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ADOPTION OF ELECTRIC VEHICLES WITHIN THE RENTAL FLEET MARKET IN CANADA: MODELING FACTORS AND DETERMINANTS

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by

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ABSTRACT

In recent years, there have been increasing concerns regarding energy sustainability and climate change. Despite the key role in alleviating these environmental burdens, the introduction of alternative fuel vehicles, particularly electric vehicles (EV), has been difficult, especially in Canada. To date, numerous studies have been conducted to develop a clear understanding of the different factors influencing EV ownership in the household context, with less attention given to commercial fleets. This thesis addresses this limitation in the literature by focusing on the demand for rental vehicles, which constitute around 54% of the total commercial fleet cars and light trucks registrations in Canada.

An online stated preference survey is developed to identify and evaluate the potential determinants influencing Canadian consumers' rental vehicle preference. Each respondent is presented with a series of hypothetical choice scenarios to enable them to assess EV rental fleets (i.e. hybrid electric vehicles, plug-in hybrid electric vehicles, and battery electric vehicles) relative to their conventional counterparts (i.e. internal combustion engine vehicles). Their responses, along with other collected survey data, were used to estimate and compare different discrete choice models, specifically the multinomial logit (MNL), the nested logit (NL), and the latent class (LC) models, to understand potential consumer demand behavior in the rental market. The results indicate that rental vehicle price, fuel cost, vehicle performance, and trunk size are the key factors in determining the choice decision of rental vehicles. In addition, the NL model results indicate that the respondents perceive the presented alternatives independent from each other, while the results from a four-class LC model suggests that a substantial group of individuals highly favor plug-in electric vehicles.

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LIST OF ACRONYMS

AFV	Alternative Fuel Vehicle
BEV	Battery Electric Vehicle
CFD	Complete Factorial Design
EV	Electric Vehicle
FFD	Fractional Factorial Design
GHG	Greenhouse Gas
HEV	Hybrid Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
IIA	Independence of Irrelevant Alternatives
IID	Independent and Identically Distributed
LC	Latent Class
ML	Mixed Logit
MNL	Multinomial Logit
NL	Nested Logit
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
RP	Revealed Preference
SP	Stated Preference
WTP	Willingness-to-Pay

1. INTRODUCTION

1.1 Overview

Increase in daily travel activities, coupled with reliance on gasoline-powered automobiles (i.e. conventional vehicles), places a significant pressure on the environment through tailpipe emissions. In 2014, the transportation sector was considered the second-largest contributor of greenhouse gasses (GHG) (approximately 171MtCO_2eq) in Canada (*Environment and Climate Change Canada, 2016*). Thus, certain transportation policies have been geared towards reducing automobile dependency. However, shifts to non-motorized methods of transportation (e.g. walking and cycling) have been marginally effective given the current nature of most metropolitan areas and societal stigmas towards said methods (*Bernardo & Bhat, 2014*). Along with current advancements in battery technology, the introduction of electric vehicles (EV) is often considered as one of the more viable solutions in combating climate change and promoting sustainable energy.

While EVs could aid in achieving sustainable transportation outcomes, they could possibly do more harm than good depending the source of electricity. EVs powered by coal-based electricity significantly increase environmental impact compared to conventional vehicles, while EVs running on electricity generated by renewable energy reduce environmental impact by at least 50% (*Tessum et al., 2014*). In the Canadian context, national electricity generation (about 167tCO_2eq/GWh) is considerably below the accepted 600tCO_2eq/GWh threshold, placing the country as one of the cleanest in the world (*Kennedy, 2015*). This implies that the scarcity of EV ownership in Canada[1] is due to other barriers not related to potential environmental drawbacks of EVs. *Egbue and*

[1] According to *FleetCarma* (*2016*), Canada only has about 20,000 plug-in electric vehicles as of early 2016.

Long (*2012*), and *Browne et al.* (*2012*) suggest that aside from high capital cost and some functional limitations like driving range and battery life, social and personal perceptions pose as a major hindrance towards EV adoption. Nonetheless, it is undeniable that as electric mobility continues to develop, shifts from conventional vehicles to EVs will become more prominent. Compared to other developed nations, Canada's share of electric vehicles (namely plug-in hybrid and battery) is one of the lowest (*IEA, 2015*).

The research conducted in this thesis is a part of a five-year research project led by the McMaster Institute for Transportation and Logistics (MITL), which strives to develop a strong understanding of significant economic, social, and environmental costs and benefits of EV adoption in different sectors (e.g. consumer, commercial, and public transit) in Canada. The project consists of several modules, including a module handling the adoption of EVs by commercial fleets. The research in this thesis pertains to parts of the latter module. As will be highlighted later on in this thesis, the primary focus is on the Canadian rental market, which accounts for about 69% of all car registrations and 47% of all light truck registrations (the largest segment in both categories) (*Canadian Automotive Fleet, 2016*).

1.2 Research Objectives

While most of existing literature has been concerned with household EV ownership, little has been done to explore the potential of adopting these emerging vehicle technologies by commercial fleets. Public and private organizations typically have high vehicle purchase rates (*Dijk et al., 2013*) and high average annual mileage (*Gnann et al., 2015*), making them ideal EV adopters; thus, it is important to understand their motivations behind EV acquisition decisions. Some of these motivations are firmspecific; government agencies' EV adoption is partly driven by restrictive legislations, while the potential profit increase through technological leadership encourages corporations' EV purchasing decisions (*Sierzchula, 2014*).

The analysis conducted in this thesis strives to strengthen areas that have not been explored and discussed extensively in the transportation literature, with emphasis on the following:

- Advance the current state of knowledge on the adoption of different types of EVs by commercial fleets, specifically in the Canadian rental market
- Design a stated preference online survey to collect appropriate information regarding the potential demand for EVs in the rental market
- Analyze the collected data to develop advance discrete choice models with focus on identifying and understanding significant factors affecting rental decisions of EV consumers
- Estimate the willingness-to-pay (WTP) to assess respondents' trade-offs between vehicle attributes

1.3 Thesis Outline

The remainder of this thesis is organized as follows. The following chapter provides an extensive discussion regarding the current state of knowledge on preference for new vehicle technology around the world, particularly EVs, which serves as the foundation for the statistical models and hypotheses used in this study. Chapter Three describes the methods of analysis used to develop the online survey, as well as the theoretical basis of the statistical modeling techniques employed in the thesis. The collected data, along with the results of the estimated models, are thoroughly discussed in Chapter Four. Chapter Five provides a set of conclusions that is drawn from the achieved results. The chapter also discusses the limitations of the conducted analyses, and important considerations for future research. Finally, a list of references and appendices containing supplemental information are found at the end of this thesis.

2. LITERATURE REVIEW

Extensive use of private vehicles for everyday travel needs has led to significant environmental concerns due to alarming rates of tailpipe emissions in large metropolitan areas. These emissions are associated with the internal combustion engine, which has been the predominant technology used to power the majority of vehicles around the world. Since reducing automobile dependency has been difficult in the past, the introduction of various alternative fuel vehicles (AFV) is considered by many as a more effective and practical solution to the tailpipe emissions problem. However, despite the benefits promised by AFVs, the market share of these vehicles remains negligible, especially in Canada. Numerous studies have been conducted to date to understand consumer demand behavior towards these types of vehicles through different choice models and survey designs. This section of the thesis will provide a comprehensive and thorough review of the key findings and research methods used in these AFV demand studies.

2.1 Different Vehicle Technology

An AFV is often described as any vehicle that does not rely entirely on fossil fuel to power its engine. With recent technological advancements, a variety of alternative fuels have been introduced and are currently used in the market such as biofuels, compressed hydrogen and natural gas, and electricity (*Browne et al., 2012*). The focus of this study, however, is on vehicle powertrain that utilize electricity (i.e. EV), specifically hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and battery electric vehicles (BEV).

An HEV utilizes an electric motor, besides a conventional gasoline engine, to aid its propulsion; its key feature is its ability to generate electric energy using a battery charged by the regenerative braking process (*U.S. Department of Energy, 2012*). Therefore, some studies argue that an HEV is not really an EV but rather a fuel-efficient conventional vehicle (*Rezvani et al., 2015; Schuitema et al., 2013*). Nevertheless, an HEV is characterized as a type of EV in this study because it is still fairly new in the market, which affects consumer behavior and could be considered as a "gateway" vehicle for more sustainable vehicle types like PHEV and BEV. On the other hand, PHEV is an improved version of HEV with better battery capacity and a plug-in charger, which is used to recharge the battery from the grid (*Egbue & Long, 2012*). Its battery allows short-range travel without emissions, while its internal combustion engine could be used for longer travel. Lastly, a BEV is an all-electric powertrain vehicle powered by large battery packs that can be recharged through an electric outlet (*Egbue & Long, 2012*). One of the main benefits of BEV is its zero tailpipe emissions. Additionally, driving range of BEVs continues to improve. An excellent example of the latter is the Tesla Model S, with a maximum range of about 500km (in a controlled condition) (*Tesla Motors, 2016*).

2.2 Types of Data

With AFVs gathering attention in recent years, understanding the factors affecting the decision to adopt such emerging technology by individuals and firms is timely and crucial for the immediate success of such vehicles. Typically, there are two types of data used to assess individuals' vehicle type preference: revealed preference (RP) and stated preference (SP) data. Revealed preference data are often used to explain consumers' actual choice behaviors towards the alternatives currently in the market, which is limited within the current market and technology structure (*Louviere et al., 2000*). On the other hand, SP data are typically used to predict the potential demand of products that are new or yet to exist in the current market by providing flexible, but hypothetical, choice scenarios (*Louviere et al., 2000*).

2.2.1 Revealed Preference Data

Historically, many economists have relied on market observations (i.e. RP data) to estimate consumers' demand and understand their behavior for it portrays current market equilibrium (*Louviere et al., 2000*). Additionally, RP data represent current market constraints and personal characteristics of the decision maker, which then provide reliable and valid market demand assessment. Hence, this type of data could be utilized to understand consumers' purchase motivations in the context of EV demand studies. However, given the scarcity of EVs, primarily PHEVs and BEVs, in the current market, gathering appropriate RP data to understand the factors affecting EV choice decisions has been focused mainly on HEV adoption.

For example, the work by *Haan et al.* (*2006*) surveyed current HEV owners during the first nine months of introducing these vehicles in the Swiss market. The authors suggest that HEV market share at that time was driven by early adopters with high household income and level of education. Next, *Ozaki and Sevastyanova* (*2011*) conducted a similar study, where a questionnaire survey was administered to recent HEV owners in the United Kingdom to investigate their reasons behind HEV adoption. It was found that the majority of individuals had stable income and were educated; in addition, monetary and non-monetary incentives, as well as social preference and technological interests, had positive influences on their purchase decisions. Likewise, *Heffner et al.*

(*2007*) interviewed current HEV owners in California to explore personal and societal symbolism that influenced their purchase decisions. The authors noted that their choices were influenced not only by practical concerns, such as possible savings and incentives, but also by consumer perceptions of vehicle image (e.g. environmentalism, maturity, and intelligence).

While RP data provide extensive information regarding market behaviors, gathering this type of information has been proven expensive and time consuming. In addition, RP data usually represent one observation per respondent at each observation point; therefore, a larger sample size is typically needed in order to reach conclusive results. It is also limited only to products currently and widely available in the market; thus, introduced explanatory variables are often highly collinear and offer little variability due to market competitions (*Louviere et al., 2000*).

2.2.2 Stated Preference Data

Although RP data provide realistic vehicle choice information, they are highly influenced by unobserved factors (i.e. personal tastes), multicollinearity among variables, and analyses are constraint by limited characteristics found in the current market. Stated preference by design overcomes some of these problems by providing flexibility through manipulation of variables, which allows the introduction of existing and/or proposed choice alternatives with new or non-existing attributes (*Louviere et al., 2000*). Thus, SP data are produced through a systematic process called experimental design, in which the variables (i.e. factors) and their levels (i.e. values) are predefined and controlled by the analyst to create different choice alternatives (*Louviere et al., 2000*). This process also allows creating series of hypothetical choice scenarios, which results in multiple observations per respondent. Similar to RP data, SP data is consistent with economic theory; hence, econometric models that utilize such type of data can be used to evaluate and predict the implications regarding real market behaviors (*Louviere et al., 2000*). Thus, the usage of SP data has been the standard practice of many studies for evaluating the potential demand for new vehicle technologies.

2.3 Experimental Design

There are various methods to develop experimental designs. A simple way is through a complete factorial design (CFD), where every possible choice situation (i.e. all combination of the attributes and their levels) is presented to the respondent. This approach estimates attributes' main and interaction effects, while maintaining negligible correlation among attributes and their levels (i.e. orthogonality) (*Louviere et al., 2000*). Main effects are attributes' independent effects on the dependent variable (in this case, rental vehicle preference), which typically account for 70% to 90% explained variance, while interaction effects pertain to attributes' effects to all other factors and capture the remaining variance (*Louviere et al., 2000*). Complete factorial design usually generates a large number of choice profiles, and could increase exponentially when additional attributes and/or levels are introduced.

To illustrate this process, an example involving two alternatives with two attributes, each of which has three levels, produces 16 (2×2^3) profiles. When an additional attribute is introduced, the design would create 54 (2×3^3) scenarios, and adding another one increases the results to 128 (2×4^3) profiles. In general, if there are J alternatives with K_j number of attributes, where each k_j has I_{jk} attribute levels, the total number of combination S^{CF} is written as (*Choice Metrics, 2014*):

$$S^{CF} = \prod_{j=1}^{J} \prod_{k=1}^{K_j} I_{jk} \tag{2.1}$$

Thus, presenting all these choice situations to a survey is simply impractical. There are two common methods used in the literature to overcome this barrier: the fractional factorial design, and the efficient design.

2.3.1 Fractional Factorial Design

Fractional factorial design (FFD) maintains the main characteristic of a CFD, orthogonality, while significantly reducing the number of choice scenarios presented to respondents by selecting a particular subset of a CFD, at the expense of losing interaction effects (*Louviere et al., 2000*). Practically, losing these interaction effects are permissible as they only account for small portion of explained variance; however, it is wise to capture these effects (at least two-way interactions) whenever possible by introducing a bilinear component based on the highest and the lowest levels of each attribute (*Louviere et al., 2000*). There are few studies that have utilized this approach (*Potoglou & Kanaroglou, 2007*), while many have developed a "main effects only" orthogonal FFD (*Axsen et al., 2013, 2009; Batley et al., 2004; Brownstone et al., 1996; Mau et al., 2008; Shin et al., 2012*) to investigate the potential demand for new vehicle technologies.

However, there are instances that an FFD is still too large for each respondent to evaluate. Hence, picking a smaller choice subset is usually generated randomly (*Bunch et al., 1993; Golob et al., 1997; Hackbarth & Madlener, 2016, 2013; Hoen & Koetse, 2014; Ito et al., 2013; Qian & Soopramanien, 2011*), or systematically constructed (*Ahn et al., 2008; Caulfield et al., 2010*); both methods give flexibility on the number of choice situations faced by respondents. Random sampling of choice scenarios is simple to implement, but an insufficient sample size could result to variables being correlated. On the other hand, carefully grouping the profiles into small subsets (i.e. blocks) maintains orthogonality and ensures that respondents are exposed to the whole range of each attribute's values (i.e. attribute level balance) (*Choice Metrics, 2014*); in other words, a blocked design guarantees that respondents are exposed to different scenarios that offer top and bottom attribute levels.

2.3.2 Efficient Design

Unlike orthogonal FFD, efficient design does not primarily focus on minimizing the correlation in the data. Instead, it aims to produce information that can minimize the standard errors in the estimate parameters. According to *Bliemer et al.* (*2008*):

> "The correlation structure between the attributes is not what is of importance. Rather, given the derivation of the models, it is the correlations of the differences in the attributes which should be of concern."

The success of the efficient design depends on specifying the utility functions for each alternative. That is, for any given alternative the variables depicting the attributes of the alternative along with the associated parameters have to be formulated. Here, initial parameter values (also known as priors) are needed. Typically, the priors are based on information from the literature or by collecting and estimating a rudimentary choice model. The latter model is usually based on a pilot SP survey that made use of an orthogonal FFD. While more expensive, an efficient design, some authors argue (*Bliemer et al., 2008*), will provide data that can produce more statistically reliable parameters.

The efficiency of the design can be based on a particular measure of error that could be derived from the asymptotic variance-covariance (AVC) matrix. The matrix is typically based on the initial priors (*Choice Metrics, 2014*). The most commonly used measure is called *D-error*, which is based on the determinant of the AVC matrix (*Choice Metrics, 2014*). Depending on the available information about the prior value $\tilde{\beta}$ or probability function $\emptyset$, there are three types of *D-error* that can be estimated for experimental design *X*:

- No available information ($\tilde{\beta} = 0$)

$$D_{zero} = \det\big(\Omega(X, 0)\big)^{1/\mathrm{K}} \tag{2.2}$$

- Uncertain information ($\tilde{\beta} =$ values estimated using Bayesian approach)

$$D_{Bayesian} = \int_{\tilde{\beta}} \det\left(\Omega\big(X, \tilde{\beta}\big)\right)^{1/\mathrm{K}} \emptyset\big(\tilde{\beta}\big|\theta\big) d\tilde{\beta} \tag{2.3}$$

- Good approximate information ($\tilde{\beta} =$ priors)

$$D_{prior} = \det\left(\Omega\big(X, \tilde{\beta}\big)\right)^{1/\mathrm{K}} \tag{2.4}$$

where *K* is the number of parameters and *Ω* is *K* × *K* AVC matrix (*Choice Metrics, 2014*).

In practice, the design that has the lowest error is considered the “most efficient” design (i.e. *D-optimal* design). Despite outperforming orthogonal designs (*Rose et al., 2008*), *D-optimal* design remained underused in EV demand studies (*Axsen et al., 2015*; *Beck et al., 2013*; *Hidrue et al., 2011*; *Parsons et al., 2014*). According to *Rose and Bliemer* (*2013*), using a *D-efficient* design with zero priors is just as good as using an orthogonal design; thus, the lack of available appropriate priors could be a primary reason why most EV demand studies utilized orthogonal designs.

2.4 Econometric Models

The majority of new vehicle technology demand studies (Table 2-1) used SP data to estimate various logit models, such as the multinomial logit (MNL) (*McFadden, 1974*), the nested logit (NL) (*Train, 2003*), the mixed logit (ML) (*Hensher et al., 2005*), and the latent class (LC) (*Swait, 2007*) models to develop a better understanding of consumers' preferences. Other techniques, such as the probit model (*Train, 2003*), the multiple discrete-continuous extreme value (MDCEV) model (*Bhat, 2005*), the energy-economy (CIMS) model (*Rivers & Jaccard, 2005*), and agent-based modeling (ABM) (*Helbing, 2012)*, have been utilized to evaluate consumer demand for new vehicle technologies.

Table 2-1: Stated Preference Studies

Study	**Location**	**Model**	**Some vehicle attributes used**
Achtnicht et al. (*2008*)	Germany	NL	Purchase price, operating cost, fuel availability, emission
Ahn et al. (*2008*)	South Korea	MDCEV	Fuel cost, operating cost, performance, fuel type
Axsen et al. (*2009*)	Canada and United States	CIMS	Purchase price, fuel cost, performance
Axsen et al. (*2015*)	Canada	LC	Purchase price, fuel cost, range, refueling/recharging time
Batley et al. (*2004*)	United Kingdom	MNL and ML	Purchase price, operating cost, range, fuel availability, emission
Beck et al. (*2013*)	Australia	LC	Purchase price, fuel cost, operating cost, vehicle size
Caulfield et al. (*2010*)	Ireland	MNL and NL	Fuel cost, emission, incentives
Ewing and Sarigöllü (*2000*)	Canada	MNL	Purchase price, fuel cost, operating cost, range, refueling/recharging time, acceleration

Study	Location	Model	Some vehicle attributes used
Hackbarth and Madlener (*2013*)	Germany	MNL and ML	Purchase price, fuel cost, range, fuel availability, refueling/recharging time, emission, incentives
Hackbarth and Madlener (*2016*)	Germany	MNL and LC	Purchase price, fuel cost, range, fuel availability, refueling/recharging time, emission, incentives
Hidrue et al. (*2011*)	United States	MNL and LC	Purchase price, fuel cost, range, refueling/recharging time, emission, acceleration
Hoen and Koetse (*2014*)	Netherlands	MNL and ML	Purchase price, fuel cost, range, incentives
Mabit and Fosgerau (*2011*)	Denmark	ML	Purchase price, operating cost, range, acceleration
Mau et al. (*2008*)	Canada	CIMS	Purchase price, fuel cost, range, fuel availability, warranty
Parsons et al. (*2014*)	United States	MNL and LC	Purchase price, fuel cost, range, refueling/recharging time, emission, incentives
Potoglou and Kanaroglou (*2007*)	Canada	NL	Purchase price, fuel cost, operating cost, fuel availability, emission, acceleration, incentives
Qian and Soopramanien (*2011*)	China	MNL and NL	Purchase price, operating cost, range, fuel availability, incentives
Shafiei et al. (*2012*)	Iceland	ABM	Purchase price, range, acceleration, luggage capacity
Shin et al. (*2012*)	South Korea	MDCEV	Purchase price, fuel cost, operating cost, fuel availability, fuel type
Tanaka et al. (*2014*)	Japan and United States	ML	Purchase price, fuel cost, range, fuel availability, emission

Study	Location	Model	Some vehicle attributes used
Zhang et al. (*2011*)	United States	ABM	Purchase price, range, fuel type, fuel economy
Ziegler (*2012*)	Germany	Probit	Purchase price, fuel cost, fuel availability, emission

2.4.1 The Multinomial Logit Model

Discrete choice models have been used extensively in various research fields, especially in marketing and transportation, to identify and analyze important factors describing a decision maker's ideal alternative compared to other presented options. Similarly, assuming an individual is a rational decision maker, s/he will choose the alternative that maximizes his/her utility (i.e. well-being), which can be mathematically presented as:

$$U_{ri} = V_{ri} + \varepsilon_{ri} \tag{2.5}$$

where U_{ri} is the total utility of alternative i perceived by individual r, $V_{ri} = \beta X_{ri}$ is the deterministic part of utility that depends on the parameter vector β associated with the vector of explanatory variables X_{ri}, and ε_{ri} is the unobserved random term (e.g. personal tastes). In the context of utility maximization, the probability of choosing alternative i is equal to the probability that the utility of i is greater than the utility of all other alternatives j. That is:

$$P_{ri} = P(V_{ri} + \varepsilon_{ri} > V_{rj} + \varepsilon_{rj}) \text{ for all } i \neq j$$

or

$$P_{ri} = P(\varepsilon < V_{rj} - V_{ri}) \tag{2.6}$$

Equation 2.6 above is the fundamental equation of discrete choice models. Different assumptions regarding the error term ε will result in different types of discrete choice models. For instance, if ε is assumed to be independent and identically distributed (IID) and follows a Gumbel distribution (*McFadden, 1974*), then the choice probability can be formulated as the multinomial logit (MNL) model. An excellent example is the study conducted by *Ewing and Sarigöllü* (*2000*), where they estimated an MNL model to analyze the determinants affecting the adoption of clean fuel vehicles in Montreal. Purchase cost, government subsidies, and vehicle performance were crucial when purchasing a new AFV.

