehicle for a hypothetical scenario of gas price increase. The five types of vehicles considered for the model, include: Hybrid Electric Vehicle (48.18%), Plug-in Hybrid Electric Vehicle (12.55%), Diesel Powered Vehicle (12.15%), Plug-in Electric Vehicle (8.50%) and Regular Gasoline Vehicle (18.62%). These types of vehicles can be identified as follows:

- *Regular gasoline vehicle*: Vehicles which are operated by means of regular gasoline fuel (e.g. Honda CR-V).
- *Diesel powered vehicle*: Vehicles which are operated by means of diesel fuel and have a diesel engine, which is also known as compression-ignition engine (e.g. BMW 328d).
- *Plug-in electric vehicle (PEV)*: Vehicles that can be recharged from an external source of electricity like wall sockets. This electricity is stored in a rechargeable battery pack that contributes to drive the wheels (e.g. Nissan Leaf).
- *Plug-in hybrid electric vehicle (PHEV)*: Vehicles that use batteries to power an electric motor and use another fuel like gasoline or diesel to power an internal combustion engine, where the battery powered electric source is the main power source that can be recharged from an external power source (e.g. Chevrolet Volt).
- *Hybrid electric vehicle (HEV)*: These vehicles are a combination of regular gasoline vehicle and electric vehicles. It combines a conventional internal combustion engine propulsion system with an electric propulsion system, where the internal combustion engine works as the main power source (e.g. Ford Fusion).

Consumers' choice behaviour towards alternative fuel vehicles in this research is analyzed based on a random utility based discrete choice modelling framework to develop a Latent Class Model (LCM) using households' cross-sectional information for a stated response component. Both random parameter logit (RPL) and LCM can capture unobserved heterogeneity due to preference variation in households. RPL captures the unobserved heterogeneity by assuming a distribution for each households' preference. However, LCM does not require any prior assumption and captures the heterogeneity across the households by sorting them into different latent classes, which remains unknown.

Let's assume, household j residing in class c can choose i alternative from a set of alternative fuel vehicles. The utility of alternative i of household j belonging to latent class c is U_{ji}. Thus the utility function can be expressed as:

$$U_{ji} \mid (j \in c) = X_{ji}\, \beta_c + \mathcal{E}_{ji} \qquad (1)$$

Where, X_{ji} is the column vector of household j's observed attributes, $\mathcal{E}_{ji}$ is the unobserved heterogeneity for household j and alternative i, and β_c is the class-specific parameter vector. The choice probability of household j belonging to class c choosing alternative i from a particular set of alternatives I, is written as:

$$P_j(i \mid c) = \frac{e^{X_{ji}\beta_c}}{\sum_{i=1}^{I} e^{X_{ji}\beta_c}}\text{, where c = 1, 2,…., C} \qquad (2)$$

The unobserved heterogeneity occurs due to preference variations. The probability of households allocated in latent classes is evaluated by the class membership model. Note that due to the latent nature of the classes, allocation of household j into class c remains unknown. In this research, the latent class membership model is defined using an observed vector of attributes from the HMTS data. Let's assume the observed attribute of household j is Y_j. Thus, the class membership model can be written as:

$$\theta_{jc} = \frac{e^{\nu_c + \varphi_c Y_j}}{\sum_{c=1}^{C} e^{\nu_c + \varphi_c Y_j}} \qquad (3)$$

Here, υ_c and φ_c are the class membership constant and parameter coefficient vectors, respectively. However, to identify the model, one of the latent classes is considered as the reference class by fixing the value of υ_c and φ_c as 'zero'. Thus the unconditional probability for the choice of alternatives by the households is expressed as (*Greene & Hensher, 2003)*:

$$P_j(i \mid \beta_1, \ldots\ldots\ldots, \beta_c) = \sum_{c=1}^{C} \{P_j(i \mid c)\}\theta_{jc} \qquad (4)$$

The class membership parameter vectors (υ_c and φ_c, for $C - 1$ classes) and class-specific parameter vector (β_c, for C classes) are obtained through a maximum likelihood estimation. The log-likelihood function for the households can be written as:

$$L = \sum_{j=1}^{J} \log[P_j(i \mid \beta_1, ..., \beta_c)]^{\lambda_{ji}} \qquad (5)$$

Here, J is the total number of households, and λ_{ji} is a dummy representing 1 when household j makes a choice of an alternative i, and 0 otherwise. To estimate the maximum likelihood of the parameters, an expectation-maximum (EM) algorithm is used. The goodness-of-fit of the models is evaluated on the basis of adjusted pseudo Rho-square, Akaike Information Criteria (AIC), and Likelihood Ratio Test.

4.5 Discussion of Results

Several variables are examined during the model estimation process. The socio-demographic characteristics include: gender, age, and educational qualification of the head of the household, household income, dwelling type, household size, presence of the children, number of workers, worker status, and number of cars in the household, among others. Accessibility measures include, distance from home to work place, distance from home to the CBD, distance from home to the nearest transit stop, shopping center, school, and park area, among others. Neighbourhood characteristics, such as, dwelling density, percentage of single-detached households, average property value, percentage of owned households, and percentage of rented households, among others, are examined. In the case of land-use characteristics, land-use index, percentage of different land uses including residential, commercial, and industrial are examined in the model. Summary statistics of the independent variables retained in the final model are presented in Table 4-1.

Table 4-1 Summary Statistics of Explanatory Variables

Variables	Description	*Mean/ Proportion*	*Standard Deviation**
Socio-demographic Variables			
Gender (male)	Dummy, if gender of the household head (primary worker) is male = 1, 0 otherwise	49.60%	-
Income > $150,000	Dummy, if annual income of household is more than $150,000 = 1, 0 otherwise	19.71%	-
Income < $50,000	Dummy, if annual income of household is less than $50,000 = 1, 0 otherwise	26.61%	-
Presence of child	Dummy, if household consists of at least 1 child = 1, 0 otherwise	35.08%	-
Household with couples	Dummy, household consists of couple = 1, 0 otherwise	38.31%	-
Education level (Master's)	Dummy, if education level of the household head (primary worker) is Master's = 1, 0 otherwise	36.69%	-
Education level (undergrad)	Dummy, if education level of the household head (primary worker) is under-graduation = 1, 0 otherwise	39.52%	-
One worker household	Dummy, if household consists of only one worker = 1, 0 otherwise	37.50%	-
Full time workers (both)	Dummy, if both workers in household are full time workers = 1, 0 otherwise	63.87%	-
Single-detached house	Dummy, if dwelling type of household is single-detached = 1, 0 otherwise	56.05%	-
Accessibility			
CBD distance	Home to Central Business District (CBD) distance (Kilometers)	12.0637	17.7328
Neighbourhood Characteristics			
Dwelling density	Dwelling density in the neighbourhood	1829.48	2870.37
Land-use Measure			
Index	Land-use index	0.1786	0.1437

** = standard deviations are not available for dummy variable (proportion reported)*

The goodness-of-fit measures suggest that the latent class model (LCM) improves adjusted pseudo rho-square value compared to the traditional multinomial logit (MNL) model (see Table 4-3). The LCM reveals a lower Akaike Information Criteria (AIC) value compared to the MNL model. Finally, in terms of the log likelihood ratio test, the LCM outperforms the MNL model with a chi-squared statistics of 170.60 (critical value of 115.83 with 83 degrees of freedom). Therefore, this research considers the LCM as the final model to explain the households' alternative fuel vehicle type choice.