2.4.2 The Nested Logit Model

While early pioneering efforts in choice modeling were based on the MNL model, a key issue with the model is the potential violation of the independence of irrelevant alternatives (IIA) property. The property indicates that the ratio of any two alternative shares is assumed independent of all other alternatives, which suggests proportional substitution (*Train, 2003*). To avoid potential restrictions of the IIA property, many studies utilized the nested logit (NL) model. *Potoglou and Kanaroglou* (*2007*) develop an NL model to examine various factors that are most likely to affect households' adoption for AFVs in Hamilton, Ontario. Results suggest that vehicle attributes (e.g. purchase price and acceleration) and socioeconomic characteristics (e.g. high level of education and household income) have significant effects on purchasing AFVs. A more recent study by *Caulfield et al.* (*2010*) examine individuals' motivations, such as fuel costs, vehicle registration tax and greenhouse gas (GHG) emissions, when purchasing HEVs and other AFVs in Ireland. Results suggest that respondents are not significantly sensitive to vehicle registration tax and GHG emissions, but monetary attributes (e.g. purchase price and fuel costs) are highly regarded.

Similarly, the study conducted by *Qian and Soopramanien* (*2011*) analyzes the likelihood of various consumers to adopt AFVs in China. It is found that covariates, such as purchase cost, household income, and vehicle performance, are influential on AFV ownership decisions, which supports priori research on the topic. It has been argued that Chinese consumers perceive certain types of AFVs, specifically HEVs, as conventional vehicles. On the other hand, *Achtnicht et al.* (*2008*) provide a more specific approach by analyzing the impact of service station availability on the demand for AFVs. Though quite different from previous studies, fuel availability is deemed a significant barrier in AFV adoption for it affects range anxiety. It is found that consumers are willing to pay for new vehicle technologies if the development of alternative fueling infrastructures improves.

2.4.3 The Mixed Logit Model

Unlike the NL model, the mixed logit (ML) model has emerged as a more robust alternative to the MNL model given its ability to account for unobserved heterogeneity (i.e. personal tastes) among the modeled observations or decision makers. The ML model relaxes the single point coefficient assumption by allowing parameter(s) to vary among the heterogeneous and unobserved groups of the modeled observations; thus, the parameter(s) is assumed to follow a known probability distribution (*Hensher et al., 2005*). For example, *Batley et al*. (*2004*) evaluate the potential market of AFVs in the United Kingdom (UK) using various formulations of the ML model. Similar to previous studies, it is found that AFV demand in the UK is negatively affected by high purchase price, fuel cost, and limited driving range and fuel availability. The authors also recognize that significant technological and legislative developments are needed to achieve substantial AFV market shares.

Moreover, the ML model has also been used to estimate the propensity of AFV adoption in Germany (*Hackbarth & Madlener, 2013*) and the Netherlands (*Hoen & Koetse, 2014*). Both studies found that some households are very reluctant towards AFVs, primarily EVs, due to their limited driving range and long recharging time. However, government incentives (though more influential in Germany than in the Netherlands), alongside with improved charging infrastructures, would positively affect AFV preference. In addition, *Mabit and Fosgerau* (*2011*) suggest that some individuals, other things being equal, are more inclined to own AFVs than conventional vehicles, and its market share would further increase if purchase price and applicable taxes are reduced for such vehicles. Moreover, *Tanaka et al.* (*2014*) utilize SP data and ML model to evaluate the acceptance of electric vehicles (EVs) in American and Japanese markets. In line with previous studies, the authors found that consumers from both countries are significantly affected by vehicle purchase price, government incentives, vehicle range limitations, and emission reduction. However, Americans seem to value fuel cost and station availability more than Japanese consumers.

2.4.4 The Latent Class Model

Similar to the ML model, the latent class (LC) model captures potential heterogeneity in the population by segmenting individuals with similar characteristics into a discrete number of unique but latent classes (*Swait, 2007*). It is also worth mentioning that the LC model has not gathered recognition in new vehicle demand studies until recent years. *Hidrue et al.* (*2011*) estimate an LC model to assess the significance of certain EV attributes on American consumers' vehicle ownership decisions. The study group is divided into two main class preferences: conventional vehicle and EV drivers. Results suggest consumers are more likely to purchase an EV due to potential fuel savings, rather than the desire to help the environment. In line with previous studies, limited range, long recharging time, and high initial vehicle cost are major barriers to EV market acceptance. The study was later extended by *Parsons et al.* (2014) to evaluate consumers' willingness-to-pay for vehicle-to-grid (V2G) electric vehicles. Accordingly, consumers would be willing to pay more for EVs if upfront discounts on the price of EVs are offered, and if power utilities would provide higher pay for their V2G services.

Beck et al. (*2013*) also use the LC model to examine consumers' environmental attitudes towards emissions charge of EVs in Australia. The authors identify four distinct classes: individuals who prefer conventional vehicles; individuals who are sensitive to emissions surcharges and prefer small fuel-efficient vehicles; individuals who are less susceptible to cost-related attributes and are less likely to be environmentally sensitive; and individuals who are more inclined choosing small HEVs, but also sensitive to vehicle price and emission surcharge. Another example is the study conducted by *Axsen et al.* (*2015*), in which heterogeneity in Canadian consumers' choice preference about plug-in vehicles are characterized using a five-class LC model. The authors found that different lifestyles have significant influence on vehicle preferences; specifically, individuals who show interest in plug-in vehicles tend to have more technological and environmental lifestyles than individuals who belong in other classes. Lastly, *Hackbarth and Madlener* (*2016*) suggest that vehicle consumers in the German market could be divided into six unique segments, two of which are inclined in choosing AFVs. Individuals who belong to these classes are likely to be young, environmentally aware with high daily mileage, but tend to be less educated.

2.4.5 Other Models

Although the probit model overcomes all the limitations of the MNL model, it requires normal distributions for all unobserved components of utility and estimating the log-likelihood of the model is only possible through simulations (*Train, 2003*). In new vehicle demand studies, different forms of probit model are used. Using the multinomial probit model, *Ziegler* (*2012*) investigates the preferences for AFVs in the German market; the author found that German consumers are less likely to adopt AFVs (e.g. hydrogen, electric and hybrid electric vehicles). In line with aforementioned studies, vehicle purchase and fuel costs, lack of refueling stations, as well as GHG emissions, have negative impacts on AFV adoption. Subsequently, the recent work of *Li et al.* (*2013*) utilized a bivariate probit model to explore the factors that significantly influence AFV ownership, specifically flexible fuel vehicles and HEVs in the United States. It was found that American consumers, who are concerned about energy security and the environment and those who already own AFVs, are more likely to purchase an AFV in the future.

In addition, the multiple discrete-continuous extreme value (MDCEV) model has been used to evaluate consumers' simultaneous discrete choice of multiple alternatives; thus, the model can collapse into the MNL model in the case of single discreteness (*Bhat, 2005*). The MDCEV model is employed by *Ahn et al.* (*2008*) to assess how the introduction of AFVs to the current South Korean market would affect the demand for passenger vehicles. The authors used a Bayesian approach to introduce a stochastic term easily into the coefficient and reflect preference heterogeneity across the individuals.

Results suggest that conventional vehicles would still be the consumers' priority choice, but specific types of AFVs (e.g. HEVs) will likely be a good substitute due to their improved fuel efficiency and compatibility with existing service stations. Later, *Shin et al.* (*2012*) utilize the same model also in South Korea, but with an emphasis on how government incentives would encourage EV adoption. They found that purchase price subsidies have a greater positive effect on EVs' competitiveness than tax incentives given the high initial cost of EVs.

Next, energy-economy model (also known as CIMS model in the literature) has been used. CIMS is a hybrid model that focused in understanding the diffusion of new technology through consumer behaviors (*Rivers & Jaccard, 2005*). Extending its capabilities, some studies estimate a CIMS model to capture the behavioral realism of the consumer preference for new technologies. These studies typically investigate role of the neighbor effect on AFV adoption, where a new technology becomes more desirable as its market share becomes more widespread. *Mau et al.* (*2008*) investigates Canadian consumer behavior towards new vehicle technologies, primarily HEVs and hydrogen fuel-cell vehicles. Results suggest that dynamics in consumer acceptance depends on the type of new technology (i.e. HEVs are more favored than hydrogen fuel-cell vehicles). In addition, the degree of market penetration of such vehicles is highly influenced by their purchase price and range. In addition, *Axsen et al.* (*2009*) employ CIMS to measure the willingness-to-pay under different levels of HEVs penetration and understand the preference dynamics in policy simulations. The authors determine the related trade-offs among vehicle attributes like purchase and fuel price, and vehicle performance.

Lastly, agent-based modeling (ABM) utilized computer-based simulations to evaluate potential heterogeneity and stochasticity in individual behavior and to determine the implications of various hypotheses (*Helbing, 2012*). Among all mentioned techniques in this review, ABM is considered the most advance and most complex approach used to understand consumer behavior regarding AFV adoption. *Zhang et al.* (*2011*) investigate certain factors that can potentially advance AFV diffusion in the US using ABM. The study suggests intuitive conclusions that rapid technological advancements and positive marketing would help the AFV diffusion. In contrary, government fuel economy mandates for vehicle manufacturers tend to decrease air pollution improvement due to increase in market share of fuel-inefficient vehicles. Later, *Shafiei et al.* (*2012*) employ the same model to understand the market share evolution of private vehicles in Iceland. It is found that EVs would dominate the market share if there were significant increase in gasoline price, substantial decrease in EV purchase price, and an increase in recharging station accessibility.

2.5 Commercial Fleets

In addition to private vehicle ownership, commercial fleet demand is expected to have significant impact on the future growth of new vehicle technology adoption. For example, *Golob et al.* (*1997*) conducted a stated preference study to determine the impact of various factors such as mandates and incentives affecting fleet managers' acquisition decisions. A more recent study also investigated the variables affecting the purchase decisions of 14 organizations in the United States and the Netherlands (*Sierzchula, 2014*). The author identified that some of the reasons for adopting electric vehicles in their fleets are to lower their environmental impact, resulting to organizations' better public image, while others were pursuing first-mover advantage. On the other hand, the study conducted by *Mahmoud et al.* (*2016*) focused on implementation of battery electric buses in the

Canadian public transit sector. They found that transit fleet managers were sensitive to operational context and energy profile of electric buses, while initial investment remains a major concern.

While there are studies that evaluate the effectiveness of new vehicle technologies in the commercial fleet as a whole, to the best of the author's knowledge, no efforts have been conducted in the past to comprehend rental fleet managers' acquisition process or consumers' rental choice decision. The majority of the existing studies on rental fleets have been focused on the optimization of fleet logistics to maximize business profits. Profit maximization is highly dependent on proper logistics management for car rental companies; thus, determining the optimal mixture and size of rental fleets while maintaining excellent service level has been a topic of interest in the literature. Various models have been formulated, such as the tactical fleet planning model (*Pachon et al., 2003*), the network flow model (*Fink & Reiners, 2006*), the binary integer programing model (*Farzaneh et al., 2012*), and the mixed integer programming model (*de Almeida Correia & Santos, 2014*), to address the concern of ideal fleet utilization and distribution that would satisfy daily demand of certain vehicle types in different rental locations.

Therefore, this thesis is built on the extensive works regarding AFV ownership and extends its analyses on consumer rental context. Vehicle attributes common among the aforementioned studies (Table 2-1) and those that are deemed important when renting a vehicle (e.g. rental price and size of trunk compartment) are used to develop SP experiments to understand realistically consumers' vehicle preferences.

3. METHODS OF ANALYSIS

The primary focus of this thesis is to determine and evaluate the preferences and motivations of Canadian consumers towards renting certain vehicle types. One could argue that choosing consumers as the focus group instead of rental fleet managers is not suitable for understanding electric vehicle (EV) adoption in the commercial context because decisions behind fleet acquisition are undertaken by the rental companies. However, the rationale for choosing to study consumers' rental decisions is twofold: first, rental companies (and any other businesses) are primarily driven by profit maximization, which is dependent on their clients (i.e. consumers). Here, rental companies would normally invest in acquiring vehicle types that are in great demand by their clients. On the contrary, if their clients are not willing to rent certain types of vehicles, then rental companies are less likely to own such vehicles. Second, there are only a handful of rental companies across the country (the most prominent are the following: *Budget*, *Enterprise*, *AVIS*, *Alamo*, *Hertz*, *DOLLAR*, *National*, *Thrifty*, *Economy*, *E-Z*, *ACE*, and *Payless*). As such, a stated preference approach to surveying few rental companies will not be practical.

The methods used in this thesis are based on state-of-the-art practice in alternative fuel vehicle (AFV) demand research, stated preference (SP) survey design, and discrete choice modeling research discussed in the previous chapter. This chapter thoroughly justifies how and why each technique is used to develop the survey, experimental design, and appropriate choice models for the study.

3.1 Survey Layout

Conventional data collections are often conducted through mail (*Bunch et al., 1993*), telephone (*Brownstone et al., 2000*), and face-to-face surveys (*Yoo & Kwak, 2009*), which could be too costly, time consuming, and restricted by limited design options. However, with an increasing number of individuals with Internet access, administration of online surveys has gained significant popularity in the past decade. Unlike traditional methods, online surveys generally cost less, provide shorter response time, and allow more flexible design options (*Potoglou et al., 2012*).

In this study, an online survey was developed to identify and evaluate important variables affecting rental vehicle consumers' potential demand for different types of EVs. Similar to traditional methods, an online survey could also suffer from low response rates. *Fan and Yan* (*2010*) suggest that response rates are influenced by various characteristics of the web survey itself, such as topics, length, ordering, and formatting. Accordingly, a world-renowned market research company, *Research Now* (*2016*), was hired to recruit Canadian consumers to participate in the survey and to guarantee complete feedback from them. This company retains a massive group of respondents around the world, who are highly likely to complete surveys and other correspondence due to significant incentives (e.g. gift cards, air miles and other rewards points) included with participation. A total of 2,130 respondents were contacted to meet the target sample of 1,000 Canadians (about 47% response rate). A pilot survey with the purpose to collect data from 100 respondents was performed on February 16, 2016, which was quickly followed by a full launch to collect data from the remaining 900 participants on February 18-19, 2016.

Prior to participating in the survey, a screening question was presented to respondents, requiring him or her to have rented a vehicle within the past 12 months from the survey deployment in order to participate in the survey. The entire web survey (Appendix A) is divided into six major sections:

a) **Rented vehicle plan and travel pattern** – Respondents are asked about their latest rental vehicle activity, such as why, where and for how long they rented a vehicle.

b) **Rented vehicle characteristics** – This section identifies the importance of certain vehicle attributes (Table 3-1) in renters' decision using a five-level Likert scale.

Table 3-1: Vehicle Attributes

R1	Low mileage on odometer
R2	Rapid acceleration
R3	Features respondent's own vehicle does not have
R4	Excellent fuel economy
R5	Reduced tailpipe emissions
R6	No tailpipe emissions
R7	Ample cargo space
R8	Room for more than three passengers
R9	Additional technology add-ons
R10	Luxury styling

c) **Rental vehicle choice –** Respondents are asked to choose the vehicle class/size they had rented recently from the eight vehicle class/size categories: economy/compact, intermediate, full-size, luxury, minivan, sport utility vehicle (SUV), pick-up, and cargo truck (e.g. U-Haul).

d) **Stated preference scenarios** – Based on their chosen vehicle class, respondents are presented with a series of hypothetical vehicle choice scenarios, in which they have to decide which vehicle powertrain technology they are more likely to rent: (i) internal combustion engine vehicle (ICEV), (ii) hybrid electric vehicle (HEV), (iii) plug-in electric vehicle (PHEV), or (iv) battery electric vehicle (BEV). Prior to the assigned task, they are presented with educational materials on vehicle technologies to provide them with clear and general ideas about the differences of each alternative.

e) **Attitudinal statements** – Respondents are also subjected to a series of attitudinal statements (Table 3-2) using a five-level Likert scale to further understand their views towards renting a vehicle and electric mobility.

Table 3-2: Attitudinal Statements

A1	I like to rent vehicles with new and innovative features
A2	I am willing to tolerate charging inconvenience for benefits of an EV
A3	I am willing to spend more money to rent an EV
A4	I like to rent a vehicle with same features as my own vehicle
A5	I like to reflect my personal image through my rented vehicle
A6	I have not rented an EV because one is not available at my preferred rental company
A7	I am well-aware of charging station locations in my city or near other places that I travel by auto
A8	I would modify my travel patterns to rent an EV
A9	I would sooner purchase an EV to own than rent one
A10	It is my responsibility to protect the environment through my decisions, including renting a vehicle
A11	Driving range would not concern me if I rented an EV
A12	Plugging in a rented EV is not practical
A13	For me a rental vehicle is about travelling from A to B

f) **Renter Characteristics** – Various demographic and socio-economic attributes of respondents are collected in this section.

3.2 Survey Development

The focal point of the survey is the consumer SP exercise to estimate the impacts of various vehicle characteristics of each alternative on consumer rental preferences. In order to increase the realism of the SP scenarios for the respondents, vehicle attributes widely used in the literature, as well as attributes some individuals might find important when renting a vehicle, were incorporated in the presented choice situations. The experimental design was generated using a software called *Ngene* (*Choice Metrics, 2014*) for the purpose of estimating logit models. *Ngene* is capable of creating a wide range of experimental designs such as orthogonal fractional factorial design and efficient designs. The following subsections describe and justify the attributes and their levels (i.e. values) used in the design, and explain the development of the optimal experimental design for the SP survey.

3.2.1 Relevant Attributes and Levels

Based on the reviewed literature (see Table 2-1), significant vehicle attributes could be classified into two main categories: monetary and non-monetary. Monetary attributes, such as purchase price, fuel and maintenance costs, and government subsidies, are typically considered the most influential factors in vehicle choice decision. Factors like station availability, long recharging time, and limited range usually hinder certain vehicle type adoption, primarily EVs. However, since the focus is on rental vehicle preference, purchase price and various annual costs, like maintenance, insurance, depreciation, registration fees, and taxes, were found irrelevant.

Twelve attributes with varying levels (Table 3-3) were used to generate choice profiles describing the alternatives (i.e. HEV, PHEV, BEV) with respect to their conventional counterpart (i.e. ICEV). The numbers of attribute levels were adopted from previous studies. Most of these attributes are also self-explanatory and capture what factors were of importance to consumers when renting a vehicle. To ensure that respondents faced realistic choice scenarios, the estimation of attribute values and levels are discussed thoroughly in the following sub-sections.

Table 3-3: Attributes and Levels Used in the Experimental Design

Attributes	ICEV	HEV	PHEV	BEV
Daily rental price (CAN $)	Base case	+50% than the base	+50% than the base	+50% than the base
		+30% than the base	+30% than the base	+30% than the base
		+10% than the base	+10% than the base	+10% than the base
		–10% than the base	–10% than the base	–10% than the base
		–30% than the base	–30% than the base	–30% than the base
		–50% than the base	–50% than the base	–50% than the base
Fueling/charging cost per 100km (CAN $)	Base case	–30% than the base	–45% than the base	–80% than the base
		–20% than the base	–35% than the base	–75% than the base
		–10% than the base	–25% than the base	–70% than the base
		Same as base	–15% than the base	–65% than the base
Monetary incentive	None	None	None	None
		Free vehicle upgrade	Free vehicle upgrade	Free vehicle upgrade
		No rental tax	No rental tax	No rental tax
		Rental price discount	Rental price discount	Rental price discount
Rental discount for GPS	None	None	50% off	50% off
			Free	Free
Non-monetary incentive	None	None	None	None
		Free parking	Free parking	Free parking
		Priority lane access	Priority lane access	Priority lane access
Maximum range per refuel/recharge (km)	300	400	550	250
	400	500	600	400
	500	600	650	550
	600	700	700	700

(*continued on the next page*)

Attributes	ICEV	HEV	PHEV	BEV
Tailpipe emission reduction	0%	10% 20% 30% 40%	50% 60% 70% 80%	100%
Acceleration time from 0 to 100km/h (s)	Base case	–20% than the base –5% than the base +5% than the base +20% than the base	–20% than the base –5% than the base +5% than the base +20% than the base	–20% than the base –5% than the base +5% than the base +20% than the base
Refueling time	5 mins 10 mins	5 mins 10 mins	5 mins 10 mins	–
Recharging time	–	–	30 mins 1 hr 4 hrs 6 hrs	10 mins 30 mins 4 hrs 8 hrs
Number of stations within a five kilometer radius	1 2 3 5	1 2 3 5	0 1 3 5	0 1 3 5
Size of storage space (i.e. trunk)	Base case	– 2 carry-ons – 1 carry-on Same as base	– 1 carry-on Same as base + 1 carry-on	Same as base + 1 carry-on + 2 carry-ons

Note(s): – Not applicable

3.2.1.1 Cost

Rental vehicle price per day for each vehicle class was estimated using an average of lowest rental cost, excluding additional fees and taxes, offered by major rental vehicle companies (e.g. Hertz, Budget, Enterprise, etc.) in Canada (Table 3-4). Since these companies have numerous franchises nationwide, daily cost estimation only included those located at international airports in major Canadian cities (e.g. Toronto, Montreal, Vancouver, etc.) during "off-peak times" (e.g. Tuesday and Wednesday). These constraints would likely lead to competitive prices that rational consumers will consider.

Fueling/charging cost is defined as total amount spent on gasoline (excluding BEVs) and/or electricity (excluding ICEVs and HEVs) to power the rented vehicle every 100km. The five-year average cost per litre of regular unleaded gasoline (August, 2011 to

August 2015) at filling stations was approximately $1.27 per litre (*Statistics Canada, 2015a*). Similarly, the five-year average of electricity prices (April, 2011 to April, 2015) for residential customers in major Canadian cities was estimated to be about $0.11 per kWh (*Hydro Quebec, 2011-2015*). Additionally, combined mileage (i.e. 55% city and 45% highway drive) of each common rental vehicle brand (*U.S. Department of Energy, 2015*) was used to estimate the average mileage for each vehicle class category. Using this information, base fuel cost was estimated and shown in in Table 3-4. This information was also used to calculate charging cost and attribute levels of other alternatives. For example, the average fuel cost for a conventional (i.e. ICEV) economy sedan is $9.33 per 100km. Assuming a typical PHEV uses 80% gasoline and 20% electricity, the cost to power the PHEV is $7.93 per 100km, which is 15% less the base cost. Similarly, an economy BEV uses $2.31 worth of electricity per 100km, which is 75% less the base cost.

Table 3-4: Estimated Attribute Values for Base Alternative

Vehicle class	**Daily Rental Price ($)**	**Fuel Cost per 100km ($)**	**Acceleration Time**	**Size of Trunk***
Economy	$42.00	$9.33	8.9 s	1 LG + 1 CO
Intermediate	$55.00	$9.64	8.1 s	2 LG + 1 CO
Full-size	$43.00	$11.06	7.6 s	3 LG
Luxury	$95.00	$12.45	5.8 s	2 LG + 1 CO
Minivan	$72.00	$14.94	6.7 s	4 LG
SUV	$94.00	$12.99	7.1 s	3 LG
Pick-up Truck	$89.00	$15.72	6.9 s	4 LG
Cargo Van	$20.00	$14.94	8.5 s	245 ft^3

* LG = luggage; CO = carry-on; 1 luggage = 4 ft^3; 1 luggage = 2 carry-ons; 1 carry-on = 2 ft^3

3.2.1.2 Incentives

The selection of monetary and non-monetary incentives was derived on previous vehicle preference studies. Monetary subsidies such as free vehicle upgrades, exclusion from rental tax, and discounted rental price were considered to promote EV alternatives. Discounts in GPS rental in favor of PHEV and BEV were also included in the choice experiment. This form of incentive was included because respondents travelling to unfamiliar locations would likely find this type of incentive important. Non-monetary incentives like free parking and access to priority lanes were also considered in this study.

3.2.1.3 Performance

Performance of rental vehicles was assessed in terms of maximum range, reduction in tailpipe emissions and acceleration time. Maximum range is defined as the maximum distance in kilometers travelled by the vehicle on a full tank of gas and/or on a fully charged battery. The maximum range values used in this experiment were within the range used in the literature. It is important to note, however, that EV alternatives were assumed to have longer range than ICEV due to their improved fuel economy. More specifically, BEV range was assumed to have longer range than those observed in the current market to capture the potential improvements in battery capacity in the future. Next, representing the pollution level of certain vehicles in terms of CO_2 equivalent was deemed too technical for individuals who were just renting a vehicle for a short period. Hence, the pollution level attribute is presented in a simpler way, as a percent reduction of tailpipe emissions. Finally, acceleration time was used as a substitute to determine the potential power of the vehicle. It is described as the average time the rental vehicle takes in seconds to accelerate from a standing start to 100km/h, which was calculated based on the average acceleration time of common vehicle brands (e.g. Ford, General Motors, Toyota, etc.) found in the current market (Table 3-4).

3.2.1.4 Convenience

Refueling time (excluding BEVs) and recharging time (excluding ICEVs and HEVs) values are based on previous literature as well as real-world observations. Refueling time typically takes between five to ten minutes, while recharging time greatly varies depending on charging power levels (*Yilmaz & Krein, 2013*). Accordingly, there is usually at least one gasoline station within any five-kilometer radius, while there are significantly less, if any, recharging stations within the same radius. Lastly, size of vehicle storage (i.e. trunk) was presented in terms of number luggage and carry-ons (as describe in most rental vehicle websites), with an exception for cargo trucks, in order to represent choices to respondents clearly (Table 3-4). However, for the purposes of the choice model, the attribute was then translated in respect to total occupied volume in cubic feet. It was assumed a typical luggage has a capacity of four cubic feet, while a carry-on has a volume of two cubic feet.

3.2.2 Experimental Design

Once the appropriate attributes and their levels in the choice experiment were determined, the modeling framework of the experimental design, which is a standard multinomial logit (MNL) model, was specified. Using eq. 2.5, the MNL model can be formulated as the choice probability P_{ri} of individual r choosing an alternative i from set I, which is characterized by the following equation:

$$P_{ri} = \frac{\exp(\beta X_{ri})}{\sum_{i=1}^{I} \exp(\beta X_{ri})} \tag{3.1}$$

The individual (i.e. decision maker) in this study pertains to each survey respondent planning to rent a vehicle in the near future. Using this model specification, *Ngene* constructed a blocked orthogonal fractional factorial design (FFD). The software produced 144 unique choice games for each vehicle class/size category, which were divided into 24 blocks, such that each respondent only has to comprehend six scenarios. The rationale behind presenting six scenarios to each respondent is to avoid fatigue and other nuisance effects, while simultaneously collecting a substantial number of observations per respondent. The syntax used to generate the experimental design is found in Appendix B.

In creating an orthogonal FFD, orthogonal coding is typically used to label the attribute levels (i.e. sum of a column of attribute equals to zero) to make it less complicated for the analyst. For example, an attribute with two levels would typically assigned with values 1 and -1, while those with three levels would have values assigned as 1, 0, and -1. Conventionally, only odd numbers are used and level assignment order does not matter. Furthermore, the order does not have to be the same when replacing the orthogonal codes with the actual levels when constructing the choice profiles (*Choice Metrics, 2014*).

Appendix C shows how each of the 144 created choice profiles is grouped into 24 blocks. Each block was assigned to respondents sequentially depending on vehicle class choice. A sampling procedure of blocks was conducted to ensure that all blocks, hence all scenarios, are presented in the experiment with equal frequencies. Figure 3-1 shows a sample choice profile.

Scenario 1 of 6

Based on your recent rental for **Business trip**, if you are to make the same trip again, please choose the vehicle (**Intermediate Sedan**) that you would most likely rent:

Vehicle Attributes	ICEV	HEV	PHEV	BEV
Cost $				
Daily Rental Price (CAN$)	$55	$39	$39	$61
Fueling/Charging Cost (CAN$ per 100km)	$9.64	$9.64	$6.27	$2.89
Monetary Incentives				
Discounts/Promotions	None	None	Discounted Rental Price	None
Hand-held GPS Navigation Device	Full Price	Full Price	50% Off	50% Off
Non-monetary Incentives				
Access to HOV, Bus Lanes, or Free Parking	None	None	Eligible for HOV and Bus Lanes	Free Parking
Performance				
Range per Refuel/Recharge (km)	300	700	550	400
Reduction in Tailpipe Emissions	No Reduction	20% Reduction	60% Reduction	100% Reduction
Acceleration from 0 to 100 km/h (sec)	8.1	6.5	9.7	8.5
Convenience				
Refueling Time	5 mins	10 mins	10 mins	N/A
Recharging Time	N/A	N/A	30 mins	8 hrs
Number of available refueling/recharging stations in a TYPICAL 5km radius	5	5	1	3
Size of Storage Space (i.e. trunk)	2 Suitcases and 1 Carry-on	1 Suitcase and 2 Carry-ons	2 Suitcases and 1 Carry-on	2 Suitcases and 1 Carry-on
Which vehicle would you choose?				

Cancel

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Next >>

Figure 3-1: Sample Choice Game

3.2.3 Pilot Survey

The effectiveness of the experimental design was tested through a nationwide pilot survey that was conducted on February 16, 2016. A total of 678 observations (113 respondents × 6 choice scenarios) pertaining to all eight vehicle class/size categories were collected. Using identical model specification to the one used to create the choice experiment (see Appendix B), a basic MNL model was estimated in the NLOGIT 5.0 (*Greene, 2007*) econometric software. However, due to small sample size, the representation of the blocks per vehicle class were unbalanced (i.e. not all 24 blocks for certain vehicle class were available), which resulted in an unstable estimation of the MNL model (i.e. counter-intuitive signs). Therefore, only the observations pertaining to the vehicle classes (i.e. intermediate, full-size, and SUV) that had all blocks presented were estimated (Table 3-5). Although some parameters remained counter-intuitive (namely, *RANGE* and *EMIS*), the preliminary results confirmed the main a priori hypotheses regarding the negative impact of key variables like rental price and fuel cost, indicating that that the respondents understand their choice tasks.

3.2.4 Full-Launch Survey

Since most estimated parameters using the pilot data were insignificant, their use as priors for a *D-optimal* efficient design would be inadequate. That is, insignificant variables cannot be differentiated from zero and as such setting the priors to zero is no different from creating an orthogonal FFD. The alternative would have been to collect more pilot information but that would increase the cost of the survey. Thus, similar experimental design (i.e. blocked orthogonal FFD) was used to collect responses from the remaining 900 respondents over the two days of February 18 and 19, 2016. A final total of 1,007 respondents or 6,042 observations were collected. Surprisingly, there were 20 respondents with incomplete values, which were dropped from the analysis. This mishap could be a technical glitch (e.g. web browser incompatibility), since respondents must answer all questions in order to advance further into the survey.

Table 3-5: Preliminary MNL Model Estimation (n = 70 respondents)

Variable	**Alternatives**	**Description**	**Beta**	**t-stat**
AHEV	HEV	Alternative-specific constant for HEV alternative	1.660	1.91
APHEV	PHEV	Alternative-specific constant for PHEV alternative	1.635	1.65
ABEV	BEV	Alternative-specific constant for BEV alternative	0.830	1.15
RENT	All	Daily rental price (CAN $)	-0.026	-7.79
FCOST	All	Fuel/charging cost per 100km (CAN $)	-0.024	-0.41
MONET	HEV, PHEV, BEV	1 if monetary incentive is offered; 0, otherwise	0.025	0.15
GPS	PHEV, BEV	1 if rental discount for GPS is offered; 0, otherwise	-0.227	-0.60
NMONET	HEV, PHEV, BEV	1 if non-monetary incentive is offered; 0, otherwise	0.177	1.13
RANGE	All	Maximum range per refuel/recharge (km)	-2E-4	-0.37
EMIS	HEV, PHEV, BEV	Tailpipe emission reduction (%)	-0.154	-0.20
ACCEL	HEV, PHEV, BEV	Acceleration time from 0 to 100km/h (s)	-0.028	-0.44
FTIME	ICEV, HEV, PHEV	Refueling time (min)	-0.026	-0.99
CTIME	PHEV, BEV	Recharging time (min)	-5E-4	-0.77
STAT	All	Number of stations within a five kilometer radius	0.023	0.65
LUGG	HEV, PHEV, BEV	1 if less than 3 luggage can fit in the trunk; 0, otherwise	-0.124	-0.58
		L(0)	-554.819	
		L(β)	-514.403	
		Pseudo R^2	0.0728	

Note(s): The same MNL specification was used to develop the experimental design

3.2.5 Response Time

It has been established that low response rate is not a major concern in this particular survey since *Research Now* (*2016*) guaranteed to provide the requested 1,000 sample size. However, the quality of the collected data is not expected to be perfect due to unavoidable insincere responses. Therefore, time spent on each section of the survey was tracked. Figure 3-2 shows that respondents spend an average of 55 seconds on the first SP profile, which gradually decreased to 18s by the last SP scenario. This result could mean the respondents became familiar with their choice task and handled the subsequent scenarios with ease.

The response time for the entire survey was also evaluated; the average and median times were found to be 9.9 minutes and 8.7 minutes respectively. However, eliminating responses below these thresholds would result to losing 61% of the collected data, which cannot be considered as all "bad" observations. Therefore, the optimal response time was incrementally assessed (i.e. 8min, 7.5min, 7min, and so on). Using the same model specification as in Table 3-5, survey response times below 5 minutes (114 respondents) were found to be more unstable than the pilot survey and these observations were dropped, in addition to the 20 incomplete responses previously mentioned. Hence, a total of 873 respondents or 5,238 observations were retained for the choice modeling exercises.

Figure 3-2: Average Response Time for Each SP Scenario

3.3 Model Formulation

The empirical analysis in this study was based on the random utility modeling framework, in which the utility represents the value attributed to each choice (i.e. ICEV, HEV, PHEV, and BEV) based on how renters perceive each alternative. The choice made by the respondent is based on rental vehicle attributes shown in Figure 3-1, as well as on socio-demographic and attitudinal characteristics of that particular respondent. The MNL model (eq. 3.1) has been used to create the experimental design, and has also been considered as the fundamental discrete choice model in this analysis. Despite its popularity, the MNL model is considered simple and has been criticized due to a number of major limitations. Many of the studies in the area of alternative fuel demand modeling has resorted to more advanced discrete choice modeling techniques, as highlighted in Chapter Two.

Among the key issues with the MNL model is violation of the independence of irrelevant alternatives (IIA) property. This property suggests that all alternatives are completely independent from one another, meaning that introducing another alternative would incur equal effects on the probability of choosing other alternatives (*McFadden, 1974*; *Train, 2003*). Hence, it implies equal competition among all alternatives, which is not applicable in most choice decisions due to person preferences. Next, the model treats consecutive choice scenarios presented to a single respondent (i.e. panel data) independently, as if each scenario in the series is presented to different respondents. Lastly, it is incapable of capturing preference heterogeneity in the population, which provides better understanding of consumers' views towards electric mobility. In order to overcome these limitations, variants of the MNL model, specifically the nested logit (NL) and the latent class (LC) models have been employed in this study, each of which is discussed in the following sub-sections.

3.3.1 The Nested Logit Model

Similar to the MNL model, the nested logit (NL) model is straightforward and does not require complex mathematical calculations. However, the NL model relaxes the IID and IIA property of the MNL model by grouping multiple alternatives that shares similarities (i.e. variances and to some extent, covariances) (*Hensher et al., 2005*). Depending on a given choice set, an NL model could have numerous nested structures, with varying complexities (i.e. multiple tiers), that could be constructed. The overall goodness-of-fit (ρ^2) measure and intuition help in selecting a suitable nested model, but they do not guarantee that the chosen structure is the "best" model.

Consequently, the inclusive value (IV) parameter, also known as log-sum variable, provides an additional guidance in creating the ideal nested structure. The IV parameter establish the association between linked choices (i.e. upper and lower nests) (*Hensher et al., 2005*). Additionally, the IV parameter consists of the total observable utilities shared between all alternatives (i.e. $i = 1, 2, \ldots, I$) in the lower level and the alternative j in the upper level, and can be mathematically shown as:

$$\mathrm{IV}_{rj} = \ln\left[\sum_{i=1}^{I|j} \exp(V_{ri|j})\right] \tag{3.2}$$

where $V_{ri|j}$ is the deterministic utility of alternative i in the lower level as a subset of alternative j. Moreover, the probability of the decision maker r picking an alternative j belonging to the top nests is written as:

$$P_{rj} = \frac{\exp(V_{rj} + \delta_j \mathrm{IV}_{rj})}{\sum_{j=1}^{J} \exp(V_{rj} + \delta_j \mathrm{IV}_{rj})} \tag{3.3}$$

where V_{rj} is the observable utility of alternative j and δ_j is the scale parameter indicating the magnitude effect for the inclusive parameter IV_{rj}. On the other hand, the choice probability for alternative i in the lower tier is determined similar to an MNL model:

$$P_{ri|j} = \frac{\exp(V_{ri|j})}{\sum_{i=1}^{I|j} \exp(V_{ri|j})} \tag{3.4}$$

Particularly, the scale parameter δ_j determines how much influence the lower nest has on the upper nest, which is typically between 0 and 1. If $\delta_j \cong 1$, the lower tier is not associated with the upper tier (i.e. nest collapses to different branches), while $\delta_j \cong 0$ suggests that the tiers are related (i.e. nest structure remains). Hence, if a nest has only one alternative on its sublevel, the scale parameter is normalized to 1 (*Hensher et al., 2005*).

In this study, various two-level and three-level NL models were created to capture decision makers' general perception of alternatives' salient differences. A sample nested structure is shown in Figure 3-3. It is important to note that the construction of each nested structure is justified by a prior expectation of respondents' possible perceptions towards different powertrain technologies. Accordingly, the ideal structure must be statistically significant and provide intuitive interpretation.

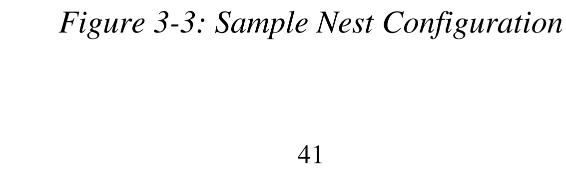

Figure 3-3: Sample Nest Configuration

3.3.2 The Latent Class Model

In addition to the NL model, the latent class (LC) model was also estimated, which is similar to mixed logit (ML) model. Both the ML model (*Hensher & Greene, 2003; McFadden & Train, 2000*) and the LC model (*Swait, 1994, 2007*) extend the capabilities of the MNL model through capturing potential behavioral variability (i.e. unobserved heterogeneity) in choice decision. The key difference, however, is that the ML model allows its random parameters to follow a continuous probability distribution, while the LC model uses a discrete number of latent classes to explain heterogeneity (*Greene & Hensher, 2003*). Additionally, the ML model has been dominant in the transportation literature, while the LC model is widely use in psychology and marketing studies (*Hess et al., 2011*). Despite the ML model's great flexibility, the LC model provides richer patterns of heterogeneity through associating class allocation with socio-demographic and latent (e.g. taste and attitude) factors (*Hess et al., 2011*). Although it is inconclusive which model is better than the other (*Greene & Hensher, 2003*), the LC model was deemed more suitable in evaluating consumers' preferences and motivations for renting certain types and understanding their perceptions towards electric mobility because it could identify different population segments that are more inclined to favor certain vehicle type over the other .

The LC model assumes that individuals are sorted into a set of *S* segments (i.e. classes), which is based on their homogeneous characteristics and attitudes, to capture the unobserved heterogeneity in the population (*Greene & Hensher, 2003*), as shown in Figure 3-4. Additionally, it takes the panel data into account (assuming there is no correlation within the series of choice scenarios) and relaxes the IIA assumption (however, the property still holds within classes) (*Greene & Hensher, 2003; Swait, 2007*).

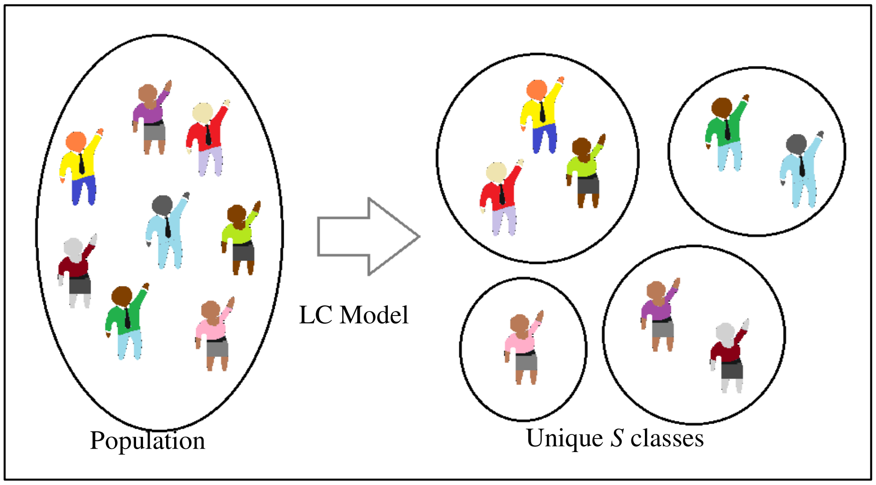

Figure 3-4: Classification of Respondents

In general, the LC model follows the utility maximization framework (eq. 2.6), and is comprised of two probabilistic models: a choice model and a class assignment model. The choice model, which is an MNL specification in class s, is described as the choice probability $P_{rti|s}$ of choosing alternative i among I alternatives by individual r of class s observed in T_r choice situations:

$$P_{rti|s} = \frac{\exp(\beta_s X_{rti})}{\sum_{i=1}^{I} \exp(\beta_s X_{rti})} \tag{3.5}$$

Since each respondent in this study was exposed in six consecutive choice tasks, panel effect is considered. Assuming independence of T_r sequential choice situations (*Greene & Hensher, 2003*), the joint probability $P_{ri|s}$ of the T_r choice situations presented to individual r of class s is expressed as:

$$P_{ri|s} = \prod_{t=1}^{T} P_{rti|s} \tag{3.6}$$

Next, the class assignment model allocates the respondents among the S segments. Thus, the probability H_{rs} of individual r belonging to class s is estimated as:

$$H_{rs} = \frac{\exp(\theta_s Z_r)}{\sum_{s=1}^{S} \exp(\theta_s Z_r)} \tag{3.7}$$

where θ_s is the class-specific parameter vector associated with the vector of observable attributes of the individual Z_r. One of the s parameter vectors is normalized to zero to ensure model's identification (*Greene & Hensher, 2003*). Thus, the unconditional probability P_{ri} of individual r choosing alternative i in a sequence of choice scenarios T is the product of eq. (3.6) and eq. (3.7):

$$P_{ri} = \sum_{s=1}^{S} P_{ri|s}\, H_{rs} \tag{3.8}$$

Since the true number of classes S is usually unknown to the analyst, a priori has to be specified and tested using various statistical measures to determine the optimal number of S (*Swait, 2007*). In addtion to goodness-of-fit measure, Akaike Information Criterion (*AIC*) and Bayesian Information Criterion (*BIC*) utilize log-likelihood at convergence (*LL*), number of parameters (k), and number of obeservations (N) to assess the quality and parsimony of the model with number of segment S:

$$AIC = -2(LL - k) \tag{3.9}$$

$$BIC = -LL + \frac{k \log N}{2} \tag{3.10}$$

Based on these measures, as S increases, the better the model performs, but too many segments would result to the deterioration of the model (i.e. extreme parameter values and large standard errors) (*Swait, 2007*). Thus, additional qualitative criteria were considered to determine the optimal number of segments. These criteria promote interpretability and usefulness of the model by avoiding models with significantly large (greater than 50% of sample) or small (less than 5% of sample) classes, and by avoiding those with identical segments (*Axsen et al., 2015*).