The LCM is estimated for two latent classes. The latent class membership model results (Table 4-2) suggest that class one consists of a larger share of households with 63.8%, and class two has a smaller share of 36.2% households. The class membership model (Table 4-2) is estimated using socio-demographic, accessibility, and neighbourhood characteristics. The model results suggest that 'age of the household head' has a positive sign for class one, which indicates that older head households have a higher probability to be included in class one. The negative sign of the 'number of cars' in the household suggests that households with a lower car ownership have a higher likelihood to be included in class one. Additionally, 'home to work distance' exhibits a negative sign, which reflects that the households with shorter commute distance are more likely to belong to class one. Moreover, the positive sign of the 'percentage of single-detached households' in the neighbourhood reveals that suburban dwellers have a higher propensity to belong to class one. Therefore, class one can be identified as a class for "*older head suburban dwellers with shorter commute distance and low car ownership*". On the other hand, class two can be identified to include "*younger head urban dwellers with longer commute distance and high car ownership*". The model results of the LCM are presented in Table 4-3.

Table 4-2 Class Membership Model

Variables	Latent Class Model			
	class 1		class 2	
	Coefficient	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*
Age of household head	0.0210	1.619 *(0.1040)*	-	-
Number of cars in household	-0.7500	-2.412 *(0.0159)*	-	-
Home to work distance	-0.0030	-2.380 *(0.0173)*	-	-
Percentage of single-detached household	0.0200	2.761 *(0.0058)*	-	-

4.5.1 Discussion of Latent Class Model (LCM) Results

4.5.1.1 *Diesel Powered Vehicles*

Higher income households represented by annual household income above $150,000 shows a higher likelihood to choose diesel powered vehicles. Interestingly, households residing in single-detached dwellings exhibit a heterogeneous behaviour. Households belonging to class two are more likely to choose diesel powered vehicles. Class two is identified to include younger head households with higher commute distance. The efficient performance of diesel vehicles for longer highway driving trips might be a potential feature for households in class two with potentially longer commute distances. On the other hand, households in class one shows a negative relationship. Households residing farther away from the CBD have a higher probability to choose diesel powered vehicles if they belong to class one, since suburban dwellers are identified to be included in class one. In contrast, households in class two reveal a negative relationship. Highly educated household heads, whose minimum educational qualification is Master's degree, reveals a lower probability for diesel powered vehicles in the case of class two. This variable shows a positive relationship for households belonging to class one. Two worker households where both have full time jobs show a similar heterogeneous behaviour as evident in variations in parametric values in two classes.

4.5.1.2 *Hybrid Electric Vehicles (HEV)*

Hybrid electric vehicles (HEV) have two power sources, where the main source is a gasoline powered internal combustion engine, and the secondary source is a battery. HEVs are high fuel economy vehicles; however, these are more expensive than the traditional gasoline and diesel vehicles. The model results suggest that highly educated household heads, represented by possessing undergraduate degree, exhibit a higher probability to choose HEVs, which might reveal their environmental consciousness. Interestingly, households with income above $150,000 have a higher probability to choose HEVs, if they belong to class two. The high fuel economy of HEVs might be an attractive incentive for households in class two, which is identified to include households with a higher car ownership and longer commute distance. In contrast, households in class one show a negative relationship. Households with children show a positive parametric relationship in class two. HEVs might offer an economic incentive to these households in class two, who possess a higher car ownership and longer commute distance, as they might have to make additional trips to accommodate the travel needs of the children. On the other hand, households with a lower car ownership and shorter commute distance belonging to class one, exhibit a negative relationship. Dwelling density in the neighbourhood shows a significant heterogeneity across the two classes. Suburban dwellers identified to be included in class one are more likely to choose HEVs, which might reflect their inclination towards reducing transportation expenses. In contrast, households in class two reveal a negative relationship. Distance from home to the CBD also exhibits heterogeneous relationship across the two classes.

Table 4-3 **Parameter Estimation of Alternative Fuel Vehicle Choice Model**

Variables	Multinomial Logit		Latent Class Model			
			class 1		class 2	
	Coefficient	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*
Diesel Powered Vehicle						
Gender of household head (male)	1.1008	1.892 *(0.0585)*	-2.8090	-0.963 *(0.3357)*	32.7210	0.687 *(0.4920)*
Household annual income more than $150,000	1.4939	1.856 *(0.0635)*	2.8320	1.873 *(0.0611)*	2.8320	1.873 *(0.0611)*
Household with couples	-0.4363	-0.637 *(0.5240)*	-1.7740	-0.811 *(0.4172)*	3.4790	0.783 *(0.4336)*
Education level of household head (Master's)	-0.3308	-0.585 *(0.5586)*	0.5390	0.307 *(0.7589)*	-17.2300	-3.409 *(0.0007)*
Full time workers (both)	0.3075	0.350 *(0.7264)*	0.8370	0.305 *(0.7602)*	-19.2400	-0.409 *(0.6825)*
Dwelling type (single-detached)	0.8160	1.340 *(0.1820)*	-8.8160	-2.789 *(0.0053)*	33.0980	3.475 *(0.0005)*
Home to CBD distance	0.0495	1.672 *(0.0946)*	0.2640	2.836 *(0.0046)*	-0.2800	-2.078 *(0.0377)*
Hybrid Electric Vehicle						
Gender of household head (male)	0.7879	1.716 *(0.0862)*	8.4350	2.830 *(0.0046)*	-4.2320	-2.749 *(0.0060)*
Household annual income more than $150,000	0.8796	1.261 *(0.2071)*	-0.7340	-0.413 *(0.6793)*	4.1120	2.524 *(0.0116)*
Presence of child in household	0.4755	0.810 *(0.4180)*	-0.4250	-0.244 *(0.8072)*	12.2280	1.833 *(0.0668)*
Household with couples	-0.1353	-0.273 *(0.7849)*	-0.7480	-0.571 *(0.5678)*	13.4280	2.890 *(0.0039)*
Education level of household head (undergrad)	0.0334	0.079 *(0.9369)*	2.6520	2.064 *(0.0390)*	1.3980	0.905 *(0.3653)*
Full time workers (both)	0.8948	1.475 *(0.1401)*	-1.7000	-1.224 *(0.2211)*	5.3620	1.952 *(0.0509)*
Dwelling density in neighbourhood	0.0001	1.168 *(0.2426)*	0.0010	2.184 *(0.0290)*	-0.0020	-3.223 *(0.0013)*
Home to CBD distance	0.0386	1.325 *(0.1851)*	-0.0430	-0.411 *(0.6890)*	0.2340	1.609 *(0.1077)*
Land-use index	0.8970	0.762 *(0.4463)*	2.5610	0.527 *(0.5980)*	1.2950	0.422 *(0.6730)*

Table 4-3 Parameter Estimation of Alternative Fuel Vehicle Choice Model (continued)