4. RESULTS AND DISCUSSION

The focus of this chapter is to gain a better insight about the current rental market in Canada and its potential demand for various vehicle technologies. The remainder of this chapter starts by summarizing the collected data from the online survey to explore the trends embedded in the gathered information. It then presents and discusses the estimation results of the discrete choice models employed in this study.

4.1 Data Exploration

The collected responses are based on 1,007 Canadian rental consumers. The discussion of these data is divided into four categories as depicted in the figure below:

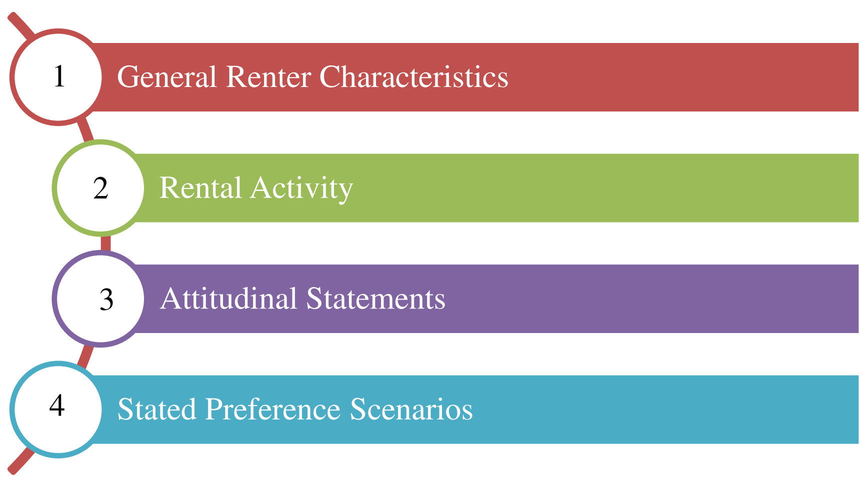

Figure 4-1: Data Categories

4.1.1 General Renter Characteristics

The data show that a majority of respondents live in the province of Ontario, while only 5% of respondents come from Quebec (Figure 4-2), despite it being the second most populated province in Canada after Ontario (*Statistics Canada, 2015b*). A possible explanation to this was the lack of French version of the web survey.

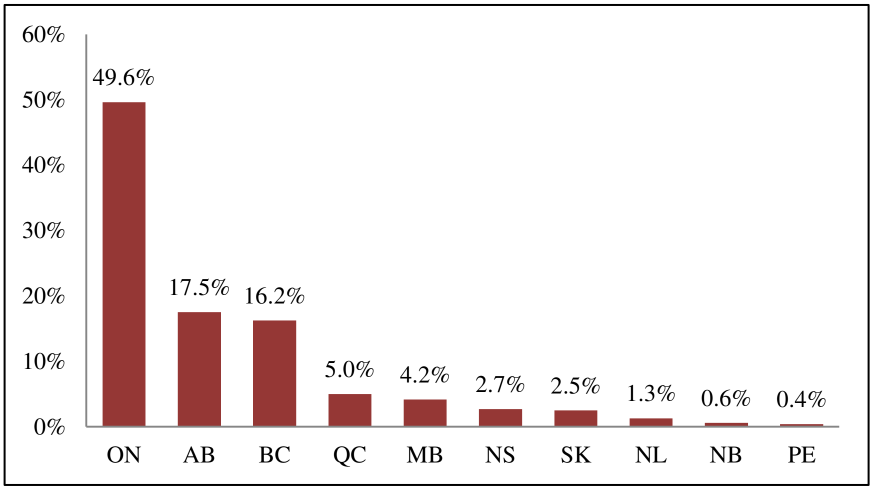

Figure 4-2: Distribution of Respondents by Province

In terms of gender, the distribution of respondents is balanced. There are 51% males and about 47% females, while 1% of respondents refused to declare their gender. As for age group, the sample is considered as "mature," with approximately 74% of respondents being 35 years of age or above. This result is expected due to the age restrictions and additional surcharges incorporated in most rental vehicle companies' policies.

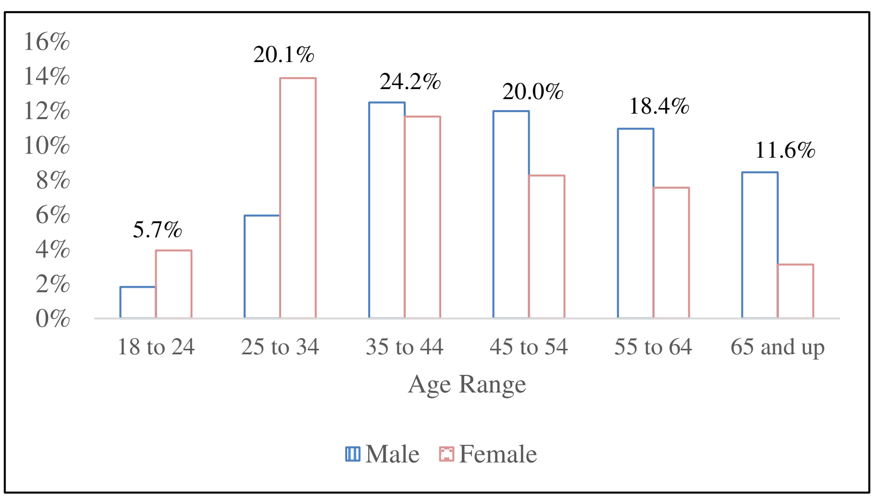

Figure 4-3: Distribution of Respondents by Gender and Age Group

Moreover, the majority of respondents are either married or common law, and part of a two-person household. This observation suggests that these respondents tend to have no children. On the other hand, about 18% of respondents are single, 9% are either widowed or divorced/separated, and approximately 2% did not want to share their marital status.

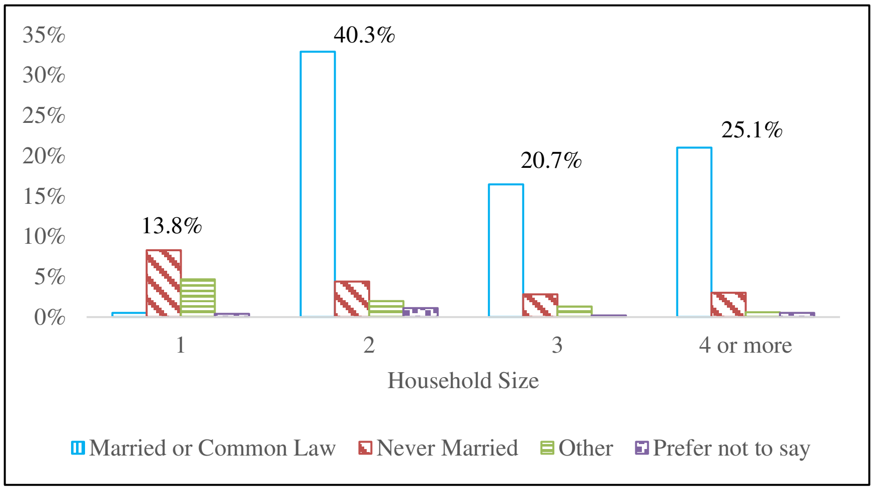

Figure 4-4: Distribution of Respondents by Marital Status and Household Size

Furthermore, most respondents (52%) are highly educated (i.e. university degree or higher). About 63% of respondents also have full-time jobs, and only 5% of them were unemployed at the time of the survey. Figure 4-5 shows that many respondents work in high-paying sectors like management and business-related sector, which supports the fact that many of them have high annual household income (i.e. $75,000 or higher) (Figure 4-6) and own new vehicle models (Figure 4-7). It is important to note that a considerable portion of respondents (13%) refuse to reveal their annual household income, which implies the sensitivity of income disparity among respondents. Lastly, Table 4-1 summarizes some demographic and socio-economic characteristics of respondents in comparison to the 2011 Canadian census (*Statistics Canada, 2012*).

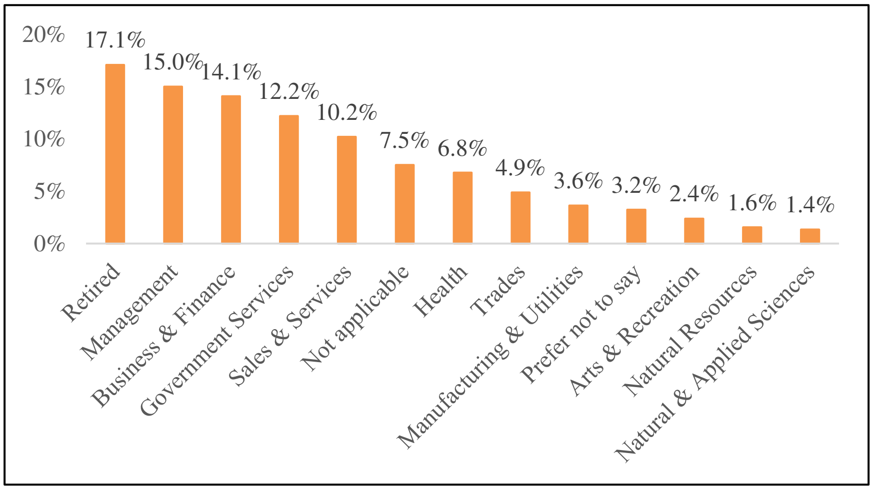

Figure 4-5: Distribution of Respondents by Occupation

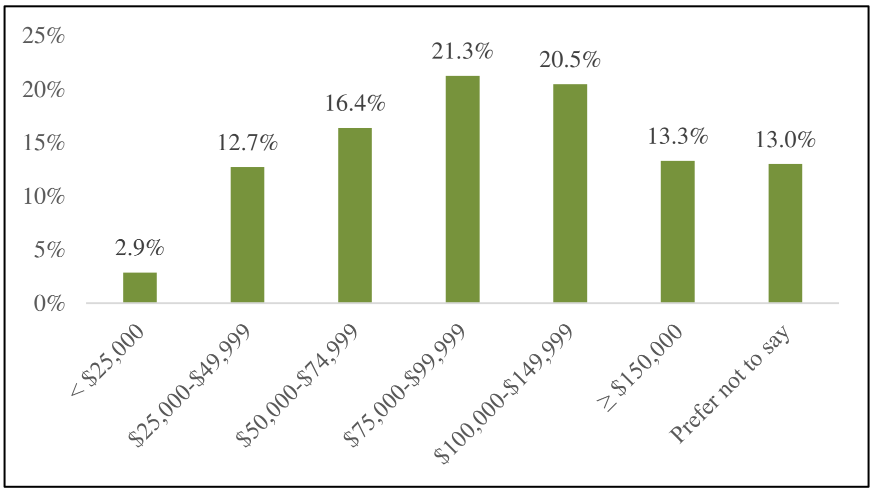

Figure 4-6: Distribution of Respondents by Household Income

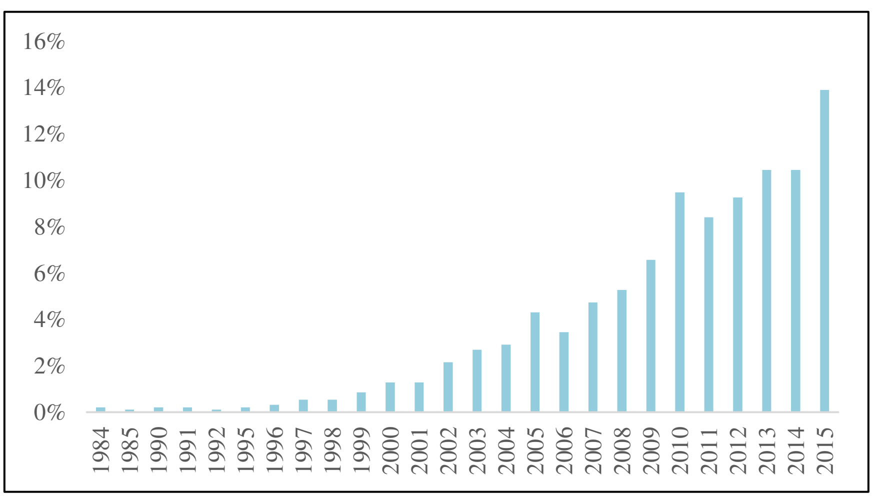

Figure 4-7: Distribution of Respondents Who Owns a Vehicle by Vehicle Year

Table 4-1: General Characteristics of Respondents

		Respondents (%)	2011 Census (%)
Gender	Females	47.9	51.5
	Males	51.1	48.5
	Prefer not to say	1.0	-
Marital status	Married/common law	70.8	57.7
	Never married	18.4	28.0
	Widowed/divorced/separated	8.6	14.3
	Prefer not to say	2.2	-
Education	High school or lower	16.3	47.8
	College diploma or alike	30.0	30.3
	Bachelor degree	31.2	14.0
	Gaduate school	21.0	7.9
	Prefer not to say	1.6	-
Household size	1	13.8	27.6
	2	40.3	34.1
	3	20.7	15.6
	4 or more	25.1	22.7
Age group	18 to 24	5.7	11.6
	25 to 34	20.1	16.3
	35 to 44	24.2	16.9
	45 to 54	20.0	20.1
	55 to 64	18.4	16.5
	65 and up	11.6	18.6

4.1.2 Rental Activity

Aside from attributes of the respondents, information regarding their most recent rental vehicle plan and travel pattern were also collected. Figure 4-8 suggests that most respondents have rented a vehicle at an airport or train station for leisure (36%) and business (9%) purposes. This result is intuitive since vacations and business trips are typically out-of-town; hence, consumers are likely to be unfamiliar with the setting and would need a vehicle for accessibility to get around town.

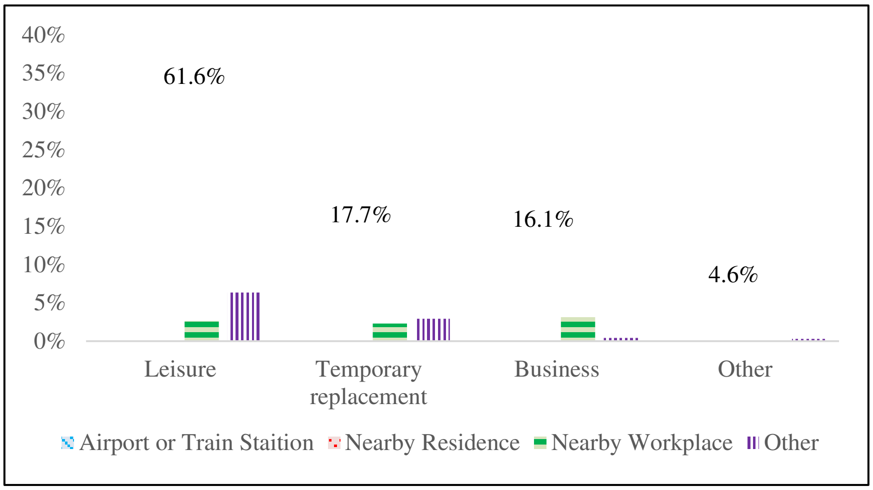

Figure 4-8: Distribution of Respondents by Rental Purpose and Location

Despite having high household income, the majority of respondents are price sensitive. This conclusion is drawn from Figure 4-9, where it shows that many of them spend no more than $60 on a rental vehicle per day and that about 81% of them indicated that they always consider discounts and promotional offers when renting a vehicle.

Concerning the characteristics of their rented vehicles, most respondents do not have preferred vehicle brand (53%), while the rest of them are either more inclined to renting domestic vehicles (26%) or imported vehicles (21%). Figure 4-10 shows that most renters drive small vehicles such as economy/compact, intermediate, or full-size sedans. Hence, vehicle class choice is likely constrained by their household size and budget.

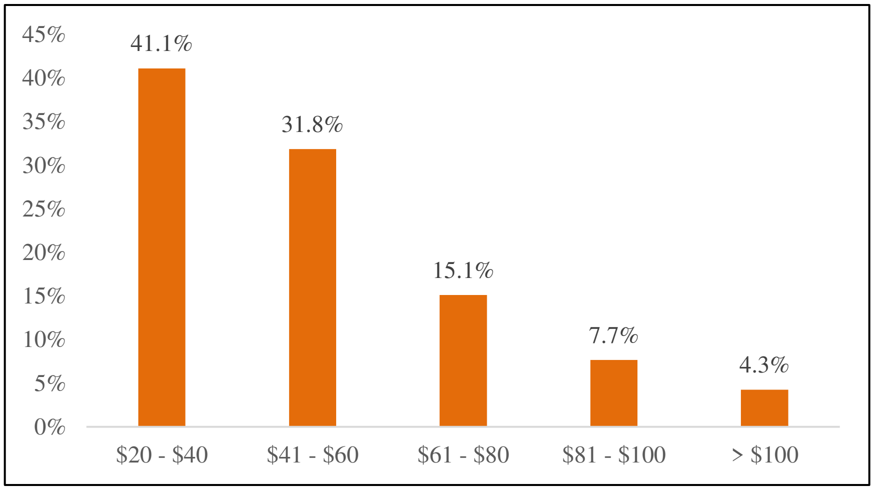

Figure 4-9: Distribution of Respondents by Rental Budget per Day

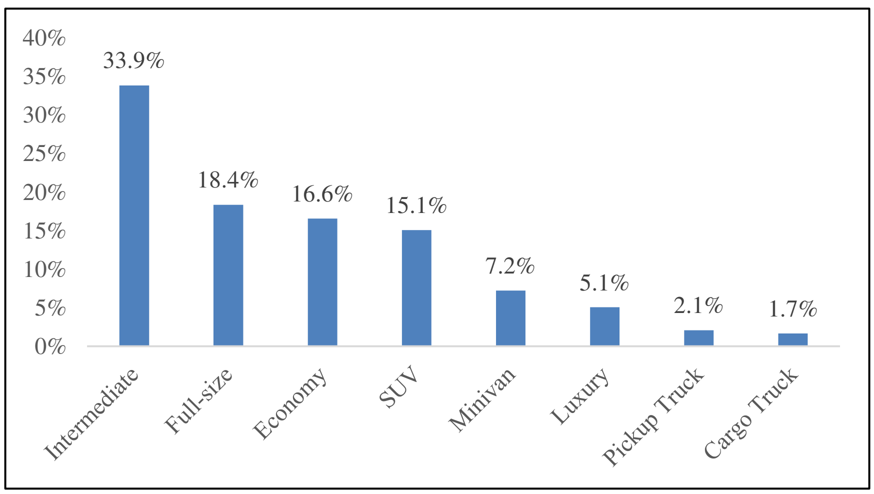

Figure 4-10: Distribution of Respondents by Preferred Vehicle Class

In line with the previous findings, Figure 4-11 indicates a majority of renters prefer vehicles with excellent fuel economy, possibly due to potential savings. They also prefer vehicles with ample cargo space and room for more than three passengers (i.e. roominess), possibly because of their household size.

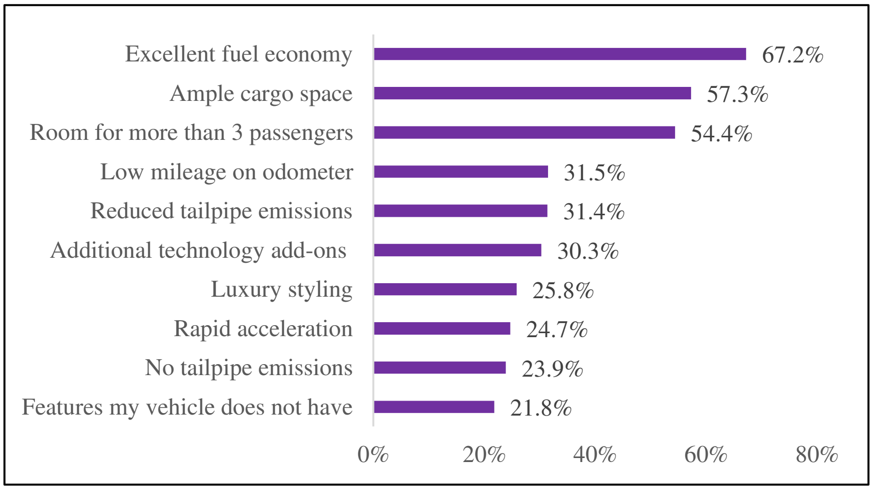

Figure 4-11: Respondents Who Find These Attributes Extremely or Very Important

4.1.3 Attitudinal Statements

Unlike physical characteristics (i.e. socio-demographic and vehicle attributes), one's attitude and behavior are more difficult to determine; thus, it is important to focus attention on the reliability of attitude measurement. In this analysis, respondents were exposed to numerous attitudinal statements (Table 3-2) and were asked whether they agree to the statements (five-level Likert scale) to capture their perceptions towards renting a vehicle and electric mobility. Figure 4-12 shows that most respondents' primary purpose of renting a vehicle is to travel from their location to their desired destination (i.e. statement *A13*). This attitude supports previous hypotheses regarding their rental vehicle, purpose, and location. Few respondents express agreement towards the statements *A2*, *A3*, *A8, A11*, and *A12*, which implies that a majority of them are less inclined in renting plug-in vehicles (i.e. PHEV and BEV) due to their limited range and charging inconveniences (i.e. range anxiety). On the contrary, about 16% of respondents indicated that they are willing to spend more to rent an EV (i.e. statement *A3*) despite of its prominent limitations. This observation suggests that these respondents tend to be EV early adopters.

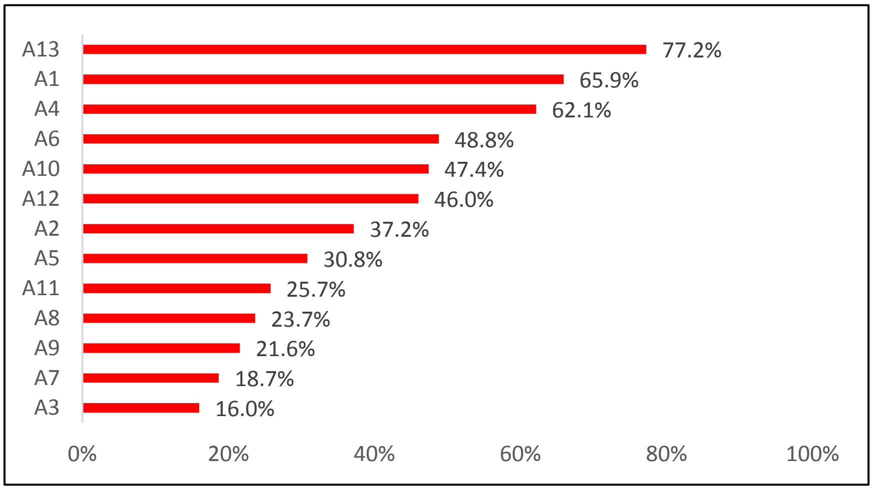

Figure 4-12: Respondents Who Agree or Strongly Agrees to the Presented Statements

4.1.4 Stated Preference Scenarios

Stated preference (SP) scenarios enable the respondents to evaluate potential trade-offs between attributes of rental vehicles. Figure 4-13 illustrates that conventional vehicles (i.e. ICEV) remain the dominant rental vehicle choice, while the battery electric vehicle (BEV) market share is quite low (although it is quite high compare to the current market). This result suggests that respondents are not wishful thinkers and understand their choice tasks very well. It also implies that the negative values (i.e. range anxiety and inconvenience) of renting a BEV outweigh the benefits (e.g. incentives and no emission) of renting one.

Figure 4-14 shows that most respondents have only driven their rented vehicle for less than 500 km, which is within the maximum range of popular BEVs in the current market like the Nissan Leaf and Tesla Model S. Therefore, these people are less likely to be hindered by EV's limited range. In addition, about 49% of respondents have not rented an EV before due to its unavailability in their preferred company (see *A6* Figure 4-12), which suggest that they are likely to rent one if it is available (i.e. potential consumers).

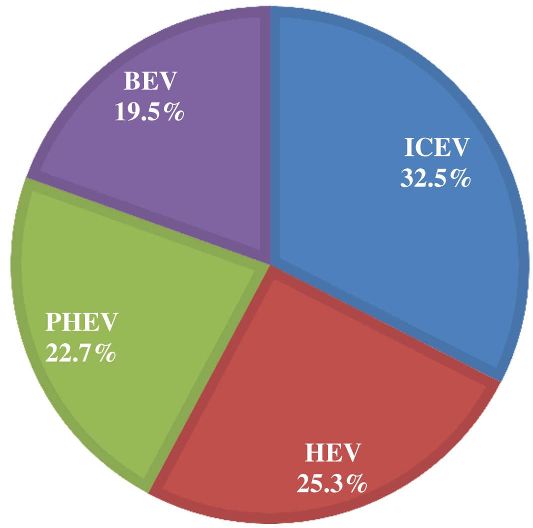

Figure 4-13: Stated Preference Results (N = 6,042 Observations)

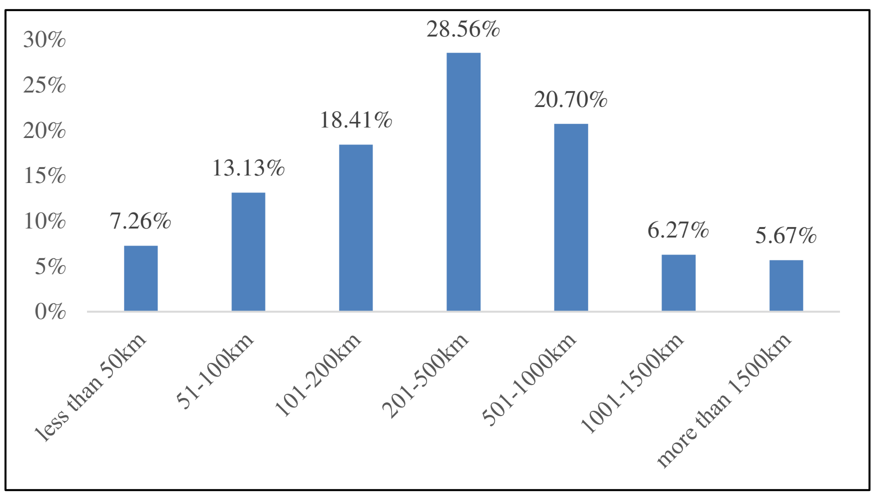

Figure 4-14: Distribution of Respondents based on Their Driven Range

4.2 Rental Vehicle Demand Modeling

Three types of discrete choice models, specifically the MNL, the NL, and the LC models, were estimated using the econometric software NLOGIT 5.0 (*Greene, 2007*) to identify and evaluate significant factors influencing consumers' rental vehicle choice decisions. Syntax used to estimate the models are provided in Appendix D. Demographic, socio-economic, rental activity, and other information collected in the online survey were introduced to examine their potential impacts on EV preference in the rental context. However, the representation of some of these variables in their raw format could introduce unwanted correlation. For example, importance of certain vehicle attributes (Table 3-1) and attitudinal statement responses (Table 3-2) were presented in a five-level Likert scale; thus, combining such variables into similar responses (e.g. extremely important and important; strongly agree and agree) reduce the risk of correlation. Additionally, some rental vehicle attributes like *RANGE* and *CTIME* were converted in terms on 100km (*RANGE**) and in terms of hours (*CTIME**) respectively for the sake of consistency. Storage space variable *LUGG* was also translated in terms of cubic feet (*LUGG**) because it yielded intuitive and more significant results.

4.2.1 Postulated Hypotheses

Table 4-2 presents the list of utilized variables in the models. Various model specifications with these variables were examined in NLOGIT 5.0 (*Greene, 2007*). However, these specifications were mainly driven by the prior theoretical considerations and general expectations regarding the potential impacts of such variables. To begin with, it is hypothesized that cost variables (e.g. daily rental price and fuel cost) have negative effect on vehicle preference (i.e. considered as disutility measures), where higher prices decrease the preference of selecting a particular alternative. On the other hand, any forms of incentives would likely promote certain alternative preferences. For instance, longer maximum range and more nearby recharging stations would likely ease range anxiety for many respondents, thus increasing the utility of EVs. A similar effect is expected for alternatives with reduced tailpipe emission and large trunk space. Acceleration time was used as a proxy for vehicle performance. Here, longer acceleration time (i.e. slower vehicle) is expected to have negative impact on rental vehicle choice. A similar result is anticipated for refueling and recharging time variables since they are indicatives of inconvenience (i.e. disutility).

Table 4-2: Description of Explanatory Variables

Vehicle Attributes	
RENT	Daily rental price (CAN $)
FCOST	Fuel/charging cost per 100km (CAN $)
MONET	1 if monetary incentive is offered; 0, otherwise
GPS	1 if rental discount for GPS is offered; 0, otherwise
NMONET	1 if non-monetary incentive is offered; 0, otherwise
*RANGE**	Maximum range per refuel/recharge (100km)
EMIS	Tailpipe emission reduction (%)
ACCEL	Acceleration time from 0 to 100km/h (s)
FTIME	Refueling time (min)
*CTIME**	Recharging time (hr)
STAT	Number of stations within a five kilometer radius
*LUGG**	Trunk space in ft^3
Renter Characteristics	
MALE	1 if respondent is male; 0 otherwise
YOUNG	1 if respondent is 18 to 34 years old; 0 otherwise
SINGLE	1 if respondent is never married; 0, otherwise
ONQC	1 if respondent lives in the province of Ontario or Quebec
HEDU	1 if respondent has Bachelor's Degree or higher
LINC	1 if respondent has household income of less than $50,000
MINC	1 if respondent has household income from $50,000 to $99,999
HINC	1 if respondent has household income of greater than $75,000
VOWN	1 if respondent owns a vehicle; 0, otherwise
VOLD	1 if respondent owns an old vehicle (i.e. 2005 or older); 0, otherwise
HHL	1 if respondent belongs to household with at least 3 individuals
RETIRE	1 if respondent is retired; 0 otherwise

(*continued on the next page*)

Rental Activity Variables	
MID	1 if respondent's preferred vehicle is either full-size, SUV, or minivan; 0, otherwise
MID2	1 if respondent's preferred vehicle is either SUV or minivan; 0, otherwise
RFOR	1 if respondent's preferred vehicle is foreign brand; 0, otherwise
LEI	1 if rental purpose is leisure; 0, otherwise
AIR	1 if a vehicle is rented at an airport or train station; 0, otherwise
LDIST	1 if respondent travelled more than 200km using the rented vehicle; 0, otherwise
P2040	1 if respondent's budget on a rental vehicle is $20 to $40 a day; 0, otherwise
DISC	1 if respondent always consider promotional offers when renting a vehicle; 0, otherwise
DAYS	Total number of days respondent rented a vehicle
Perceptions	
YESR2	1 if respondent finds rapid acceleration important; 0, otherwise
YESR3	1 if respondent finds features his/her own vehicle does not have; 0, otherwise
YESR4	1 if respondent finds excellent fuel economy important; 0, otherwise
YESR5	1 if respondent finds reduced tailpipe emissions important; 0, otherwise
YESR6	1 if respondent finds no tailpipe emissions important; 0, otherwise
YESA1	1 if respondent like to rent vehicles with new and innovative features; 0, otherwise
YESA2	1 if respondent is willing to tolerate charging inconvenience for benefits of an EV; 0, otherwise
YESA3	1 if respondent is willing to spend more money to rent an EV; 0, otherwise
YESA4	1 if respondent like to rent a vehicle with same features as his/her own vehicle; 0, otherwise
YESA5	1 if respondent like to reflect his/her personal image through the rented vehicle; 0, otherwise
YESA8	1 if respondent would modify my travel patterns to rent an EV; 0, otherwise
YESA10	1 if respondent thinks its his/her responsibility to protect the environment through his/her decisions, including renting a vehicle; 0, otherwise
YESA11	1 if respondent thinks driving range is not a concern if s/he rented an EV; 0, otherwise
YESA12	1 if respondent thinks plugging in a rented EV is not practical; 0, otherwise
YESA13	1 if respondent thinks rental vehicle is about travelling from A to B

As for respondents' characteristics, older individuals tend to choose conventional vehicles because they tend to be more reserved towards unfamiliar products than young people. High-income respondents would be more likely to afford renting an EV since they are not hindered by its high rental cost. All things being equal, individuals from Ontario and Quebec are likely to choose plug-in vehicles due to the higher presence of such vehicles in these provinces (i.e. the neighbor effect) compared to other provinces (*FleetCarma, 2016*). On the contrary, it is also hypothesized that males prefer powerful and fast vehicles, and large households would be more likely to rent large vehicles, which do not fit the characteristics of typical EVs in the market. Similarly, consumers who are renting for leisure would likely prefer vehicles with large trunk space to accommodate their luggage. People who own vehicles are usually more inclined to rent a vehicle similar to theirs (very likely to be conventional vehicles) because they are more familiar with it.

Intuitively, individuals who prefer to minimize the spending on their rented vehicle (i.e. on budget) and those who are likely to rent a vehicle for a long period of time are less likely to choose vehicles with high rental price and fuel costs. Due to EVs' limited range, respondents who are travelling a long distance (e.g. more than 200 km) would probably decline from renting such vehicles. Finally, respondents' perceptions, as indicated by attitudinal statements, have significant effect on their rental choice decision.

4.2.2 The MNL Model

It has been established that due to its major shortcomings, the MNL model is not suitable in the context of SP analysis. However, an MNL model was still estimated in this thesis (Table 4-3) to provide a general, but limited understanding of rental vehicle behavior. An extensive discussion of the estimated model is located in Appendix E. Although a majority of the results are in line with the a priori expectations, the MNL model treats the panel data independently, as if each scenario in the series is presented to different respondents. The inability of the model to account for panel data causes serial correlation, which produces bias. Therefore, readers should focus their attention on the alternative models, specifically on the LC model.

Table 4-3: Estimated Results of the MNL Model

Parameters	Alternative	β	t-stats
AHEV	HEV	-6.1522	-10.10
APHEV	PHEV	-6.4074	-10.43
ABEV	BEV	-6.5911	-10.40
RENT	All	-0.0361	-26.46
FCOST	All	-0.1293	-5.42
MONET	HEV	0.1710	2.05
*RANGE**	HEV, PHEV, BEV	0.0618	3.58
ACCEL	ICEV	-0.5268	-9.07
*CTIME**	PHEV, BEV	-0.0535	-3.94
*LUGG**	All	0.0278	2.69
RENT × *RETIRE*	HEV, PHEV, BEV	-0.0053	-3.54
RENT × *VOWN* × *YESA4*	PHEV	-0.0042	-3.25
	BEV	-0.0083	-6.05
RENT × *P2040*	HEV, PHEV, BEV	-0.0020	-1.86
RENT × *RFOR*	HEV, PHEV, BEV	0.0050	3.99
RENT × *DAYS*	HEV, PHEV, BEV	-0.0003	-2.92
RENT × *YESR3* × *YESA1*	PHEV, BEV	0.0045	4.19
RENT × *YESA3*	HEV	0.0109	4.97
	PHEV	0.0146	7.25
	BEV	0.0167	7.99
FCOST × *YESR4*	HEV, PHEV, BEV	0.0535	2.83
FCOST × *YESA10*	HEV, PHEV, BEV	0.0400	5.12
MONET × *DISC* × *ONQC*	HEV, PHEV, BEV	0.1729	2.98
GPS × *AIR* × *YOUNG*	PHEV, BEV	0.2065	1.67
NMONET × *HINC*	HEV, PHEV, BEV	0.1068	2.13
EMIS × *YOUNG*	HEV, PHEV, BEV	0.3587	3.22
EMIS × *HEDU*	HEV	1.0128	3.99
	PHEV, BEV	0.1664	2.11
EMIS × *YESR5*	HEV, PHEV	0.5433	3.99
EMIS × *YESR6* × *YESA10*	BEV	0.3735	5.86
ACCEL × *SINGLE* × *MALE* × *YESR2*	HEV, PHEV	-0.1394	-4.14
	BEV	-0.2121	-4.37
*CTIME** × *YESA2*	PHEV, BEV	0.1553	10.31
*CTIME** × *YESA12*	PHEV	-0.0844	-4.29
	BEV	-0.1187	-6.54
STAT × *LEI* × *LDIST*	HEV, PHEV	0.0398	2.40
	BEV	0.0597	2.58
*LUGG** × *HHL* × *MID*	HEV, PHEV, BEV	0.0115	1.84
*LUGG** × *LEI*	HEV, PHEV, BEV	0.0069	2.46
L(0)	-7,261.4099		
L(C)	-7,176.1962		
L(β)	-6,127.9415		

4.2.3 The NL Model

Similar to the MNL model, the NL model is incapable of accounting for serial correlation in the data. However, the NL model is still considered in the analysis to gain an initial understanding how respondents perceive the presented vehicle alternatives, and how the vehicles' similarities and differences potentially affect their rental preference behavior. Hence, one should still practice caution in interpreting the estimated results.

Using the same specification as in Table 4-3 and the nested configurations in Figure 4-15, different NL models was estimated. Full model specifications are found in Appendix F. Each nest was created based on how consumers might identify each alternative. For example, respondents might consider HEVs and PHEVs to be similar because they have dual power sources, while they could also group ICEVs and BEVs for having one power source. Respondents might also identify the alternatives as plug-in (PHEV and BEV) and not plug-in (ICEV and HEV) vehicles. On the other hand, consumers might perceive their options as conventional vehicles and electric vehicles, where HEVs, PHEVs, and BEVs are considered relevant (i.e. correlated) alternatives. Lastly, the latter nested structure can also have sub-structure containing dual power source alternatives or plug-in alternatives.

The ρ^2 value of each NL model does not show significant improvement compare to the MNL model, and the log-sum values suggest that the alternatives nested together are independent from each other since the inclusive values are approximately equals to 1 in all cases (Table 4-4). Therefore, each of the tested NL models collapses into an MNL model (Figure 4-16) rendering the need to use the nested approaches (Figure 4-15) in explaining rental choice behavior of vehicles.

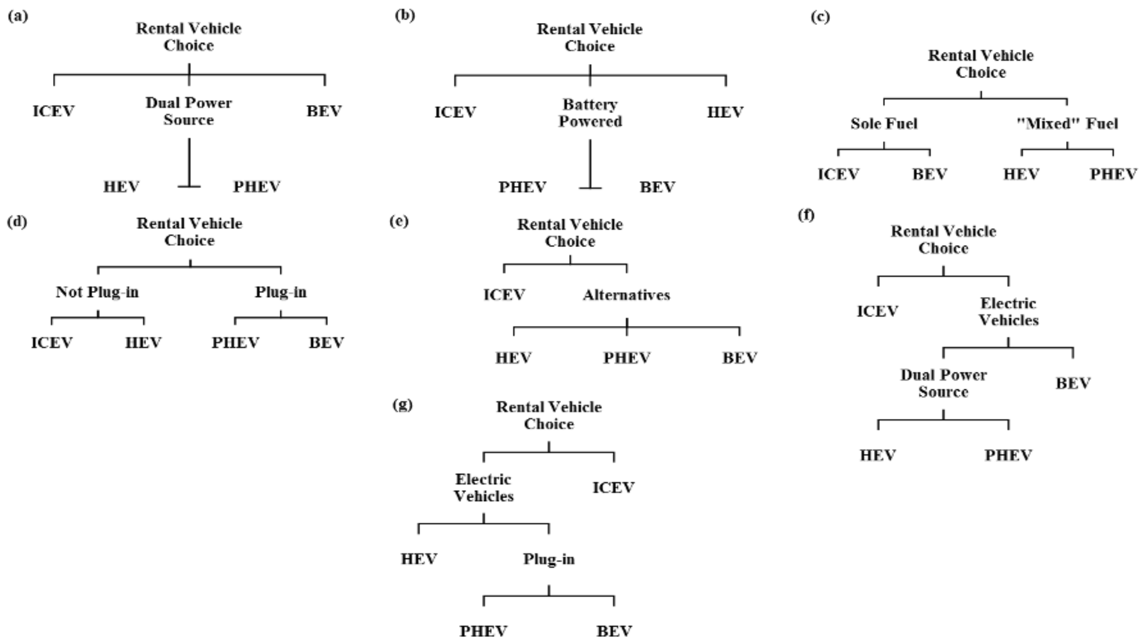

Figure 4-15: Nested Structures

Table 4-4: NL Models Summary Results

Nest	Adjusted ρ^2	Nest Name	IV Value	t-stats
(a)	0.1461	*Dual Power Source*	0.9787	43.54
(b)	0.1462	*Battery Powered*	1.0339	41.60
(c)	0.1462	*Sole Fuel*	0.9222	15.37
		“Mixed Fuel”	0.9142	16.95
(d)	0.1462	*Not Plug-in*	1.0172	15.64
		Plug-in	1.0483	17.50
(e)	0.1462	*Alternatives*	1.0553	24.69
(f)	0.1464	*Electric Vehicles*	1.0740	25.96
		Dual Power Source	0.9544	34.68
(g)	0.1463	*Electric Vehicles*	1.0364	25.86
		Plug-in	1.0233	33.32

Note(s): Inclusive parameter is set to 1.00 for branches with only one alternative

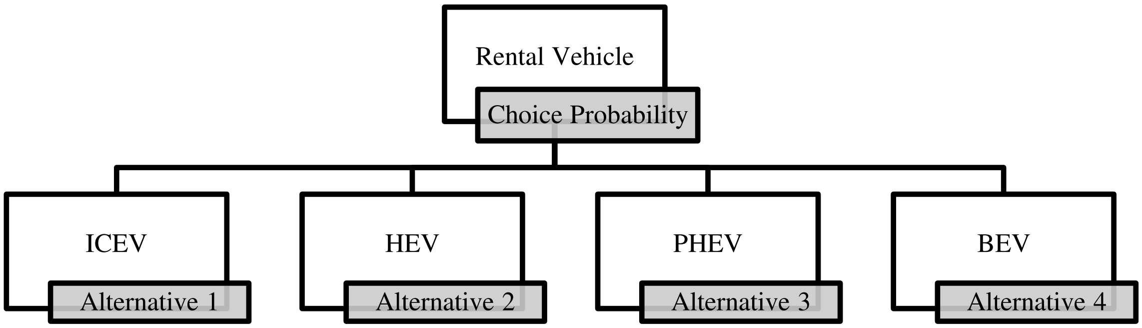

Figure 4-16: Multinomial Rental Vehicle Structure

4.2.4 The LC Model

In addition to serial correlation, the MNL and NL models are not able to capture unobserved heterogeneity in the modeled data. However, variation in taste preference, which is common in choice behavior, can give rise to unobserved heterogeneity. That is, not all groups in the modeled population are expected to have the same preferences. Failing to account for such latent classes does not provide a full picture regarding the choice behavior. To account for that, the Latent Class (LC) discrete choice modeling approach can be employed. When using the (LC) approach, the number of classes (S) is unknown to the analyst. Therefore, the choice of optimal number of classes is a crucial part of the LC model development. Based on the previously discussed criteria, the LC model of this study was estimated over two to six classes (Table 4-5) The model with six classes started to deteriorate (i.e. inflated parameters with huge standard errors), which suggested that attempting to add classes would be irrelevant (*Swait, 2007*). After careful consideration, it was found that the LC model with four distinct classes is the most suitable for this study.