Variables	Multinomial Logit		Latent Class Model			
			class 1		class 2	
	Coefficient	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*
Plug-in Hybrid Electric Vehicle						
Gender of household head (male)	0.6167	1.031 *(0.3024)*	1.6440	0.991 *(0.3215)*	8.8500	2.441 *(0.0146)*
Household annual income less than $50,000	0.5085	0.862 *(0.3889)*	4.4490	2.614 *(0.0089)*	-16.5940	-3.361 *(0.0008)*
Presence of child in household	0.7058	0.975 *(0.3294)*	-0.2490	-0.147 *(0.8832)*	-2.6230	-0.466 *(0.6410)*
Education level of household head (undergrad)	1.0064	1.764 *(0.777)*	0.1490	0.116 *(0.9078)*	26.4040	4.170 *(0.0000)*
Full time workers (both)	0.4552	0.617 *(0.5374)*	-0.1630	-0.901 *(0.4011)*	-2.0930	-0.649 *(0.5164)*
Dwelling type (single-detached)	-0.0331	-0.060 *(0.9524)*	-3.1540	-1.639 *(0.1012)*	-3.1540	-1.639 *(0.1012)*
Land-use index	2.1530	1.335 *(0.1819)*	3.0930	0.791 *(0.4289)*	52.3290	3.644 *(0.0003)*
Plug-in Electric Vehicle						
Gender of household head (male)	2.2838	3.065 *(0.0022)*	7.5150	3.085 *(0.0020)*	15.8140	1.699 *(0.0892)*
Household annual income less than $50,000	1.7449	2.310 *(0.0209)*	4.2110	2.895 *(0.0038)*	4.2110	2.895 *(0.0038)*
Households with couples	-0.0021	-0.008 *(0.9937)*	-0.9050	-1.545 *(0.1223)*	2.2090	1.259 *(0.2082)*
Education level of household head (Master's)	1.1446	1.533 *(0.1254)*	-0.3050	-0.230 *(0.8179)*	4.2200	1.426 *(0.1537)*
Dwelling density in neighbourhood	0.0004	0.305 *(0.7606)*	0.0010	1.298 *(0.1943)*	-0.0050	-2.207 *(0.0273)*
Home to CBD distance	0.0231	0.655 *(0.5126)*	-0.7160	-1.823 *(0.0683)*	0.2930	1.857 *(0.0634)*
Land-use index	1.1862	0.616 *(0.5387)*	2.0710	0.400 *(0.6895)*	20.6130	1.032 *(0.3019)*

Table 4-3 **Parameter Estimation of Alternative Fuel Vehicle Choice Model (continued)**

Variables	Multinomial Logit		Latent Class Model			
			class 1		class 2	
	Coefficient	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*	*Coefficient*	*t-statistics (p-value)*
Regular Gasoline Vehicle						
Household annual income more than $150,000	1.3876	1.669 *(0.0951)*	13.6410	2.590 *(0.0096)*	-1.2670	-0.455 *(0.6492)*
Presence of child in household	-0.7233	-0.951 *(0.3417)*	-18.1040	-2.820 *(0.0048)*	17.0570	2.324 *(0.0201)*
Households with couples	-0.3893	-0.593 *(0.5529)*	-3.0160	-1.471 *(0.1414)*	13.9960	2.561 *(0.0104)*
Education level of household head (Master's)	-0.9704	-1.678 *(0.0934)*	-3.5960	-1.886 *(0.0593)*	-1.6900	-1.106 *(0.2686)*
One worker household	-0.6465	-1.193 *(0.2327)*	-2.6230	-1.185 *(0.2362)*	1.0470	0.918 *(0.3586)*
Dwelling type (single-detached)	0.5152	0.980 *(0.3270)*	-4.3460	-1.945 *(0.0518)*	8.0870	3.264 *(0.0011)*
Dwelling density in neighbourhood	0.0001	0.940 *(0.3470)*	-0.00033	-0.435 *(0.6638)*	0.0004	0.974 *(0.3299)*
Home to CBD distance	0.0468	1.533 *(0.1252)*	-0.0150	-0.137 *(0.8909)*	0.2480	1.702 *(0.887)*
Constants						
Diesel Powered Vehicle	-1.8065	-1.567 *(0.1172)*	-7.3800	-2.124 *(0.0337)*	-7.3800	-2.124 *(0.0337)*
Hybrid Electric Vehicle	-0.7680	-0.793 *(0.4276)*	-13.7430	-2.771 *(0.0056)*	9.2560	2.337 *(0.0194)*
Plug-in Hybrid Electric Vehicle	-1.9253	-1.627 *(0.0946)*	-8.2900	-2.838 *(0.0045)*	-8.2900	-2.838 *(0.0045)*
Plug-in Electric Vehicle	-3.1591	-2.327 *(0.0200)*	-8.7320	-1.936 *(0.0528)*	-8.7320	-1.936 *(0.0528)*
Model Fit						
Log-likelihood	-241.71		-185.82			
Adjusted Pseudo Rho-square	0.0232		0.23301			
AIC	2.91		2.76			

Note: | *t-statistics* | ≥ 1.60 indicates significance level at least at 10%
| *t-statistics* | ≥ 1.96 indicates significance level at least at 5%

4.5.1.3 *Plug-in Hybrid Electric Vehicles (PHEV)*

Plug-in hybrid electric vehicles (PHEV) primarily depend on battery power over an internal combustion engine. The main power source is the battery powered electric motor which makes it energy and fuel efficient. Although, the upfront cost is higher than diesel and hybrid electric cars, in the long run, operational costs of PHEV are comparatively lower. Additionally, having higher electrical driving range, PHEV lowers the fuel cost more than diesel and hybrid electric vehicles. The model results suggest that highly educated households where the head of the household has an educational qualification of undergraduate degree, shows a higher propensity to choose PHEV in both classes, which might reflect their environmental consciousness. Two worker households both having full time job status, reveal a negative relationship, which indicates a price insensitive attitude of the high income group. Low income households with annual income below $50,000 exhibit heterogeneity across the two classes. A similar negative relationship is found for the variable representing households residing in single-detached households. Households residing in mixed land-use areas exhibit a higher likelihood for choosing PHEV. The parameter estimate suggests that households in class two are significantly more sensitive (coefficient value of 52.33) compared to class one (coefficient value of 3.09), since class two is identified to include households with a longer commute distance.

4.5.1.4 *Plug-in Electric Vehicles (PEV)*

Plug-in electric vehicles (PEV) are highly environmental friendly, since these vehicles use an electric power source only. Although, the upfront cost is significantly higher for PEV, the operation cost of a PEV is comparatively lower in the long run. The model results suggest that households with a male head show a higher probability to choose PEV. Heads of households having a Master’s degree (proxy as highly educated households) show heterogeneous behaviour across the two classes. Households show a higher probability to choose PEV in class two, which is identified to include younger head households with a higher vehicle ownership and longer commute distance. This result arguably reflects the environmental consciousness of the younger generation. In contrast, older head households with a lower car ownership and shorter commute distance reveal a negative parametric relationship in class one. This result reflects the preference of the older population, who are less likely to change their current vehicle type. Interestingly, home to CBD distance shows a heterogeneous relationship in the two classes. The land-use index shows a positive relationship in both classes, which might reflect that PEVs are more preferable for city areas rather than highway driving.

4.5.1.5 *Regular Gasoline Vehicles*

Household heads having a Master's degree reveals a lower propensity to choose regular gasoline vehicles. Interestingly, higher income households represented by annual household income above $150,000 show a negative relationship in class two, which is identified as urban dwellers. In contrast, a positive relationship is found for households in class one. Households with children exhibit a lower probability to choose regular gasoline vehicles in class one. On the other hand, class two reveals a positive parametric relationship. Distance from home to the CBD and dwelling density in the neighbourhood exhibit heterogeneity across the two classes.

In addition to the above mentioned variables, several other variables including household size, average property value in the neighbourhood, and percentage of different land-uses in the neighbourhood, among others, were tested during the model estimation process. However, these variables did not confirm prior hypothesis and showed poor statistical significance. Therefore, these variables were not retained in the final model. Furthermore, the final model retains some variables which are below the 5% level of statistical significance. These variables offer significant policy implications and are retained in the model assuming that if a larger dataset were available they might exhibit statistical significance.