Table 4-5: LC Model Diagnostics

S Classes	Number of parameters	Log-likelihood	AIC	BIC	Adjusted ρ^2	Identical classes	With "small/large" classes
2	39	-5,297	10,673	5,370	0.2618	No	Yes
3	66	-4,949	10,030	5,072	0.3104	No	No
4★	93	-4,672	9,529	4,845	0.3490	No	No
5	120	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
6	147	-4,508	9,311	4,782	0.3718	Yes	Yes

Note(s): NLOGIT was not able to estimate an LC model with 5 classes for specification identical to previous LC models

When estimating the LC model, NLOGIT 5.0 provides results for a class utility model. The provided parameter estimates for this class model pertain to the variables characterizing the vehicle alternatives. The software also provide estimates of a single MNL for comparison purposes. In addition, NLOGIT provides estimated parameters for the variables representing the attributes of the renters (i.e. decision-makers) in what is refered to as a class assignment model. Here, one of the four classes is treated as a reference class. All the components of the LC model are estimated simultaneously (Table 4-6). In what follows, we discuss both submodels: class utility model and class assignment model, separately.

4.2.4.1 The Class Utility Model

Starting with the constants of the MNL under the class utility model, all things being equal, respondents are more likely to rent an ICEV than an EV (i.e. HEV, PHEV, and BEV). In line with previous studies, cost variables (e.g. daily rental price and fuel cost) have a negative and significant influence on the rental vehicle choice probability, which suggests that respondents make rational choices. In addition, increasing the number

Table 4-6: Estimated Results of Latent Class Model

Variable	Alternative	MNL Model	LC Model			
			Class 1: ICEV-oriented	Class 2: EV-curious	Class 3: HEV-leaning	Class 4: PEV-oriented
Class Probability			*0.218*	*0.336*	*0.245*	*0.201*
Class Utility Model						
AHEV	HEV	–3.4542***	–13.7519***	–2.9975***	–2.8943	0.5619
APHEV	PHEV	–3.6672***	–13.5688***	–4.3382***	–2.1295	2.4634
ABEV	BEV	–4.2157***	–13.9814***	–6.3427***	–2.7886	2.6709
RENT	All	–0.0348***	–0.0383***	–0.0389***	–0.1510***	–0.0175***
FCOST	All	–0.0689***	–0.0732	–0.0550*	–0.2316***	–0.0131
STAT	All	0.0208**	–0.1065	0.0442**	0.0552	–0.0113
LUGG	All	0.0402***	0.1346**	–0.0027	0.0145	0.0912***
ACCEL	ICEV	–0.3047***	–1.0142***	–0.3334***	–0.3225	0.0024
MONET	HEV	0.2389***	1.6685	0.0678	0.6505**	0.5286
RANGE	HEV, PHEV, BEV	0.0629***	0.1937	0.1045**	0.0072	0.0683*
EMIS	HEV, PHEV, BEV	0.0043**	–0.0155	0.0102***	0.0024	–0.0036
CTIME	PHEV, BEV	–0.0251***	0.0172	–0.0296	–0.1214***	–0.0364*
Class Assignment Model						
Constant			–2.9216***	–1.5462***		–1.5584***
MID2			0.7161**	0.9984***		1.6223***
YOUNG			–0.6595*	0.1952		0.4380
LINC			1.3596***	0.7644*		1.2625***
MINC			0.8635***	0.3832		0.5401*
VOLD			–0.6175*	–0.6214**		–0.9635**
YESR5			0.4417	0.9457***		0.8182**
YESA2			–2.7371***	–1.3348***	BASE	0.1065
YESA3			0.9815*	0.9237*		1.9090***
YESA4			0.5577**	0.3766		0.0365
YESA5			0.4417	-0.0078		0.5529*
YESA8			–0.8509**	–0.5098*		0.2702
YESA10			0.1330	0.2973		0.5920*
YESA12			0.3441	0.3327		–0.6639**
YESA13			–0.4756	–0.4994		–0.7452**
		Adjusted ρ2	0.3490			
		AIC	9,529			
		BIC	4,845			

*Note(s): ***,**, and * indicate significance at 1%, 5%, and 10% level*
This model does not contain identical or "small/large" classes

of refueling/recharging stations and maximum range, as well as reducing tailpipe emissions, have positive effects on vehicle utilities, especially on EVs. Large trunk space is also found to be important for renters. On the other hand, long acceleration time has negative significant impact only on ICEVs, while monetary incentives in general promotes HEV preferences. As expected, long recharging time is likely to discourage individuals from renting PEVs (i.e. PHEV and BEV).

In the case of the LC utility models, the results are not as clear-cut, implying that rental preference heterogeneity exists among the respondents. Table 4-6 shows that parameters greatly vary among the four different classes. That is, the characteristics of the altenative vehicles have varying effects on the choices made by the respondents. Daily rental price has the same disutility effect on the choices made by classes 1 and 2. The variable has the least impact on the choices made by class 4 and the most impact on the choices made by class 3.

Respondents in class 1 have the strongest preference for ICEVs than those in other classes, as indicated by highly negative alternative-specific constants. Furthermore, class 1 individuals are more likely to be negatively affected by an increase in ICEVs' acceleration time than those from other classes. Thus, these individuals can be described as ICEV-oriented renters.

Next, respondents in class 2 share a similar view towards renting ICEV as class 1 respondents, though not as much based on class 2's lower alternative-specific constants. They also appraise fuel cost and reduced tailpipe emission as more important than class 1 members. In addition, their rental vehicle choice is influenced by the number of refueling/recharging stations and EVs' maximum range. These observations suggest that class 2 respondents are more likely to rent fuel-efficient vehicles, but not necessarily EVs. Therefore, class 2 can be identified as EV-curious consumers.

On the other hand, rental decisions by consumers in class 3 are mainly influenced by rental price and fuel cost. They also tend to rent an HEV if any monetary incentive is offered, while they are not likely to choose PEVs due to their long recharging times. Based on prior information and negative alternative-specific constants, though insignificant, class 3 renters can be considered as HEV-leaning individuals.

Lastly, class 4 consists of renters who have a strong preference for vehicles with large trunk space. In addition, their rental vehicle choice is moderately affected by EVs' maximum range and recharging time, compared to other groups. Although not significant, alternative-specific constants for class 4 are positive, which indicates that class 4 individuals prefer EVs, especially PHEV and BEVs, all things being equal; nonetheless, class 4 can be seen as PEV-oriented[2] renters. Socio-demographic and attitudinal variables described in the class assignment model are important to further identify and understand behavioral differences among all the latent classes.

4.2.4.2 The Class Assignment Model

Descriptions of demographic and socio-economic characteristics, as well as rental activity and attitudinal statements of each respondent were defined in Table 4-2. All these factors were considered as dummy variables, and only those found to be significant were kept in the model. The coefficients of one segment, class 3 in this case, are normalized to zero to guarantee model indentification (*Greene & Hensher, 2003*). The parameters of all

[2] PEV includes all types of plug-in electric vehicles, which in this case stand for plug-in hybrid electric and battery electric vehicles (i.e. alternatives 3 and 4 in our choice set).

other segments are interpreted in relation to base group (i.e. reference class). By combining the most noticeable vehicle attribute preferences with their socio-economic and attitudinal attributes, the initial identification of each class can be further described.

Class 1 renters tended to be middle-aged individuals, who are likely to be part of low to medium income households, and possibly own newer vehicles. They also indicated that they prefer renting roomy vehicles, like SUV and minivan, and those with the same features as their own vehicles. In addition, they are not willing to tolerate charging inconveniences and modify their travel patterns just to rent an EV. This information supports the preliminary assumption that members in class 1 are ICEV-oriented individuals.

Respondents in class 2 share similar features with class 1 in terms of vehicle ownership and preferred rental vehicle class. They also share the disinterest of renting EVs due to their charging inconvenience and other limitations. However, class 2 renters value low emission vehicles and are slightly willing to spend more money to rent an EV. Along with their vehicle attribute preferences, this class can be described as individuals who potentially have EV range anxiety, but are enticed by their potential benefits and are ready to pay more for a “better” EV; thus, confirming the initial description of class 2: EV-curious consumers.

Interestingly, class 4 individuals also belong to medium income households who own newer vehicle models. They also prefer to rent SUVs or minivans. Unlike the previous classes, class 4 members suggest that renting a vehicle is not just about travelling from point A to point B; they also like to reflect their personal image through their rented vehicle because they believe it is their responsibility to protect the environment. Furthermore, they prefer low emission vehicles, think plugging in rental

EVs is practical, and are more willing to pay more just rent an EV than other classes. Hence, these attitudes describe those of PEV-oriented individuals.

Lastly, it can be established that the base group (i.e. class 3) is composed of middle-aged, high income, but cost sensitive, individuals who own old vehicle models. It is also implied that they are not pleased with EVs' charging inconveniences and that they are not willing to modify their travel patterns because of it. Relating these observations with class 3's vehicle attribute preferences solidifies the previous notion that HEV-leaning renters belong in this particular segment.

4.2.5 Willingness-to-Pay

To understand further certain vehicle renters' preferences for specific vehicle features, their marginal willingness-to-pay (WTP) was calculated. The WTP is measured to evaluate an individual's willingness to disburse particular monetary amount to obtain benefits or avoid certain drawbacks (*Louviere et al., 2000*). It is derived from the ratio between a class-specific vehicle attribute coefficient β_{sx} and a class-specific cost attribute coefficient β_{sc}:

$$WTP = -\frac{\beta_{sx}}{\beta_{sc}} \tag{4.4}$$

Based on the estimated results presented in Table 4-6, renters' marginal WTP are expressed in terms of additional daily rental price for marginal changes in different attributes' levels. The WTP values vary considerably across all four segments, as shown in Table 4-7. Each distinct renter group shows a varying appreciation to different vehicle attributes; thus, not all potential attribute improvements are valued with its actual cost in every segment.

Table 4-7: Willingness-to-Pay Estimates

	Alternative	Class 1	Class 2	Class 3	Class 4
Fuel cost reduction of $1 CAN per 100km	All	–	$1.41	$1.53	–
Available station within 5km increase by 1	All	–	$1.14	–	–
Storage space increase by $1ft^3$	All	$3.51	–	–	$5.21
Acceleration time decrease by 1sec	ICEV	$26.48	$8.57	–	–
Any monetary incentive offered	HEV	–	–	$4.31	–
Driving range increase by 100km	HEV, PHEV, BEV	–	$2.69	–	$3.90
Tailpipe emission reduction by 1%	HEV, PHEV, BEV	–	$0.26	–	–
Battery recharging time reduction by 1hr	PHEV, BEV	–	–	$0.80	$2.08

Note(s): – indicates insignificant attribute coefficients

For example, EV-curious (i.e. class 2) and HEV-leaning (i.e. class 3) respondents are willing to spend an additional $1.41 and $1.53, respectively, on their rental vehicle per day to save $1.00 on fuel every 100 km. To put it into perspective, the respondents would be willing to spend an extra dollar and a half on their rental price for a vehicle that will reduce their fuel cost by one dollar for every 100 km. This is reasonable especially for those who plan to travel more than 150 km when renting the vehicle (i.e. break-even point). In addition, members of class 2 are willing to pay $1.14 more per day for their rental vehicle if the prevalence of refueling/recharging stations increases every 5km. This trade-off could potentially ease the range anxiety these respondents might have. Moreover, class 2 respondents are the only one willing to pay more (i.e. $0.26 per day) for a cleaner vehicle.

Interestingly, ICEV-oriented (i.e. class 1) and PEV-oriented (i.e. class 4) individuals greatly appreciate large storage space that they are willing to pay between $3 and $5 more for every cubic foot increased in their rental vehicle, which suggests that these individuals prefer larger vehicle classes. Furthermore, class 1 respondents prefer fast vehicles, and would pay a substantial amount ($26) to decrease the rented vehicle's acceleration time by 1 second. However, this result does not seem realistic given the noticeably high WTP, which could signify that the respondents did not understand the actual meaning of the attribute when completing the choice games given to them.

In addition, HEV-leaning individuals are willing to pay up to $4.31 more in renting an HEV per day, if this means that they are eligible for either a free vehicle upgrade, daily rental vehicle discount, or no rental tax (i.e. monetary incentives), which are worth more than the additional rental price. Lastly, class 4 respondents significantly value the potential improvements in range and charging capability of EVs that they are willing to spend $3.90 and $2.08 more, respectively, on rental vehicles for every 100km increased in range and a one-hour reduction in battery charging. Compare to other respondents, class 4 individuals would spend $3.90 more on renting EVs per day if their range increases by 100 km, and an additional $2.08 if their recharging time is reduced by at least an hour, which further supports their preference attitudes towards PEVs.

5. CONCLUSIONS

5.1 Background

Despite electric vehicles (EV) being an ideal solution to alleviate petroleum dependency and air pollution, their market share, especially in Canada, remains negligible. However, as electric mobility continues to develop since the beginning of the past decade, there has been increasing interest in EVs, which encourages researchers from a variety of disciplines to analyze and quantify the impacts of potential EV diffusion. For example, the McMaster Institute of Transportation and Logistics (MITL) is currently conducting a five-year research project to identify and understand different economic, social, and environmental costs and benefits of EV adoption in various Canadian sectors (e.g. consumer, commercial, and public transit). Specifically, this thesis is part of a submodule of the project that is responsible to determine the potential adoption of EVs within the rental vehicle market. The latter is the largest sector among the commercial vehicle fleets registered in the country.

The primary goal of this thesis is to develop a clear understanding of the factors influencing Canadian consumers' rental vehicle choice decisions. To date, the majority of the existing efforts have been focused on private vehicle ownership; hence, this thesis developed a nationwide online stated preference (SP) survey that focus on the rental market. To our knowledge, this is the first study to address this market from a consumer choice behavior perspective. An orthogonal fractional factorial design (FFD) was implemented to create unique hypothetical choice scenarios presented to a target sample of about 1,000 respondents, which were recruited by Research Now Inc., a commercial marketing research company.

5.2 Summary of the Collected Data

The web survey was conducted in two phases: a pilot and a full-launch survey. The primary purpose of the pilot was to verify the quality of the experimental design portion of the survey using a portion of the target sample. After confirming a priori hypotheses, which suggest that respondents understand their assigned choice tasks, the full-launch survey was implemented to collect the remaining responses. A total of 1,007 Canadian renters successfully completed the online survey. Based on these collected data, most respondents were from Ontario, which was expected being the most populated province in Canada. The majority of respondents were also middle aged (i.e. 35 to 54 years old) married individuals. Moreover, most of them were high-educated decision makers, who have an annual household income of at least $75,000.

In addition, the majority of the respondents (more than 90%) own a vehicle, and most of them (about 34%) have newer models (i.e. vehicle year 2013 to 2015). Next, about 61% of the them rented a vehicle for leisure puposes, 58% of which were rented either at an airport or train station. Moreover, approximately 87% of the respodents rented a vehicle for a no more than a week, and about 41% of them spent $20 to $40 per day. When gauging respondents about the importance of the charactersitics of the vehicles they rented, 50% to 55% indicated that performance, roominess, fuel economy and low mileage were either very or extremely important.

When respondents were asked to express their views regarding the driving range of EVs, a majority (74%) were concerned about the limited range of EVs. Also, around 81% of the renters had limited knowledge of the location of public recharging stations in their cities or in places they traveled to by car, which could explain why about 76% of them refuse to modify their travel patterns just to rent an EV. In addition, potential charging inconvenience from renting EVs hinders approximately 63% of respondents from choosing such vehicle type. Similarly, about 54% of renters find charging a rented EV impractical. These limitations could be the reasons why most of the respondents (84%) are not willing to spend more money just to rent an EV.

When it came to inquiring about the inclination of renting EVs, 49% of renters had never rented an EV before due to unavailability of such vehicles at their preferred rental companies. This information suggests that these respondents could be potential clientele for renting EVs. Moreover, those who prefer to rent vehicles with new and innovative features (66%) are likely to be renters of EVs. On the other hand, certain individuals (about 62%) would probably rent EVs if the rented vehicle shares similar features as their own vehicles. Respondents who like to reflect their personal image through their rented vehicle (31%) or believe it is their responsibility to protect the environment (47%) could also be potential target for promoting the rental of EVs.

Prior to choice modeling, the quality of the data was improved by eliminating respondents who spent inadequate time (i.e. less than five minutes) completing the survey. The rationale behind this was it would be nearly impossible to complete the entire survey diligently in such a very short time frame, and excluding these observations would remove potential noise in the results. Hence, only 873 respondents or 5,238 observations were kept for the choice modeling exercises.

5.3 Summary of Modeling Results

Variations of discrete choice models, specifically the multinomial logit (MNL), nested logit (NL) and latent class (LC) models were specified and estimated to evaluate the influence of rental vehicle attributes and respondents' characteristics on their vehicle choice decisions. However, the focus of the discussion is on the LC model since both the MNL and NL models are not able to account for serial correlation in the SP data. Nonetheless, these models were still estimated for comparison purposes. In the case of the NL model, several nested structures were configured to estimate the best NL model. Interestingly, the inclusive values (IV) (i.e. log-sum parameter) obtain for these NL structures suggested that the tested structures were not different from the standard MNL model.

The advantage of using the LC model over the more conventional MNL and NL models is the ability to account for the unobserved heterogeneity in rental vehicle preferences. The mixed logit (ML) model is another valid type of discrete choice model for capturing unobserved heterogeneity. However, individuals' preference heterogeniety is captured by determining the potential distribution of parameter(s) utilized in the ML model, which could be difficult to interpret in the context of consumer behavior. An advantage of using the LC model is its ability to divide the population into different segments to identify which segment (class) is more inclined to favor certain vehicle type over the other.

Concisely, the LC model distributed the entire population into four distinct classes that we classified as follows: ICEV-oriented, EV-curious, HEV-leaning, and PEV-oriented individuals. The classification was based on the estimated parameters of the model. First, ICEV-oriented renters tend to be middle-aged individuals with low to medium household income, who are likely to own new vehicle models. This type of renters prefers to rent large and fast vehicle, and is less likely to choose EVs due to potential charging convenience. Next, EV-curious consumers share similar attributes with the ICEV-oriented class in terms of preferred rental vehicle characteristics and views towards the disutility of renting EVs. However, members of this class value low emission vehicles and are slightly willing to pay more for an “improved” EV. Similar to previous classes, PEV-oriented individuals could also be described as consumers with medium household income, who own new vehicle models and prefer to rent large vehicle class. However, they are more environmentally sensitive than members of other classes. Lastly, HEV-leaning renters tend to be middle-aged, high income, but cost sensitive, individuals who own old vehicle models. Their choices are also hindered by EVs’ charging inconveniences and they would not modify their travel patterns just to rent an EV.

Marginal Willing-to-Pay (WTP) estimates also suggest that Canadian vehicle renters would pay to acquire greater savings in the long run and for various vehicle attribute improvements. It is crucial to note, however, that like other choice experiments, this study evaluates behavioral intentions as opposed to actual behaviors; thus, there is no guarantee that renters with the same characteristics as the respondents in our survey will show similar response when exposed to exact scenario(s) in real-time.

5.4 Contributions and Policy Implications

To the best of the author’s knowledge, the analysis of EV demand in the context of rental market is absent from the literature; thus, this thesis offers seminal results on this topic by understanding the current nature of the rental vehicle market and by evaluating the potential EV adoption for this sector. The analysis also provided an understanding of potential consumer behavior towards renting specific types of vehicle technologies in Canada. Results from the survey show that approximately 49% of respondents indicated that they have not rented an EV before because it was not available in their preferred rental companies. Knowing that there is a potential market for EVs will help these companies identify the best conditions for introducing sustainable types of vehicle technologies in the Canadian market. Additionally, a majority of respondents (67%) have indicated that they only have driven their rented vehicle for less than 500 km, which is within the range of common EVs in the market; hence, these people are less likely to be hindered by EV's limited range. With this information, rental companies could promote EV adoption by recommending such vehicle type to their clients based on their total travel distance.

Future policies could also be geared towards encouraging certain Canadian consumers (i.e. EV-curious, HEV-leaning, and PEV-oriented individuals) to rent more EVs. The analysis in this study indicates that these types of renters are already intrigued by the potential benefits of such vehicle types, but are frustrated by their limitations. Monetary incentives employed in the analysis were fairly significant only to certain respondents, while non-monetary incentives were found to be ineffective; thus, more "aggressive" incentives, such as (limited) free trial and higher vehicle-specific discounts, might persuade these consumers to choose EVs. Additionally, offering 100% money back satisfaction guarantee, although risky, would give consumers great confidence towards renting EVs.

In addition to rental price and fuel cost, better performance (i.e. short acceleration time) and larger trunk space are appreciated by many respondents, to the point that they are willing to pay more on their rental to attain these attributes. This result suggests the need for more powerful batteries to sustain bigger EVs, which are lacking in the current market. Therefore, advancing the knowledge in battery technology and investing on its commercialization are crucial in the advancement of EVs in the rental market. Moreover, pushing policies towards development of public fast-charging infrastructures and optimization of their locations would ease consumers' range anxiety, which is significantly affecting the current EV adoption in general. By studying the demand of the largest segment of the Canadian fleet market, the achieved results could help the automotive sector, government, and utilities to prepare for the future of electric mobility in Canada.

5.5 Limitations and Recommendations

Although the analysis presented here offers a pioneering effort to apprehend the potential demand for EVs in the rental market, it relied solely on stated preference (SP) data. In that respect, respondents' stated preferences might not represent the true choices that would occur in real-world situations. In addition, the results were not validated due to the lack of rental vehicle demand studies. Although most of the estimated parameters were intuitive and in line with the results found in the household vehicle ownership literature, one can argue the comparison is similar to the apples and oranges fallacy because consumers' mentality towards buying versus renting a vehicle is largely different. Another limitation is that the collected data might not be fully representative of the various markets in Canada especially those from the Province of Quebec. This is the case because the survey was only administered in the English language. In addition, the respondents participating in the survey belong to a panel maintained by Research Now Inc. As such, there is no guarantee that the panel is representative of the true population of vehicle renters in Canada although the preliminary analysis to explore the data suggests an acceptable representation compared to the Canadian Census.

Despite orthogonal FFD being common in the literature, more efficient experimental designs, such as D-optimal design (*Axsen et al., 2015; Beck et al., 2013;*

Hidrue et al., 2011; Parsons et al., 2014) could have been utilized in the analysis. However, an orthogonal design was deemed sufficient due to lack of prior information on the topic and because of budget constraints. Therefore, future developments of this research could aim to develop an efficient experimental design using the results found in this study and using a stratified and representative sample of respondents. Moreover, future work could perform comparative analysis using other econometric models, such as mixed logit models, for the rental market of other countries.

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APPENDICES

Appendix A: Sample Pages of the Survey

Social Sciences and Humanities Research Council of Canada

Consumer Vehicle Rental Survey

Dear Participant,

This survey is a major component of a five year research project funded by the *Social Science and Humanities Research Council of Canada* (SSHRC) to evaluate the future of automobile demand in Canada. The project is being led by the McMaster Institute of Transportation and Logistics in partnership with the University of Windsor, Ford Motor Company of Canada, Ontario Ministry of Transportation, Canadian Automobile Association, Electric Mobility Canada, Burlington Hydro, and Purolator Courier.

Advancements in technology continue to improve the competitiveness of non-gasoline vehicles in terms of efficiency and price relative to gasoline-based vehicles. This survey tries to identify and understand the factors influencing the choice of rented vehicles by Canadian.

The survey consists of the following sections:

I. Rented Vehicle Plan and Travel Pattern
II. Rented Vehicle Characteristics
III. Vehicle Rental Choice
IV. Stated Preference Scenarios
V. Attitudinal Statements
VI. General Renter Characteristics
VII. Additional Demographic Information

The completion of the full questionnaire will require approximately 15 minutes. Names, residential street addresses, or any other personal data that could potentially identify you or members of your household will not be collected during this survey. All provided information will be kept strictly confidential and will be used for University research purposes only. Participation is voluntary, and you may decide to withdraw from the study at any time while completing the survey. The data related to you would then be deleted. If you choose to be part of this study, please answer all questions as honestly as possible.

For further details and to view or print the Letter of Information for Consent to Participate in Research please click **here**.

To complete the survey, please visit the following link: **Consumer Vehicle Rental Survey**.

Sincerely,

Dr. H. Maoh
Associate Professor
Department of Civil and Environmental Engineering
University of Windsor

University of Windsor

Social Sciences and Humanities Research Council of Canada

McMaster University

Consumer Vehicle Rental Survey

- This is the first time I am attempting the survey
- I have the access code that I saved from my previous attempt

Start Survey

Note: During the survey please do not use the Next/Previous buttons of your web browsers, instead use the buttons provided at the end of each survey form.

University of Windsor

Social Sciences and Humanities Research Council of Canada

McMaster University

Consumer Vehicle Rental Survey

Record the access code shown in red below if you wish to complete the survey at a later time. You will be able to resume from where you left.
Your access code is: E9R5P8I9

0%

Screening Question: Please note that this survey is intended for people who have rented a vehicle in the recent past.

1. Have you rented a vehicle in the past 12 months for either personal or business use? Yes No

Cancel Next >>

University of Windsor

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7%

I. Rented Vehicle Plan and Travel Pattern

1. What is your usual reason for renting a vehicle?
   - ○ Business trip
     - ☐ Within the city/municipality ☐ Out of the city/municipality
   - ○ Leisure
     - ☐ Within the city/municipality ☐ Out of the city/municipality
   - ○ Temporary replacement
     - ☐ Avoid placing mileage on my vehicle ☐ My current vehicle was broken ☐ My vehicle had an accident
   - ○ Car sharing program
   - ○ Other purposes

2. Do you rent through a car rental loyalty program to take advantage of rental discounts? ○ Yes ○ No

3. Do you consider promotions and/or discounts when renting a vehicle? ○ Yes ○ No

4. Where did you rent your last vehicle?
   - ○ Nearby my place of residence
   - ○ Nearby my workplace
   - ○ At an airport or train station
   - ○ Other

5. How far did you drive your last rental vehicle before returning it? [Please Choose:]

6. Approximately, how much do you usually spend on renting a vehicle per day? [Please Choose:]

7. Average number of days that you usually rent a vehicle for? [1]

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14%

II. Rented Vehicle Characteristics

The goal of this section is to identify the attributes of the potential rented vehicle

1. What type of vehicle do you prefer?
   - North American Brands (for example Chrysler, Ford and General Motors)
   - Foreign Brands (for example Honda, Toyota and Volkswagen)
   - Does not matter

2. Please indicate the importance of the following attributes of the rented vehicles:

Features	**Extremely Important**	**Very Important**	**Moderately Important**	**Slightly Important**	**Not at Al Importar**
Low mileage on the odometer	○	○	○	○	○
Rapid acceleration	○	○	○	○	○
Features that my own vehicle does not have	○	○	○	○	○
Excellent fuel economy	○	○	○	○	○
Reduced tailpipe emissions	○	○	○	○	○
No tailpipe emissions	○	○	○	○	○
Ample cargo space	○	○	○	○	○
Room for passengers (more than 3)	○	○	○	○	○
New technology add-ons	○	○	○	○	○
Luxury styling	○	○	○	○	○

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21%

III. Vehicle Rental Choice

What is the type of vehicle you normally rent or have rented recently?

○ Economy Sedan

○ Intermediate Sedan

○ Full Sedan

○ Luxury Sedan

○ Minivan / Wagon

○ Sports Utility Vehicle

○ Pickup Truck

○ Cargo Trucks (e.g. U-Haul)

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29%

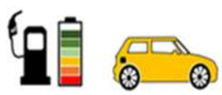
IV. Stated Preference Scenarios

Based on your recent rental for **Business trip**, you will now be presented with six (06) choice scenarios. Each scenario will be presented one at a time. Befor completing these choice scenarios, please review the below instructions carefully:

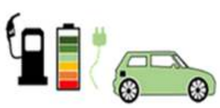
1. Each scenario will feature four different **Economy Sedan** types with different fuel technologies and associated attributes;
2. Evaluate each of the four vehicle types based on its attributes and features, and choose the vehicle that you would most likely rent;
3. You can click on i icon for a detailed description of a particular vehicle attribute.

The following are the vehicle types to choose from for each given scenario. Please take a moment and review these vehicle types carefully to understand th key difference among them.

Internal Combustion Engine Vehicles (ICEVs) - are the most common type of vehicles. They are usually powere by fossil fuels such as gasoline or diesel fuel.



Hybrid Electric Vehicles (HEVs) - are more fuel-efficient than ICEVs, especially within city driving. No charging o plugging-in is required. While idling or travelling at low speeds, HEVs are powered by battery and do not generate tailpipe emissions. A good example of an HEV is the Toyota Prius.



Plug-in Hybrid Electric Vehicles (PHEVs) – run on both battery and petroleum. The battery allows short range travel without emissions, while the conventional engine could be used for longer distance traveling. Chevrolet Volt is a prominent example of PHEV.

Battery Electric Vehicles (BEVs) - are powered only by a large battery, resulting in zero tailpipe emission. BEVs can be recharged at home or other designated recharging stations. Driving range of BEVs continues to improve throughout the years; an excellent example of a BEV is the Tesla Model S, with a trip range of 426 km per charge.

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36%

Scenario 1 of 6

Based on your recent rental for **Business trip**, if you are to make the same trip again, please choose the vehicle (**Economy Sedan**) that you would most likely rent:

Vehicle Attributes	**ICEV**	**HEV**	**PHEV**	**BEV**
Cost $				
Daily Rental Price (CAN$)	$42	$63	$29	$46
Fueling/Charging Cost (CAN$ per 100km)	$9.33	$7.46	$6.06	$3.27
Monetary Incentives				
Discounts/Promotions	None	No Rental Tax	No Rental Tax	Discounted Rental Price
Hand-held GPS Navigation Device	Full Price	Full Price	Free	Free
Non-monetary Incentives				
Access to HOV, Bus Lanes, or Free Parking	None	Eligible for HOV and Bus Lanes	Free Parking	Eligible for HOV and Bus Lanes
Performance				
Range per Refuel/Recharge (km)	500	600	650	700
Reduction in Tailpipe Emissions	No Reduction	30% Reduction	50% Reduction	100% Reduction
Acceleration from 0 to 100 km/h (sec)	8.9	9.3	8.5	8.5
Convenience				
Refueling Time	10 mins	10 mins	10 mins	N/A
Recharging Time	N/A	N/A	4 hrs	4 hrs
Number of available refueling/recharging stations in a TYPICAL 5km radius	3	3	3	5
Size of Storage Space (i.e. trunk)	1 Suitcase and 1 Carry-on	1 Suitcase	1 Suitcase and 2 Carry-ons	1 Suitcase and 1 Carry-on
Which vehicle would you choose?	○	○	○	○

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43%

Scenario 2 of 6

Based on your recent rental for **Business trip**, if you are to make the same trip again, please choose the vehicle (**Economy Sedan**) that you would most likely rent:

Vehicle Attributes	ICEV	HEV	PHEV	BEV
Cost $				
Daily Rental Price (CAN$)	$42	$21	$38	$55
Fueling/Charging Cost (CAN$ per 100km)	$9.33	$8.40	$7.00	$2.33
Monetary Incentives				
Discounts/Promotions	None	Discounted Rental Price	Free Vehicle Upgrade	Free Vehicle Upgrade
Hand-held GPS Navigation Device	Full Price	Full Price	50% Off	Free
Non-monetary Incentives				
Access to HOV, Bus Lanes, or Free Parking	None	Free Parking	None	Free Parking
Performance				
Range per Refuel/Recharge (km)	500	500	550	250
Reduction in Tailpipe Emissions	No Reduction	10% Reduction	70% Reduction	100% Reduction
Acceleration from 0 to 100 km/h (sec)	8.9	8.5	9.3	8.5
Convenience				
Refueling Time	10 mins	10 mins	5 mins	N/A
Recharging Time	N/A	N/A	30 mins	8 hrs
Number of available refueling/recharging stations in a TYPICAL 5km radius	1	5	5	0
Size of Storage Space (i.e. trunk)	1 Suitcase and 1 Carry-on	2 Carry-ons	1 Suitcase and 1 Carry-on	2 Suitcases
Which vehicle would you choose?	○	○	○	○

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Your access code is: E9R5P8I9

50%

Scenario 3 of 6

Based on your recent rental for **Business trip**, if you are to make the same trip again, please choose the vehicle (**Economy Sedan**) that you would most likely rent:

Vehicle Attributes	ICEV	HEV	PHEV	BEV
Cost $				
Daily Rental Price (CAN$)	$42	$29	$46	$63
Fueling/Charging Cost (CAN$ per 100km)	$9.33	$6.53	$6.06	$2.80
Monetary Incentives				
Discounts/Promotions	None	Free Vehicle Upgrade	None	None
Hand-held GPS Navigation Device	Full Price	Full Price	Free	50% Off
Non-monetary Incentives				
Access to HOV, Bus Lanes, or Free Parking	None	None	Eligible for HOV and Bus Lanes	None
Performance				
Range per Refuel/Recharge (km)	300	700	600	400
Reduction in Tailpipe Emissions	No Reduction	30% Reduction	50% Reduction	100% Reduction
Acceleration from 0 to 100 km/h (sec)	8.9	9.3	7.1	8.5
Convenience				
Refueling Time	10 mins	5 mins	5 mins	N/A
Recharging Time	N/A	N/A	6 hrs	8 hrs
Number of available refueling/recharging stations in a TYPICAL 5km radius	2	1	0	1
Size of Storage Space (i.e. trunk)	1 Suitcase and 1 Carry-on	1 Suitcase and 1 Carry-on	1 Suitcase	1 Suitcase and 2 Carry-ons
Which vehicle would you choose?	○	○	○	○

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57%

Scenario 4 of 6

Based on your recent rental for **Business trip**, if you are to make the same trip again, please choose the vehicle (**Economy Sedan**) that you would most likely rent:

Vehicle Attributes	ICEV	HEV	PHEV	BEV
Cost $				
Daily Rental Price (CAN$)	$42	$46	$63	$29
Fueling/Charging Cost (CAN$ per 100km)	$9.33	$9.33	$5.13	$2.80
Monetary Incentives				
Discounts/Promotions	None	No Rental Tax	Discounted Rental Price	None
Hand-held GPS Navigation Device	Full Price	Full Price	Free	Free
Non-monetary Incentives				
Access to HOV, Bus Lanes, or Free Parking	None	Free Parking	None	Free Parking
Performance				
Range per Refuel/Recharge (km)	400	500	550	550
Reduction in Tailpipe Emissions	No Reduction	10% Reduction	50% Reduction	100% Reduction
Acceleration from 0 to 100 km/h (sec)	8.9	9.3	8.5	10.7
Convenience				
Refueling Time	5 mins	5 mins	5 mins	N/A
Recharging Time	N/A	N/A	6 hrs	8 hrs
Number of available refueling/recharging stations in a TYPICAL 5km radius	3	5	0	1
Size of Storage Space (i.e. trunk)	1 Suitcase and 1 Carry-on	2 Carry-ons	1 Suitcase and 1 Carry-on	2 Suitcases
Which vehicle would you choose?	○	○	○	○

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64%

Scenario 5 of 6

Based on your recent rental for **Business trip**, if you are to make the same trip again, please choose the vehicle (**Economy Sedan**) that you would most likely rent:

Vehicle Attributes	**ICEV**	**HEV**	**PHEV**	**BEV**
Cost $				
Daily Rental Price (CAN$)	$42	$38	$55	$21
Fueling/Charging Cost (CAN$ per 100km)	$9.33	$6.53	$7.00	$2.33
Monetary Incentives				
Discounts/Promotions	None	Free Vehicle Upgrade	Free Vehicle Upgrade	Free Vehicle Upgrade
Hand-held GPS Navigation Device	Full Price	Full Price	50% Off	50% Off
Non-monetary Incentives				
Access to HOV, Bus Lanes, or Free Parking	None	Eligible for HOV and Bus Lanes	Free Parking	Eligible for HOV and Bus Lanes
Performance				
Range per Refuel/Recharge (km)	600	500	700	700
Reduction in Tailpipe Emissions	No Reduction	40% Reduction	80% Reduction	100% Reduction
Acceleration from 0 to 100 km/h (sec)	8.9	8.5	10.7	10.7
Convenience				
Refueling Time	5 mins	5 mins	10 mins	N/A
Recharging Time	N/A	N/A	1 hr	10 mins
Number of available refueling/recharging stations in a TYPICAL 5km radius	1	3	0	0
Size of Storage Space (i.e. trunk)	1 Suitcase and 1 Carry-on	1 Suitcase	1 Suitcase and 2 Carry-ons	1 Suitcase and 1 Carry-on
Which vehicle would you choose?	○	○	○	○

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Your access code is: E9R5P8I9

71%

Scenario 6 of 6

Based on your recent rental for **Business trip**, if you are to make the same trip again, please choose the vehicle (**Economy Sedan**) that you would most likely rent:

Vehicle Attributes	ICEV	HEV	PHEV	BEV
Cost $				
Daily Rental Price (CAN$)	$42	$55	$21	$38
Fueling/Charging Cost (CAN$ per 100km)	$9.33	$6.53	$7.93	$1.87
Monetary Incentives				
Discounts/Promotions	None	No Rental Tax	None	None
Hand-held GPS Navigation Device	Full Price	Full Price	50% Off	50% Off
Non-monetary Incentives				
Access to HOV, Bus Lanes, or Free Parking	None	None	Eligible for HOV and Bus Lanes	None
Performance				
Range per Refuel/Recharge (km)	600	700	550	700
Reduction in Tailpipe Emissions	No Reduction	10% Reduction	80% Reduction	100% Reduction
Acceleration from 0 to 100 km/h (sec)	8.9	10.7	9.3	8.5
Convenience				
Refueling Time	10 mins	10 mins	10 mins	N/A
Recharging Time	N/A	N/A	1 hr	10 mins
Number of available refueling/recharging stations in a TYPICAL 5km radius	5	3	1	1
Size of Storage Space (i.e. trunk)	1 Suitcase and 1 Carry-on	1 Suitcase and 1 Carry-on	1 Suitcase	1 Suitcase and 2 Carry-ons
Which vehicle would you choose?	○	○	○	○

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Record the access code shown in red below if you wish to complete the survey at a later time. You will be able to resume from where you left.
Your access code is: E9R5P8I9

79%

V. Attitudinal Statements

Statements	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
I like to rent vehicles with new and innovative features					
I am willing to tolerate some battery charging inconvenience for the benefits of renting an Electric Vehicle					
I am willing to spend more money to rent an Electric Vehicle					
I like to rent a vehicle that has the same features as my current vehicle					
I like to reflect my personal image through my rented vehicle					
I have not rented an electric vehicle because one is not available at my preferred rental company					
I am well-aware of charging station locations in my city or near other places that I travel by auto					
I would modify my travel patterns somewhat to rent an Electric Vehicle					
I would sooner purchase an Electric Vehicle to own than rent one					
It is my responsibility to protect the environment through my consumer decisions, including when renting a vehicle					
Driving range would not concern me if I rented an Electric Vehicle					
Plugging in a rented Electric Vehicle is not practical					
For me a rental vehicle is about travelling from A to B					

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Your access code is: E9R5P8I9

86%

VI. General Renter Characteristics

1. What is your town/city and province/territory of residence?
   Town/City [ ] Province [Please Choose:]
2. Please provide your postal code [ ]
3. Please select your age range [Please Choose:]
4. Your sex [Please Choose:]
5. How many people live in your household? ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 or more
6. Do you or any member in your household own a vehicle? ○ Yes ○ No
7. Please specify the make, model and year of your vehicle or the primary household vehicle
   Make [Please Choose:]
   Model [Please Choose:]
   Year [Please Choose:]

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Your access code is: E9R5P8I9

93%

VII. Additional Demographic Information

1. What is your highest achieved education level? [Please Choose:]
2. What is your present occupation? [Please Choose:]
3. Do you work full-time? ○ Yes ○ No ○ Prefer not to say
4. What is your total gross annual household income? [Please Choose:]
5. What is your marital status? ○ Married or Common Law ○ Never Married ○ Other (Widowed / Divorced / Separated) ○ Prefer not to say
6. How many dependent children live in your household? ○ 0 ○ 1 ○ 2 ○ 3 ○ 4 or more ○ Prefer not to say

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Appendix B: Syntax for *Ngene*

Blocked Orthogonal Fractional Factorial Design

```
Design
; alts = ICEV, HEV, PHEV, BEV (1)
; rows = 144 (2)
; orth = sim (3)
; block = 24 (4)
; model: (5)
U(ICEV) = b5*range[-3,-1,1,3] + b6*ftime[-1,1] + b8*stat[-
3,-1,1,3]/
U(HEV) = b13 + b1*rent[-5,-3,-1,1,3,5] + b2*fcost[-3,-1,1,3]
+ b3*disc[-3,-1,1,3] + b4*incen[-1,0,1] + b5*range[-3,-
1,1,3] + b6*ftime[-1,1] + b8*stat[-3,-1,1,3] + b9*emis[-3,-
1,1,3] + b11*trunk[-1,0,1] + b12*acc[-3,-1,1,3]/
U(PHEV) = b14 + b1*rent[-5,-3,-1,1,3,5] + b2*fcost[-3,-
1,1,3] + b3*disc[-3,-1,1,3] + b4*incen[-1,0,1] + b5*range[-
3,-1,1,3] + b6*ftime[-1,1] + b7*Chtime [-3,-1,1,3]  +
b8*stat[-3,-1,1,3] + b9*emis[-3,-1,1,3] + b10*gps[-1,1] +
b11*trunk[-1,0,1] + b12*acc[-3,-1,1,3]/
U(BEV) = b15 + b1*rent[-5,-3,-1,1,3,5] + b2*fcost[-3,-1,1,3]
+ b3*disc[-3,-1,1,3] + b4*incen[-1,0,1] + b5*range[-3,-
1,1,3] + b7*Chtime[-3,-1,1,3] + b8*stat[-3,-1,1,3] +
b10*gps[-1,1] + b11*trunk[-1,0,1] + b12*acc[-3,-1,1,3]$
```

(1) Definition of the alternatives per segmentation

(2) Number of choice profiles in a choice set

(3) Orthogonal design, in which orthogonality holds within and across alternatives

(4) Number of blocks to be created

(5) Utility function with β parameter estimates (priors equals to zero) and attribute levels in orthogonal coding inside [ ]

Appendix C: Blocks

Block Number	Scenario Number	Block Number	Scenario Number	Block Number	Scenario Number	Block Number	Scenario Number
1	1	**7**	4	**13**	22	**19**	66
1	26	**7**	6	**13**	51	**19**	88
1	27	**7**	33	**13**	91	**19**	98
1	54	**7**	47	**13**	118	**19**	112
1	94	**7**	57	**13**	119	**19**	139
1	123	**7**	79	**13**	144	**19**	141
2	21	**8**	32	**14**	2	**20**	45
2	43	**8**	35	**14**	25	**20**	56
2	52	**8**	39	**14**	28	**20**	95
2	117	**8**	50	**14**	93	**20**	106
2	120	**8**	89	**14**	102	**20**	110
2	143	**8**	100	**14**	124	**20**	113
3	11	**9**	16	**15**	7	**21**	14
3	41	**9**	17	**15**	64	**21**	19
3	68	**9**	38	**15**	75	**21**	23
3	70	**9**	122	**15**	77	**21**	107
3	81	**9**	126	**15**	104	**21**	128
3	138	**9**	131	**15**	134	**21**	129
4	30	**10**	9	**16**	5	**22**	29
4	71	**10**	60	**16**	10	**22**	59
4	84	**10**	62	**16**	44	**22**	72
4	101	**10**	73	**16**	61	**22**	83
4	135	**10**	86	**16**	74	**22**	85
4	140	**10**	116	**16**	115	**22**	136
5	65	**11**	8	**17**	3	**23**	31
5	87	**11**	46	**17**	40	**23**	36
5	92	**11**	55	**17**	48	**23**	49
5	97	**11**	96	**17**	53	**23**	90
5	105	**11**	109	**17**	58	**23**	99
5	142	**11**	114	**17**	80	**23**	137
6	63	**12**	13	**18**	12	**24**	15
6	76	**12**	20	**18**	18	**24**	34
6	78	**12**	24	**18**	42	**24**	37
6	103	**12**	108	**18**	67	**24**	121
6	127	**12**	111	**18**	69	**24**	125
6	133	**12**	130	**18**	82	**24**	132