4.5.2 Elasticity Effects

This research estimates elasticity of the independent variables across the two classes to understand how the magnitude of the effects of different independent variables varies across the two classes (Table 4-4). The elasticity estimates suggest that, in general, socio-demographic characteristics strongly influence the choice of alternative fuel vehicles for households across the two classes. Interestingly, the effect of land-use and accessibility measures is also substantial. In the case of plug-in hybrid electric vehicles (PHEV), head of the household having an educational qualification of an undergraduate degree, and land-use index in the neighbourhood have strong positive influences for households in class two. Perhaps, younger head urban dwellers with higher education in class two refer to a higher level of environmental consciousness, which influences a higher likelihood of choosing PHEV. Moreover, urban dwellers residing in highly mixed land-use neighbourhoods have a preference for PHEVs, as identified in class two. For plug-in electric vehicles, gender of the head of the household has the most dominant positive impact in class two. Interestingly, male head of the households reveals a more than two times stronger positive effect in class two compared to class one. In the case of diesel powered vehicles, male head of the households and households residing in single-detached dwellings have strong positive impacts in class two. On the other hand, education of the head of the household is holding a Master's degree, two worker households where both have full time jobs, and distance from home to the CBD have strong negative impacts in class two. For the regular gasoline vehicles, households residing in single-detached dwellings and households with children show a strong positive impact in class two. On the other hand, the same variables reveal a negative impact in class one. Overall, the elasticity effects suggest that strong variation in the effects of magnitude exist among the households across the two classes.

Table 4-4 Elasticity Effects

Variables	class 1	class 2
Diesel Powered Vehicle		
Gender of household head (male)	-1.2789	10.8886
Household annual income more than $150,000	0.3574	0.3440
Households with couples	-0.5698	1.0090
Education level of household head (Master's)	0.1601	-5.7760
Full time workers (both)	0.6038	-14.5205
Dwelling type (single-detached)	-4.3040	13.9615
Home to CBD distance	1.7286	-2.8667

Table 4-4 Elasticity Effects (continued)

Variables	class 1	class 2
Hybrid Electric Vehicle		
Gender of household head (male)	1.9326	-1.5356
Household annual income more than $150,000	-0.0877	0.2721
Presence of child in household	-0.1007	2.7516
Households with couples	-0.218	2.4289
Education level of household head (undergrad)	0.674	0.3776
Full time workers (both)	-1.0386	2.5230
Dwelling density in neighbourhood	1.4158	-2.9636
Home to CBD distance	-0.4050	1.5235
Land-use index	0.3203	0.1322
Plug-in Hybrid Electric Vehicle		
Gender of household head (male)	0.7660	3.5647
Household annual income less than $50,000	0.6175	-2.9415
Presence of child in household	-0.0837	-1.0124
Education level of household head (undergrad)	0.0506	6.8644
Full time workers (both)	-0.1267	-1.6220
Dwelling type (single-detached)	-1.6340	-1.7532
Land-use index	0.4689	7.3325
Plug-in Electric Vehicle		
Gender of household head (male)	3.0051	7.3329
Household annual income less than $50,000	0.6112	0.8393
Households with couples	-0.2547	0.7926
Education level of household head (Master's)	-0.0957	1.4639
Dwelling density in neighbourhood	1.1997	-10.0941
Home to CBD distance	-8.4822	3.1814
Land-use index	0.3171	3.5945
Regular Gasoline Vehicle		
Household annual income more than $150,000	1.3186	-0.1989
Presence of child in household	-7.1387	4.9195
Household with couples	-0.7212	4.4500

Table 4-4 Elasticity Effects (continued)

Variables	class 1	class 2
Regular Gasoline Vehicle		
Education level of household head (Master's)	-1.1462	-0.4401
One worker household	-0.7077	0.2819
Dwelling type (single-detached)	-1.9686	3.7489
Dwelling density in neighbourhood	-0.5647	0.4381
Home to CBD distance	-0.1431	2.4211

4.6 Conclusion

This chapter presents the findings of an alternative fuel vehicle type choice model. The model investigates the choice of alternative fuel vehicles due to a 100% increase in gasoline price in Halifax, Canada. This model accommodates the choice of a wide range of vehicle types including: Diesel Powered Vehicle, Hybrid Electric Vehicle (HEV), Plug-in Hybrid Electric Vehicle (PHEV), Plug-in Electric Vehicle (PEV), and Regular Gasoline Vehicle. One of the key features of this research is that it develops a latent class modelling framework that captures latent heterogeneity among the sample households. Latent heterogeneity is captured by developing a class membership component model within the LCM framework that distributes the households into discrete latent classes. The LCM examines the impacts of several socio-demographics, land-use and accessibility characteristics, and neighbourhood characteristics.

The LCM is assumed to have two latent classes. The latent class membership model results suggest that class one can be identified to include older head suburban dwellers with shorter commute distances and lower car ownership. Class two can be identified to include younger head urban dwellers with longer commute distances and higher car ownership. The LCM results suggest that households with a highly educated head exhibit a higher propensity to choose alternative fuel vehicles including HEVs, and PHEVs. These results suggest the environmental consciousness of the highly educated population. Highly educated households have a lower probability to choose regular gasoline vehicles. High income group with household income above $150,000 are more likely to choose diesel powered vehicles. The model results suggest that significant heterogeneity exists among the households in two classes. For instance, presence of children in the households shows a positive relationship in class two for hybrid electric vehicles. Hybrid electric vehicles might offer an economic alternative to accommodate the additional travel needs of the children of these households in class two, who have a higher car ownership and longer commute distance. Households with a lower car ownership and shorter commute distance belonging to class one show a negative relationship. Moreover, household heads having an educational qualification of a Master's degree refers to highly educated households and reveals a heterogeneous relationship across the two classes for choosing plug-in electric vehicles (PEV). Younger head households with higher car ownership and longer commute distance belonging to class two shows a higher propensity to choose PEV, which might reflect the environmental consciousness of the younger generation. Older head households with lower car ownership and shorter commute distance reveal a negative relationship in class one, which might reflect the preference of the older population to not change their current chosen vehicle type. Two worker households, both having full time job status, show a lower probability to choose plug-in hybrid electric vehicles, which reflects the price insensitive attitude of the high income households. Higher income households represented by annual household income above $150,000, show heterogeneous behaviour in choosing HEVs.

The elasticity estimates suggest that households residing in mixed land-use neighbourhoods and consist of the household head with an educational qualification of an undergraduate degree, exhibit significant positive influence for the choice of plug-in hybrid electric (PHEV) vehicles in class two. This result suggests that urban dwellers as identified in class two, residing in highly mixed land-use neighbourhoods have a preference for PHEV vehicles. Gender of the head of the household shows significant positive impact on the choice of hybrid electric vehicles and plug-in electric vehicles in class one. Interestingly, gender of the head of the households and households residing in single-detached dwellings show the strongest positive impact for choosing diesel powered vehicles in class two. High income households, represented by households residing in single-detached dwellings, as well as households with children, reveal a positive effect for choosing regular gasoline vehicles in class two. In summary, significant variation exists across the classes among the households in choosing vehicle types. This variation should be addressed within the policies to promote the adoption of alternative fuel vehicles in the future.

Finally, this research contributes significantly by providing an in-depth understanding of the factors affecting the choice behaviour of future vehicles due to gas price increase. The research also captures the heterogeneity among the sample households in the two classes. The elasticity estimation provides useful information to policy makers in the development of effective strategies considering alternative fuel vehicles as an alternate choice for consumers during a sudden increase in gas price.

Chapter 5

Conclusion

This thesis presents a comprehensive analysis of vehicle ownership modelling framework utilizing longitudinal information from a retrospective survey. The biographical research anticipating life-course oriented approach explains the influence of several life-cycle events, along with socio-demographics and neighbourhood characteristics on vehicle ownership states and type choice behaviour of the households. Life-cycle events act as critical factors behind several household decision processes, and impact of the life-cycle events on long-term household vehicle ownership is strong over the lifetime. Additionally, as panel random parameter models have the ability to capture unobserved heterogeneity for households' repeated choice during their lifetime, a panel random parameter accelerated hazard-based model has been used to develop vehicle ownership state models. This research significantly contributes to the existing literature by **investigating a biographical modelling approach in the case of continuing or termination of no-car and transient ownership state in a household**. This research found that, events, such as, the birth of a child, members' move-in, and increase in employment increases the probability of termination of no-car ownership state, leading to the first-time vehicle ownership. On the other hand, death of a member, members' move-out, and decrease of employment in households result in rapid failure of transient ownership state by increasing the probability of fleet size changes in the household. Several socio-demographic and neighbourhood characteristics also influence the vehicle ownership states. For instance, households consist of older primary workers and high income households exhibit higher likelihood of no-car ownership state termination. However, age of the primary worker also exhibits a statistically significant standard deviation in the case of transient ownership state. As the household size increases, households tend to stay longer in their transient ownership state. Furthermore, households living in high dwelling density and mixed land use areas have a higher probability of staying longer in the no-car ownership state. As expected, transient ownership state exhibits the opposite.

This research also accounts for the **investigation of households' first-time vehicle type choice behaviour due to no-car state termination, and the behavioural variation with the transient owners' vehicle type choice behaviour during various transaction events** in terms of the vehicle attributes, life-cycle events, socio-demographics and neighbourhood characteristics. To capture the unobserved heterogeneity due to repeated vehicle choice events of the households during their lifetime, a panel random parameter logit model has been developed to understand the vehicle type choice behaviour of the first-time and transient vehicle owners. Results of the vehicle type choice models suggest that, for the vehicle choice behaviour of both first-time and transient owners, vehicle attributes and life-cycle events have significant impacts. While choosing a vehicle for the first-time, space and performance are two vital factors. For instance, due to higher space factor, households exhibit a high probability of choosing SUV and vans as their first-time ownership. Transient owners also show similar behaviour for SUV and vans. When it comes to the performance factor, both first-time and transient owners are highly likely to choose luxury vehicles. In the case of life-cycle events, newly formed households have a higher probability of choosing midsize and compact vehicles after the termination of no-car ownership state, however, during transaction events, households exhibit a higher likelihood of preferring subcompact and compact vehicles. Additionally, in the event of employment increase, first-time vehicle owners are highly likely to choose compact vehicles, and transient owners show higher likelihood for subcompact, compact, midsize and luxury vehicles. Certain socio-demographics and neighbourhood characteristics also have significant influence on first-time and transient vehicle ownership. For example, as a first-time vehicle owner, older primary worker households have a higher probability of choosing subcompact and compact vehicles. In contrast, older primary workers are more likely to make a choice of luxury vehicles and vans during transaction events in their lifetime. Meanwhile, as expected, irrespective of first-time and transient ownership, high income households have higher likelihood for luxury vehicles. In both vehicle type choice models, with the increase of number of children in the household, the likelihood of choosing midsize vehicle increases. While purchasing the first-time vehicle, households living in mixed land areas are more likely to make the choice of subcompact and compact vehicles. Transient owners living in high mixed land use areas also show positive relationships with subcompact, compact and midsize vehicles' choice behaviour during transactions. Finally, the two critical decision components developed in this thesis will lead towards an implementation of "vehicle ownership" module of the proposed integrated Transportation, Land-use and Energy (iTLE) model for Halifax. As a dynamic integrated urban system modelling is assumed for this purpose, the biographical research will assist in developing an event-based microsimulation framework for the modelling system. The immediate future work will include developing a computational framework to implement these econometric models within the microsimulation model of iTLE software. It is expected that these models will evolve keeping consistency to the principles and modelling framework of the Integrated Land Use, Transportation and Environment (ILUTE), currently operational modelling software in the Greater Toronto and Hamilton Area (GTHA).

Another notable contribution of this research is to **estimate the future type choice behaviour of alternative fuel vehicles due to a sudden gas price increase scenario**. A latent class logit model is developed to investigate the future vehicle choice due to a hypothetical gas price rise. A comprehensive set of vehicle types are considered, including Diesel Powered Vehicle, Hybrid Electric Vehicle, Plug-in Hybrid Electric Vehicle (PHEV), Plug-in Electric Vehicle (PEV), and Regular Gasoline Vehicle. The LCM results suggest that in both classes, households consist of household head with at least an undergraduate degree are more likely to choose HEVs and PHEVs, also households with household head holding at least a Master's degree, exhibit less probability to stay on the regular gasoline vehicle during a sudden gas price hike scenario. Presumably, high educated people are environmentally concerned and prefer to choose alternative fuel type of vehicles. In the case of high income (i.e. annual income more than $150,000), households have higher likelihood to choose diesel powered vehicles, although, heterogeneous behaviour is seen for HEVs' and regular gasoline vehicles' choice across the classes. Model results indicate that significant heterogeneity exists among the households in two latent classes. For instance, households living in single-detached houses are more likely to choose diesel powered vehicles in class two, whereas, a negative relationship is observed in class one. Male household heads exhibit a higher likelihood to choose hybrid electric vehicle in class one, and a negative relationship in class two. Additionally, households consisting of a highly educated head (i.e. holding a Master's degree) exhibit heterogeneity in the choice of plug-in electric vehicle. In these highly educated households, younger household heads with higher car ownership and higher commute distance show a positive relationship in class two, which might show their environmental consciousness. However, lower likelihood to choose plug-in electric vehicle has been observed in class one, which consists of older household heads with less commute distance and less car ownership. This might be because older people might not be willing to change their current vehicle type. Furthermore, high income households exhibit heterogeneity in choosing regular gasoline vehicles. This result indicates that older household heads, living in suburban areas (i.e. higher percentage of single-detached house) with less car ownership and less commute distance in class one might be less price sensitive and environmentally conscious, leading to unwillingness to change their current regular gasoline vehicle.

The results of this thesis also have certain policy implications. The behavioural insights and understanding of the effects of life-cycle events could inform transportation policies that aim to reduce auto-ownership. For instance, target marketing could be used to prolong the duration of no-car ownership state for the first-time owners. Also, land-use mix changes could effectively be utilized to attain desired levels of vehicle ownership and the types of vehicles in the transportation network. As the factors that affect duration also affect the vehicle choice, further research should aim to develop a joint model of vehicle ownership state and type choice. Moreover, residential location choice might have influence on household vehicle ownership decision, for which, modelling the residential location choices simultaneously with the vehicle ownership state and type choice in households' lifetime will be interesting. Further research also includes the development of set of policies which could reduce vehicle ownership within urban system. For policy analysis, the integrated Transport, Land-use and Energy (iTLE) model is already under development, which can forecast households' behaviour on long-term vehicle ownership decisions. The iTLE system will capture the behaviour of real-world entities within a microsimulation platform by testing different transport policies or scenarios. Due to the complex interactions in urban system and extensive heterogeneity in households' attributes and behaviour, an agent-based vehicle ownership within iTLE system will be developed by utilizing the micro-models of '*ownership states*' and '*vehicle type choice*' developed in this thesis. Such modelling system will provide an in-depth understanding of potential responses at disaggregate level and forecast long-term impacts of policy decisions. In addition, the system will implement the developed micro-models of this research to evolve the status of an urban system over time by not only forecasting vehicle ownership state and type choice, but also effects of vehicles on energy consumption and emission. Essentially, vehicle ownership models developed in this thesis open the potential to include '*vehicle ownership*' module explicitly within the proposed dynamic, micrsoimulation-based integrated urban system model for Halifax region.

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Appendix

A1: List of Definitions

Vehicle ownership level	Number of vehicles in the household
Vehicle holding	Household's possession of a particular set of vehicles
Vehicle transaction event	Events of vehicle acquisition, replacement or disposal in a household
Cross-sectional survey	Collection of data from a sample population at a specific point of time
Longitudinal survey	Collection of data from a same household over a period of time
Retrospective survey	A category of longitudinal study that collects information of historic events (i.e. events that have already occurred) of the sample household at once
Panel survey	A category of longitudinal survey that collects information from the same households over multiple time period
Episode	Duration between two events
No-car ownership state	No car ownership duration of a household
Transient ownership state	Duration between two consecutive vehicle transaction events
First-time vehicle owner	Household purchasing their first vehicle in their lifetime
Transient vehicle owner	Household having vehicle transaction events in their lifetime
Event termination	Failure of an event at a certain time
Right censoring event	If a study ends before the termination of an event, then that event is a right censored event

A2: Principal Component Analysis and Varimax Rotation

Principal Component Analysis:

Principal Component Analysis (PCA) is a multivariate statistical technique that converts the correlated variables into a linearly uncorrelated set of original variables called principal components. It is a method of maximizing the variance of the uncorrelated variable set, where, the first component always has the possible highest variance, and second component has the second highest possible variance and so on.

Varimax Rotation Method:

Varimax rotation is a process of obtaining the maximum variance of sum of the squared loadings of the components. It is an orthogonal rotation method that is generally applied after the principal component analysis (PCA). Varimax rotation method is applied when the component loadings of the variables are found less explainable (i.e. higher loading on one variable, and lower or near zero loading on other variables).

A3: Type of Vehicles

1. *Subcompact vehicles:* According to US Environmental Protection Agency (US-EPA), vehicles having passenger and cargo volume in between 85 to 99 cubic feet is considered as subcompact vehicles. Ford Fiesta, Mazda RX 8, Toyota Yaris, Mitsubishi Eclipse, Mini Clubman etc. are some examples of subcompact vehicles.
2. *Compact vehicles:* Vehicles larger than the subcompact vehicles, having passenger and cargo volume between 100 to 119 cubic feet are compact vehicles. Hyundai Accent, Kia Forte, Mitsubishi Lancer, Mazda 6, Chrysler 200 coupe, Dodge Challenger etc. are compact vehicles.
3. *Midsize vehicles:* More than 110 cubic feet passenger and cargo volume vehicles are considered as midsize vehicles. Honda Accord, Chrysler 300, Chevrolet 300, Ford Taurus etc. are some examples of midsize vehicles.
4. *Luxury vehicles:* Vehicles with higher comfort, innovative, modern and high quality technological machineries and precise construction are considered as luxury vehicles. Generally, these vehicles are high price range vehicles. Luxury vehicles can be subcompact, compact, midsize or SUV. Audi A8, Mercedes-Benz GLK, BMW X3, Lexus GS450h are some examples of luxury vehicles.
5. *SUV (Sport Utility Vehicle):* According to US-EPA, if vehicles' gross vehicle weight rating (i.e. vehicle weight plus varying capacity) are under 10,000 pounds, then those vehicles are considered as SUV. Examples of SUVs are: Ford Escape, Chevrolet Avalanche, GMC Terrain, Honda CR-V, Toyota Rav-4 etc.
6. *Vans (van/minivan/truck):* Due to lack of data, this thesis combines vans, minivans, trucks, pickup trucks as Vans. Some examples of this category are: GMC Savana, Ford E150, Silverado c15, Dodge Ram 1500 Pickup etc.

A4: Sample Canadian Vehicle Specification Database (Year 2012)

Make	Model	OL (m)	OW (m)	OH (m)	WB (m)	CW (m)	A (m)	B (m)	C (m)	D (m)	E (m)	F (m)	G (m)	TWF (m)	TWR (m)
ACURA	MDX 4DR SUV AWD /TECH/ELITE	485	199	173	275	2064	117	183	42	85	126	100	110	172	172
AUDI	A5 2DR CABRIOLET 2.0 TFSI QUATTRO PREMIUM /PRE	464	185	137	275	1829	124	48	33	77	111	88	101	157	157
BMW	Z4 sDRIVE35i /35is 2DR CONV RWD	424	179	129	250	1590	156	73	24	74	125	86	89	151	156
CHRYSLER	300 4DR SEDAN 300C AWD	505	191	149	305	2047	139	63	34	89	118	92	108	163	162
FORD	MUSTANG GT 2DR CONVERTIBLE RWD	478	188	142	272	1687	158	72	N/A	80	123	93	113	158	160
HONDA	INSIGHT 4DR HATCHBACK LX/EX	438	169	143	256	1235	96	102	37	76	114	91	92	150	148
MINI	COOPER CLUBMAN S 3DR HATCH FWD	396	168	143	255	1295	99	122	37	77	96	69	74	144	145
MITSUBISHI	LANCER 4DR SEDAN AWD SE-AWD	457	176	149	264	1415	109	50	36	82	108	96	98	153	152
VOLKSWAGEN	PASSAT CC 4DR SEDAN 2.0T	480	186	142	271	1510	117	52	31	78	120	100	110	154	155

Source: Canadian Vehicle Specifications System: Version 2015.1

A5: Abbreviations for Canadian Vehicle Specification Database (Year 2012)*

OL (Overall Length) = The vehicle overall length is the distance measured from the foremost point on the front surface of the vehicle to the rearmost point on the rear surface, with the exception of equipment that may have been considered optional.

OW (Overall Width) = The vehicle overall width is measured at the widest point of the vehicle, excluding the exterior rearview mirrors.

OH (Overall Height) = The vehicle overall height is measured to the highest point on the vehicle, excluding any optional equipment such as roof racks.

WB (Wheelbase) = The wheelbase is the distance measured between the front and rear wheel centres.

CW (Curb Weight) = The vehicle curb weight is defined as the weight of the vehicle in operational status, with all standard equipment, the weight of fuel at nominal tank capacity, and the weight of optional equipment. The curb weight does not include the driver, passengers, or cargo.

A (Front End Length) = The A-dimension is defined as the longitudinal distance between the centre of the front bumper and the centre of the base of the windshield.

B (Rear End Length) = For standard passenger cars, such as sedans and coupes, the B-dimension is defined as the longitudinal distance between the centre of the rear bumper and the centre of the base of the backlight (rear window glass). For hatchbacks, station wagons, vans, and sport utility vehicles (SUV's), the B-dimension is defined as the longitudinal distance between top of the backlight top moulding and front door latch pillar.

C (Side Glass Height) = The C-dimension is defined as the maximum vertical height of the side glass. The measurement is taken from the lower edge of the side window glass, to the top edge of the window opening, at the point on the vehicle in which the height of the glass opening is the largest.

D (Body Side Height) = The D-dimension is defined as the vertical distance between the base of the side glass and the lower edge of the rocker panel. The D-dimension is measured from the base of the rocker panel, up to the lower edge of the side window opening, at the same position on the vehicle as the base of the C-dimension.

E (Roof Width) = The E-dimension is defined as the distance between the side rails or maximum width of the top.

F (Front Overhang) = The F-dimension is defined as the longitudinal distance between the centre of the front bumper and the centre of the front wheel.

G (Rear Overhang) = The G-dimension is defined as the longitudinal distance between the centre of the rearmost projection and the centre of the rear wheel.

TWF (Front Track Width) = The front track width is the lateral distance measured between the wheel centres on front axle.

TWR (Rear Track Width) = The front track width is the lateral distance measured between the wheel centres on rear axle.

**Source: Guide to the Canadian Vehicle Specifications Database, Transport Canada*

A6: Sample Fuel Economy Guide (Year 2011)

2011 MODEL YEAR VEHICLES

This section contains the fuel economy values for 2011 model year vehicles. Additional information for alternative fuel vehicles can be found on pages 16–24. Alternative fuel vehicles are highlighted with a blue bar, and those that can use two kinds of fuel, such as flexible fuel vehicles, have an entry for each fuel type. The most fuel-efficient automatic and manual vehicles per class are listed in black boldface type and marked with a black pointer (▶).

	Trans Type/ Speeds	Eng Size/ Cylinders	MPG City/Hwy	Annual Fuel Cost	Notes
TWO SEATERS					
ASTON MARTIN					
V12 Vantage	M-6	5.9/12	11/17	$4,395	P Tax
V8 Vantage	AM-6	4.7/8	14/20	$3,572	P Tax
	M-6	4.7/8	13/19	$3,812	P Tax
AUDI					
R8	AM-6	4.2/8	13/21	$3,572	P Tax
	M-6	4.2/8	11/20	$4,081	P Tax
	AM-6	5.2/10	13/19	$3,812	P Tax
	M-6	5.2/10	12/19	$4,081	P Tax
R8 Spyder	AM-6	4.2/8	13/21	$3,572	P Tax
	M-6	4.2/8	11/20	$4,081	P Tax
	AM-6	5.2/10	13/19	$3,812	P Tax
	M-6	5.2/10	12/19	$4,081	P Tax
TT Roadster Quattro	A-S6	2.0/4	22/31	$2,200	P T
BENTLEY					
Continental Supersports	A-S6	6.0/12	12/19 8/14	$4,081 $4,125	Gas P E85
BMW					
Z4 sDrive30i	A-S6	3.0/6	18/28	$2,600	P
	M-6	3.0/6	18/28	$2,600	P
Z4 sDrive35i	A-S7	3.0/6	17/24	$3,006	P T
	M-6	3.0/6	19/26	$2,720	P T
Z4 sDrive35is	A-S7	3.0/6	17/24	$3,006	P T
BUGATTI					
Veyron	A-S7	8.0/16	8/15	$5,715	P T Tax
CHEVROLET					
Corvette	A-S6	6.2/8	15/25	$2,977	
	M-6	6.2/8	16/26	$2,817	
	M-6	6.2/8	14/20	$3,572	P S Tax
	M-6	7.0/8	15/24	$3,178	P
HONDA					
▶ **CR-Z**	**AV-S7**	**1.5/4**	**35/39**	**$1,446**	**HEV**
▶	**M-6**	**1.5/4**	**31/37**	**$1,574**	**HEV**
LAMBORGHINI					
Gallardo Coupe	AM-6	5.2/10	13/20	$3,572	P Tax
	M-6	5.2/10	12/20	$3,812	P Tax
Gallardo Spyder	AM-6	5.2/10	13/20	$3,572	P Tax
	M-6	5.2/10	12/20	$4,081	P Tax
MAZDA					
MX-5	A-S6	2.0/4	21/28	$2,486	P
	M-5	2.0/4	22/28	$2,286	P
	M-6	2.0/4	21/28	$2,383	P

	Trans Type/ Speeds	Eng Size/ Cylinders	MPG City/Hwy	Annual Fuel Cost	Notes
MERCEDES-BENZ					
SL550	A-7	5.5/8	14/22	$3,360	P Tax
SL63 AMG	AM-7	6.3/8	12/19	$4,081	P Tax
SL65 AMG	A-5	6.0/12	12/18	$4,081	P T Tax
SLK300	A-7	3.0/6	19/26	$2,720	P
	M-6	3.0/6	17/26	$2,858	P
SLK350	A-7	3.5/6	19/25	$2,720	P
	M-6	3.5/6	18/26	$2,858	P
SLS AMG	AM-7	6.2/8	14/20	$3,572	P Tax
NISSAN					
370Z	A-S7	3.7/6	19/26	$2,600	P
	M-6	3.7/6	18/26	$2,720	P
370Z Roadster	A-S7	3.7/6	18/25	$2,720	P
	M-6	3.7/6	18/25	$2,858	P
PORSCHE					
911 GT2 RS	M-6	3.6/6	16/23	$3,006	P T
911 GT3	M-6	3.8/6	14/21	$3,572	P Tax
911 GT3 RS	M-6	3.8/6	14/21	$3,572	P Tax
911 Speedster	A-7	3.8/6	19/26	$2,600	P
Boxster	A-7	2.9/6	20/29	$2,383	P
	M-6	2.9/6	19/27	$2,600	P
Boxster S	A-7	3.4/6	20/29	$2,486	P
	M-6	3.4/6	19/26	$2,600	P
Boxster Spyder	A-7	3.4/6	20/29	$2,486	P
	M-6	3.4/6	19/27	$2,600	P
Cayman	A-7	2.9/6	20/29	$2,383	P
	M-6	2.9/6	19/27	$2,600	P
Cayman S	A-7	3.4/6	20/29	$2,486	P
	M-6	3.4/6	19/26	$2,600	P
SMART					
fortwo cabriolet	AM5	1.0/3	33/41	$1,589	P
fortwo coupe	AM5	1.0/3	33/41	$1,589	P
fortwo electric drive cabriolet	A-1	-/-	94/79	$644	Elec
fortwo electric drive coupe	A-1	-/-	94/79	$644	Elec
MINICOMPACT CARS					
ASTON MARTIN					
DB9	A-S6	5.9/12	13/20	$3,812	P Tax
	M-6	5.9/12	11/17	$4,395	P Tax
DBS	A-S6	5.9/12	12/18	$4,081	P Tax
	M-6	5.9/12	11/17	$4,395	P Tax
JAGUAR					
XK	A-S6	5.0/8	16/24	$3,006	P
	A-S6	5.0/8	15/22	$3,360	P S
XK Convertible	A-S6	5.0/8	16/22	$3,178	P

ABBREVIATIONS:

▶.................. Highest MPG in Class
2WD.............. Two-Wheel Drive
4WD.............. Four-Wheel Drive
A.................. Automatic Transmission
AFM.............. Active Fuel Management
A-S................ Automatic Transmission-Select Shift
AM................ Automated Manual
AV................ Continuously Variable Transmission
AV-S............. Continuously Variable Transmision with
.... Select Shift
AWD............. All-Wheel Drive
City............... MPG on City Test Procedure
CNG.............. Compressed Natural Gas
Convsn.......... Conversion
D.................. Diesel
E85............... 85% Ethanol/15% Gasoline
Elec............... ELectricity
Eng Size......... Engine Volume in Liters
FFV............... Flexible Fuel Vehicle
FWD.............. Front-Wheel Drive
Gas............... Regular Gasoline
HEV.............. Hybrid-Electric Vehicle
HP................ Horsepower
Hwy.............. MPG on Highway Test Procedure
Li-Ion............ Lithium Ion
LWB.............. Long Wheel Base
M..................Manual Transmission
Mid............... Midgrade Gasoline
MPG............. Miles per Gallon
NA................ Not Available at Press Time
Ni-MH........... Nickel-Metal Hydride
ORP............. Off-Road Package
P.................. Premium Gasoline Recommended
Phev............. Plug-in Hybrid
PR................ Premium Gasoline Required
PT4WD..........Part-time 4WD
S.................. Supercharger
T.................. Turbocharger
Tax............... Subject to Gas Guzzler Tax
Trans............ Transmission
VCM............. Variable Cylinder Management

Source: U.S. Environmental Protection Agency, Office of Transportation and Air Quality

A7: Correlation of the Vehicle Attributes of First-time Owner Households

	wb	*ol*	*ow*	*oh*	*capacity*	*cw*	*eng*	*fe*	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*TWF*	*TWR*
wb	1.00																
ol	0.87	1.00															
ow	0.76	0.71	1.00														
oh	0.44	0.23	0.54	1.00													
capacity	0.86	0.68	0.84	0.82	1.00												
cw	0.66	0.59	0.72	0.71	0.80	1.00											
eng	0.16	0.18	0.17	0.13	0.17	0.18	1.00										
fe	-0.15	-0.17	-0.17	-0.08	-0.13	-0.18	-0.78	1.00									
A	-0.56	-0.18	0.63	0.66	0.15	0.11	0.12	0.34	1.00								
B	0.58	0.35	-0.26	-0.86	-0.19	-0.58	-0.63	-0.19	-0.81	1.00							
C	0.91	0.10	-0.56	-0.62	0.63	-0.09	-0.16	0.13	-0.83	0.68	1.00						
D	0.46	-0.25	-0.96	-0.58	-0.24	-0.05	-0.15	0.08	0.91	0.50	0.56	1.00					
E	-0.54	-0.12	-0.15	-0.10	-0.16	-0.13	0.29	-0.66	0.19	0.59	0.39	0.34	1.00				
F	0.63	0.11	-0.11	-0.20	-0.95	-0.15	0.17	-0.14	-0.24	0.32	0.86	0.21	0.35	1.00			
G	0.84	0.39	0.26	0.31	0.59	0.13	-0.93	0.11	0.47	0.16	0.38	0.50	0.23	0.11	1.00		
TWF	0.82	0.11	0.50	-0.73	0.30	-0.70	-0.82	0.47	-0.14	0.42	0.43	0.44	0.34	0.38	0.28	1.00	
TWR	0.66	0.74	0.56	-0.15	0.50	-0.20	-0.22	0.49	0.26	0.32	0.37	0.46	0.29	0.24	0.42	0.91	1.00

Where,

eng = Engine Size (litre)

fe = Fuel Economy (litre/100 kilometer)

A8: Correlation of the Vehicle Attributes of Transient Owner Households

	eng	*fe*	*wb*	*ol*	*ow*	*oh*	*capacity*	*cw*	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*TWF*	*TWR*
eng	1.00																
fe	-0.70	1.00															
wb	0.33	-0.19	1.00														
ol	0.53	-0.35	0.49	1.00													
ow	0.51	-0.38	0.33	0.56	1.00												
oh	0.51	-0.40	0.31	0.44	0.69	1.00											
capacity	0.55	-0.38	0.78	0.64	0.75	0.81	1.00										
cw	0.25	-0.21	0.19	0.24	0.21	0.23	0.26	1.00									
A	-0.52	-0.86	-0.77	-0.13	-0.45	-0.02	-0.13	0.03	1.00								
B	0.16	-0.18	0.28	0.16	0.29	0.28	0.22	0.16	-0.02	1.00							
C	0.13	-0.16	0.60	0.24	0.27	0.26	0.22	0.13	-0.21	0.75	1.00						
D	-0.22	-0.11	-0.05	0.04	0.11	0.10	0.05	0.05	-0.26	0.65	0.50	1.00					
E	0.18	-0.23	0.07	0.27	0.29	0.32	0.27	0.16	-0.17	0.74	0.75	0.67	1.00				
F	0.07	-0.01	-0.54	0.05	0.74	0.04	0.35	0.04	0.19	0.31	0.28	0.25	0.14	1.00			
G	0.05	-0.09	0.06	0.14	0.42	0.15	0.13	0.09	-0.03	0.54	0.51	0.51	0.50	0.27	1.00		
TWF	0.12	-0.13	0.21	0.17	0.21	0.21	0.16	0.14	0.08	0.80	0.72	0.69	0.80	0.47	0.56	1.00	
TWR	0.10	-0.15	0.66	0.15	0.22	0.24	0.18	0.23	0.13	0.76	0.67	0.66	0.71	0.51	0.53	0.93	1.00

Where,

eng = Engine Size (litre)

fe = Fuel Economy (litre/100 kilometer)

A9: Sample Neighbourhood Characteristics According to Dissemination Area ID

Dissemination Area (DA) ID	Total Population (2011)	Total dwelling	Dissemination Area (square kilometers)	Single-detached house	Own house	Rental house	Semi-detached house	Row House	Apart ment	Index
12090159	551	228	0.25	210	115	130	0	0	15	0.0009
12090160	493	210	0.28	205	100	55	5	0	0	0.0841
12090161	429	209	0.47	100	105	75	45	0	55	0.4832
12090162	502	230	0.46	110	155	85	5	0	110	0.4667
12090163	419	178	0.15	110	140	0	55	0	10	0.0100
12090164	643	367	0.15	45	140	45	75	0	220	0.1980
12090165	596	287	0.29	120	120	35	45	0	95	0.4855
12090166	1133	485	0.42	405	45	35	0	5	80	0.2777
12090202	648	328	0.3	0	150	225	0	50	260	0.5591
12090203	323	161	0.16	105	235	135	10	10	35	0.1256
12090244	618	366	0.41	125	210	200	10	0	215	0.5756
12090330	394	227	0.31	45	235	0	5	0	120	0.2846
12090351	499	296	0.33	40	120	65	5	5	215	0.3342
12090355	630	344	0.5	90	75	65	0	15	215	0.5137
12090356	566	258	0.31	5	180	265	5	80	150	0.4446
12090357	807	510	0.53	15	230	90	10	95	330	0.5536
12090358	569	336	0.06	15	55	0	25	70	200	0.2729
12090359	608	483	0.05	0	215	25	0	0	400	0.3364
12090362	616	270	0.62	130	105	30	15	0	105	0.1510
12090365	498	218	0.18	130	175	125	20	0	60	0.0041
12090672	509	241	3.15	205	90	65	5	0	0	0.2306
12090673	773	366	2.44	320	85	135	0	0	5	0.3333
12090674	979	377	18.37	340	125	80	20	10	0	0.0758
12090678	1747	525	242.69	520	65	165	0	0	0	0.0010
12090878	503	258	0.06	45	180	105	5	15	160	0.0073
12110091	659	319	0.62	100	70	75	5	10	85	0.3970
12110092	446	210	0.24	140	40	130	15	0	45	0.0462
12110093	497	230	0.35	170	35	115	5	0	40	0.1020
12110094	423	219	0.19	135	90	0	5	10	50	0.0123
12110095	460	249	1	100	110	95	0	0	5	0.3333
12110096	468	248	0.17	115	180	80	15	0	85	0.2161
12110097	439	249	0.21	70	145	180	15	0	125	0.0071
12110098	422	214	0.43	75	90	85	30	5	80	0.4125
12110099	515	312	0.3	80	75	155	15	30	160	0.0828
12110100	571	278	0.4	95	105	90	15	10	125	0.3333
12110101	388	213	0.34	85	85	40	10	20	95	0.0001
12110102	442	206	0.23	145	30	165	5	0	35	0.0017
12110103	446	276	0.17	80	130	55	10	0	135	0.1280

Source: Canadian Census (2011), National Household Survey (2011), Desktop Mapping Technologies Inc. Database