Appendix D: Syntax for NLOGIT 5.0

Multinomial Logit Model

```
DISCRETECHOICE; (1)
LHS = CHOICE; (2)
Choices = ICEV, HEV, PHEV, BEV; (3)
Model: (4)
U(ICEV) = Rent*rent + Fcost*fcost + Lugg*lugg +
Accel1*accel/
U(HEV)  = AHEV  + Rent*rent + Fcost*fcost + Lugg*lugg +
Monet2*monet + Range*range + RInt1*rint1 + RInt2*rint2 +
RInt3*rint3 + RInt4*rint4 + RInt62*rint6 + FCInt1*fcint1 +
FCInt2*fcint2 + MonInt1*monint1 + EmiInt1*emiint1 +
EmiInt22*emiint2 + EmiInt3*emiint3 + AccInt12*accint1 +
StaInt13*staint1 + LuInt1*luint1 + LuInt2*luint2 +
NMInt1*nmint1/
U(PHEV) = APHEV + Rent*rent + Fcost*fcost + Lugg*lugg +
Ctime*ctime  + Range*range  + RInt1*rint1 + RInt2*rint2 +
RInt3*rint3 + RInt4*rint4 + RInt534*rint5 + RInt63*rint6 +
RInt73*rint7 + FCInt1*fcint1 + FCInt2*fcint2 +
MonInt1*monint1 + EmiInt1*emiint1 + EmiInt24*emiint2 +
EmiInt3*emiint3 + AccInt12*accint1 + CTInt1*ctint1 +
CTInt23*ctint2 + StaInt13*staint1 + LuInt1*luint1 +
LuInt2*luint2 + NMInt1*nmint1 + GPSInt1*GPSInt1/
U(BEV)  = ABEV  + Rent*rent + Fcost*fcost + Lugg*lugg +
Ctime*ctime  + Range*range + RInt1*rint1 + RInt2*rint2 +
RInt3*rint3 + RInt4*rint4 + RInt534*rint5 + RInt64*rint6 +
RInt74*rint7 + FCInt1*fcint1 + FCInt2*fcint2 +
MonInt1*monint1 + EmiInt1*emiint1 + EmiInt24*emiint2 +
EmiInt4*emiint4 + AccInt14*accint1 + CTInt1*ctint1 +
CTInt24*ctint2 + StaInt14*staint1 + LuInt1*luint1 +
LuInt2*luint2 + NMInt1*nmint1 + GPSInt1*GPSInt1$
```

(1) Command to model an MNL

(2) Dependent variable, which in this case is the rental vehicle choice

(3) Definition of the alternatives considered

(4) Utility function with β parameter estimates

<u>Nested Logit Model</u>

```
DISCRETECHOICE; (1)
LHS = CHOICE; (2)
Choices = ICEV, HEV, PHEV, BEV; (3)
Tree = Conv(ICEV), EV(HEV,PHEV,BEV); (4)
Start = logit; (4)
IVSET: (Conv)=[1]; (4)
Model: (5)
U(ICEV) = Rent*rent + Fcost*fcost + Lugg*lugg +
Accel1*accel/
U(HEV)  = AHEV  + Rent*rent + Fcost*fcost + Lugg*lugg +
Monet2*monet + Range*range + RInt1*rint1 + RInt2*rint2 +
RInt3*rint3 + RInt4*rint4 + RInt62*rint6 + FCInt1*fcint1 +
FCInt2*fcint2 + MonInt1*monint1 + EmiInt1*emiint1 +
EmiInt22*emiint2 + EmiInt3*emiint3 + AccInt12*accint1 +
StaInt13*staint1 + LuInt1*luint1 + LuInt2*luint2 +
NMInt1*nmint1/
U(PHEV) = APHEV + Rent*rent + Fcost*fcost + Lugg*lugg +
Ctime*ctime  + Range*range  + RInt1*rint1 + RInt2*rint2 +
RInt3*rint3 + RInt4*rint4 + RInt534*rint5 + RInt63*rint6 +
RInt73*rint7 + FCInt1*fcint1 + FCInt2*fcint2 +
MonInt1*monint1 + EmiInt1*emiint1 + EmiInt24*emiint2 +
EmiInt3*emiint3 + AccInt12*accint1 + CTInt1*ctint1 +
CTInt23*ctint2 + StaInt13*staint1 + LuInt1*luint1 +
LuInt2*luint2 + NMInt1*nmint1 + GPSInt1*GPSInt1/
U(BEV)  = ABEV  + Rent*rent + Fcost*fcost + Lugg*lugg +
Ctime*ctime  + Range*range + RInt1*rint1 + RInt2*rint2 +
RInt3*rint3 + RInt4*rint4 + RInt534*rint5 + RInt64*rint6 +
RInt74*rint7 + FCInt1*fcint1 + FCInt2*fcint2 +
MonInt1*monint1 + EmiInt1*emiint1 + EmiInt24*emiint2 +
EmiInt4*emiint4 + AccInt14*accint1 + CTInt1*ctint1 +
CTInt24*ctint2 + StaInt14*staint1 + LuInt1*luint1 +
LuInt2*luint2 + NMInt1*nmint1 + GPSInt1*GPSInt1$
```

(1) Command to model an MNL

(2) Dependent variable, which in this case is the rental vehicle choice

(3) Definition of the alternatives considered

(4) Commands to create nest level(s) and estimate/normalize log-sum parameter(s)

(5) Utility function with β parameter estimates

Latent Class Model

```
LCLOGIT; (1)
LHS = CHOICE; (2)
Choices = ICEV, HEV, PHEV, BEV; (3)
Maxit = 300; (4)
Model: (5)
U(ICEV) = Rent*rent + Fcost*fcost + Station*station +
Lugg*lugg + Accel1*accel/
U(HEV)  = AHEV  + Rent*rent + Fcost*fcost + Station*station
+ Lugg*lugg + Monet2*monet  + Range*range + Emis*emis/
U(PHEV) = APHEV + Rent*rent + Fcost*fcost + Station*station
+ Lugg*lugg + Ctime34*ctime + Range*range + Emis*emis /
U(BEV)  = ABEV  + Rent*rent + Fcost*fcost + Station*station
+ Lugg*lugg + Ctime34*ctime + Range*range + Emis*emis ;
LCM (6) = Midsize, Young, LowInc, MedInc, OldCar, C5, NoA2,
YesA3, YesA4, YesA5, NoA8, YesA10, YesA12, YesA13;
PDS = 6; (7)
PTS = 4$(8)
```

(1) Command to model an LC

(2) Dependent variable, which in this case is the rental vehicle choice

(3) Definition of the alternatives considered

(4) Number of maximum iteration

(5) Utility function with β parameter estimates

(6) Class assignment variables (i.e. characteristics of respondents)

(7) Number of choice situations

(8) Number of classes to be modeled

Appendix E: Discussion of the Final MNL Model

The estimation results of the MNL model are presented in Table 4-3. As far as the achieved ρ^2 values (pseudo-R^2) are concerned, the model has decent fit (i.e. naïve ρ^2 = 0.1561 and adjusted ρ^2 = 0.1461). Alternative-specific constants were found to be significantly negative, which suggest that there are other unobserved factors not included in the model that added to the disutility of the EV alternatives. However, the effect of the constants in the goodness-of-fit of the model (ρ^2 = 0.0117) is minor, suggesting that propensity of each alternative was already captured by the specified variables.

All parameter estimates are consistent with our a priori theoretical expectations. Cost variables like daily rental price and fuel cost are negative and significant, which imply that all things being equal, individuals are rational decision makers and prefer to rent low-cost vehicles. Specifically, as the rental price of EV alternatives increases, retired individuals or those who are on a strict budget (*P2040*) are less likely to rent such vehicles. Moreover, the interaction term *RENT* × *VOWN* × *YES_A4* suggests that individuals who prefer renting vehicles with similar features as their own vehicle are less inclined in choosing plug-in vehicles, especially when their rental prices are high. This interaction suggests that these consumers probably own gasoline-powered vehicles and are not willing to spend more money on an unfamiliar technology.

On the other hand, the term *RENT* × *YES_R3* × *YES_A1* supports the idea that renters who prefer vehicles with new and innovative technology, primarily if their own vehicles that do not have these features, are more likely to drive an EV alternative despite of the potential increase in its rental price. There are also consumers who are willing to spend extra money just to try an EV, particularly BEV, as shown by the parameter *RENT* × *YESA3*. Similarly, people who value fuel savings are more receptive to renting an EV because it is a fuel-efficient vehicle, as indicated by the interaction term *FCOST* × *YES_R4*. Additionally, individuals who believe it is their duty to protect the environment are more likely to choose EVs as fuel cost increases. Interestingly, individuals who prefer foreign brand vehicles are less susceptible to the high rental price of an EV. Since most EVs available in the market are imported (*FleetCarma, 2016*), this particular attitude suggests consumers' loyalty towards certain brands.

Different forms of incentives can also be introduced to promote EV adoption in the rental market. However, all things being equal, renters in general are likely to choose HEVs over plug-in EVs when a monetary incentive is offered. A possible explanation could be that general consumers do not see these incentives (e.g. rental price discount, no rental tax, and free vehicle upgrade) as viable compensation for plug-in vehicles' limitations (e.g. limited range and long charging time). On the other hand, the interaction term *MONET* × *DISC* × *ONQC* suggests that renters from Ontario and Quebec will gravitate towards choosing EVs if they are given promotional rental offers and monetary incentives. Since plug-in vehicles' market share is significant in these provinces (*FleetCarma, 2016)*, this interaction potentially captures the influence of the neighbor effect in their rental vehicle decisions. *Mau et al.* (*2008*) define the neighbor effect as the influence of the market penetration of certain products (e.g. electric vehicles) on one's preference. Although GPS rental discount was found to be generally insignificant, young respondents who rented vehicles at an airport or a train station valued this type of incentive more than others. This interaction explains their potential need for navigation system in an unfamiliar location. Similarly, any non-monetary incentives did not increase the utilities of EV alternatives, but rental preference of high income individuals is positively affected. One can argue that this type of consumer is not hindered by the potential high cost of EVs; hence, non-monetary incentives are favored more than monetary incentives.

Choice decisions of certain individuals are also influenced by various vehicle attributes. For example, consumers in general are more likely to rent an EV as its maximum range increases. Similarly, the number of recharging stations is important for renters going on an out-of-town vacation trip, as indicated by the interaction term *STAT* × *LEI* × *LDIST*. On the contrary, long acceleration time has a negative and significant effect on choice probability of ICEVs. Specifically, single males tend to prefer powerful vehicles (i.e. short acceleration time); thus, they are not inclined in renting any EV options, especially BEVs. Young and highly educated individuals are more likely to select low emission vehicles (i.e. EV options). This preference could be due to better environmental awareness among young and highly educated consumers. Regardless of the purpose of the trip, there are renters who simply find low or zero emission vehicles appealing; hence, they are likely to drive EVs. Furthermore, long charging time is a major disutility for plug-in vehicles. To some renters, longer charging time of an electric vehicle (BEV or PHEV) is considered impractical, as depicted by the interaction effect *CTIME** × *YESA12*. On the other hand, individuals who are not likely to be sensitive to longer charging times are more inclined to rent EVs in order to enjoy its benefits. Lastly, having a large storage space for a rented vehicle is important to consumers. Specifically, individuals who are renting for leisure are more likely to choose an EV alternative if its trunk space increases. A similar situation applies to consumers who belong to large households. In such case, they would be more inclined to select midsize vehicles with a larger trunk.

Calculating parameter elasticities is an important part of the analysis to evaluate consumers' sensitivity to changes in any attributes of specific alternatives. There are two types of elasticities: (i) direct elasticity, that measures the change in the probability of choosing an alternative i for a 1% change in the k^{th} attribute X_{ik}; and (ii) cross elasticity, that measures the change in the probability of choosing an alternative i for a 1% change in the k^{th} attribute X_{jk} (*Hensher et al., 2005*). In default, NLogit calculates both elasticities using the point elasticity method:

Direct Elasticity: $$E_{X_{ik}}^{P_i} = -\beta_{ik} X_{ik} (1 - P_i) \tag{E.1}$$

Cross Elasticity: $$E_{X_{jk}}^{P_i} = -\beta_{jk} X_{jk} P_j \tag{E.2}$$

However, eq. E.2 will produce equal cross elasticities for all j alternatives, such that $j \neq i$, due to the IID assumption of the MNL model (*Hensher et al., 2005*). To avoid that, the cross elasticities are aggregated using the probability weighted sample enumeration technique:

$$E_{X_{jkq}}^{\bar{P}_i} = \frac{\sum_{q=1}^{Q} \hat{P}_{iq} E_{X_{jkq}}^{P_{iq}}}{\sum_{q=1}^{Q} \hat{P}_{iq}} \tag{E.3}$$

where $\bar{P}_i$ is the aggregate choice probability of alternative i by individual q and $\hat{P}_{iq}$ is an estimated choice probability. Based on the results shown in Table E-1, most attributes are relatively inelastic, except for daily rental price and acceleration time. More specifically, when the rental price of each vehicle option increases by 1%, consumers are about 1.3% and 1.2% less likely to rent a conventional vehicle and any EV alternatives, respectively. On the other hand, when ICEV becomes 1% slower, renters are 2.4% less likely to choose such vehicle and rather choose an HEV (1.2%), a PHEV (1.1%), or a BEV (1.1%).

Table E-1: Elasticity Results of the MNL Model

Variable	Alternatives	ICEV	HEV	PHEV	BEV
Daily Rental Price	ICEV	**-1.2598**	0.6390	0.6015	0.5741
	HEV	0.4261	**-1.2138**	0.3809	0.3684
	PHEV	0.3602	0.3454	**-1.2467**	0.3854
	BEV	0.3052	0.3001	0.3461	**-1.2350**
Fuel Cost per 100km	ICEV	**-0.8379**	0.4259	0.3991	0.3819
	HEV	0.2729	**-0.7893**	0.2503	0.2433
	PHEV	0.1912	0.1878	**-0.6666**	0.2045
	BEV	0.0655	0.0649	0.0721	**-0.2632**
Range (100km)	HEV	-0.0780	**0.2256**	-0.0716	-0.0694
	PHEV	-0.0747	-0.0740	**0.2608**	-0.0796
	BEV	-0.0498	-0.0504	-0.0555	**0.2023**
Acceleration time (s)	ICEV	**-2.3877**	1.2251	1.1319	1.0799
Charging time (hr)	PHEV	0.0283	0.0290	**-0.1014**	0.0319
	BEV	0.0257	0.0263	0.0308	**-0.1071**
Storage space (ft^3)	ICEV	**0.2417**	-0.1184	-0.1171	-0.1133
	HEV	-0.0801	**0.2611**	-0.0897	-0.0892
	PHEV	-0.0794	-0.0878	**0.3004**	-0.0992
	BEV	-0.0767	-0.0853	-0.0974	**0.3338**

*Note(s): **Bolded** values represent direct elasticity effects*

Appendix F: Estimated Results of NL Models

Parameters	Alternative	Nest A	Nest B	Nest C	Nest D
AHEV	HEV	-6.3633***	-6.0719***	-6.4966***	-6.0489***
APHEV	PHEV	-6.6183***	-6.1128***	-6.7552***	-6.1054***
ABEV	BEV	-6.6599***	-6.2931***	-6.8708***	-6.2864***
RENT	All	-0.0362***	-0.0360***	-0.0371***	-0.0357***
FCOST	All	-0.1298***	-0.1267***	-0.1379***	-0.1263***
MONET	HEV	0.1723**	0.1706**	0.1799**	0.1695***
*RANGE**	HEV, PHEV, BEV	0.0621***	0.0614***	0.0641***	0.0611***
ACCEL	ICEV	-0.5336***	-0.5191***	-0.5499***	-0.5172***
*CTIME**	PHEV, BEV	-0.0539***	-0.0518***	-0.0549***	-0.0514***
*LUGG**	All	0.0320***	0.0281***	0.0301**	0.0282***
RENT × *RETIRE*	HEV, PHEV, BEV	-0.0054***	-0.0050***	-0.0056***	-0.0050***
RENT × *VOWN* × *YESA4*	PHEV	-0.0043***	-0.0038***	-0.0043***	-0.0037***
	BEV	-0.0081***	-0.0078***	-0.0082***	-0.0078***
RENT × *P2040*	HEV, PHEV, BEV	-0.0022*	-0.0018*	-0.0022*	-0.0018*
RENT × *RFOR*	HEV, PHEV, BEV	0.0051***	0.0049***	0.0052***	0.0049***
RENT × *DAYS*	HEV, PHEV, BEV	-0.0003***	-0.0003***	-0.0003***	-0.0003***
RENT × *YESR3* × *YESA1*	PHEV, BEV	0.0045***	0.0046***	0.0046***	0.0045***
RENT × *YESA3*	HEV	0.0111***	0.0108***	0.0114***	0.0109***
	PHEV	0.0149***	0.0141***	0.0151***	0.0140***
	BEV	0.0168***	0.0163***	0.0167***	0.0161***
FCOST × *YESR4*	HEV, PHEV, BEV	0.0543***	0.0525***	0.0584***	0.0524***
FCOST × *YESA10*	HEV, PHEV, BEV	0.0412***	0.0395***	0.0424***	0.0393***
MONET × *DISC* × *ONQC*	HEV, PHEV, BEV	0.1744***	0.1689***	0.1768***	0.1679***
GPS × *AIR* × *YOUNG*	PHEV, BEV	0.2137*	0.2021*	0.2145*	0.2003*
NMONET × *HINC*	HEV, PHEV, BEV	0.1069**	0.1064**	0.1067**	0.1053**
EMIS × *YOUNG*	HEV, PHEV, BEV	0.3513***	0.3441***	0.3548***	0.3388***
EMIS × *HEDU*	HEV	1.0213***	1.0260***	1.0480***	1.0249***
	PHEV, BEV	0.1657**	0.1670**	0.1683**	0.1667**
EMIS × *YESR5*	HEV, PHEV	0.5576***	0.5272***	0.5700***	0.5232***
EMIS × *YESR6* × *YESA10*	BEV	0.3679***	0.3584***	0.3733***	0.3555***
ACCEL × *SINGLE* × *MALE* × *YESR2*	HEV, PHEV	-0.1414***	-0.1361***	-0.1459***	-0.1357***
	BEV	-0.2142***	-0.2063***	-0.2154***	-0.2045***
*CTIME** × *YESA2*	PHEV, BEV	0.1556***	0.1525***	0.1607***	0.1520***
*CTIME** × *YESA12*	PHEV	-0.0847***	-0.0830***	-0.0860***	-0.0824***
	BEV	-0.1185***	-0.1173***	-0.1216***	-0.1167***
STAT × *LEI* × *LDIST*	HEV, PHEV	0.0399**	0.0400**	0.0419***	0.0399**
	BEV	0.0603***	0.0600***	0.0607**	0.0596***
*LUGG** × *HHL* × *MID*	HEV, PHEV, BEV	0.0116*	0.0118*	0.0116*	0.0117*
*LUGG** × *LEI*	HEV, PHEV, BEV	0.0073**	0.0063**	0.0072**	0.0063**
L(C)		-7,176.1962	-7,176.1962	-7,176.1962	-7,176.1962
L(β)		-6,127.5553	-6,126.9265	-6,126.7396	-6,126.8913

*Note(s): ***,**, and * indicate significance at 1%, 5%, and 10% level*

Parameters	Alternative	Nest E	Nest F	Nest G
AHEV	HEV	-5.5963***	-5.8717***	-5.7269***
APHEV	PHEV	-5.8502***	-6.129***	-5.8391***
ABEV	BEV	-6.0251***	-6.0097***	-6.0151***
RENT	All	-0.0360***	-0.0363***	-0.0360***
FCOST	All	-0.1258***	-0.1243***	-0.1253***
MONET	HEV	0.1703**	0.1731**	0.1702**
*RANGE**	HEV, PHEV, BEV	0.0610***	0.0620***	0.0613***
ACCEL	ICEV	-0.5010***	-0.5112***	-05044***
*CTIME**	PHEV, BEV	-0.0523***	-0.0528***	-0.0516***
*LUGG**	All	0.0213**	0.0264***	0.0236**
RENT × *RETIRE*	HEV, PHEV, BEV	-0.0049***	-0.0050***	-0.0049***
RENT × *VOWN* × *YESA4*	PHEV	-0.0039***	-0.0042***	-0.0037***
	BEV	-0.0081***	-0.0076***	-0.0078***
RENT × *P2040*	HEV, PHEV, BEV	-0.0016	-0.0017	-0.0016
RENT × *RFOR*	HEV, PHEV, BEV	0.0049****	0.0050***	0.0049***
RENT × *DAYS*	HEV, PHEV, BEV	-0.0003***	-0.0003***	-0.0003***
RENT × *YESR3* × *YESA1*	PHEV, BEV	0.0046***	0.0047***	0.0046***
RENT × *YESA3*	HEV	0.0102***	0.0105***	0.0104***
	PHEV	0.0139***	0.0142***	0.0138***
	BEV	0.0159***	0.0159***	0.0159***
FCOST × *YESR4*	HEV, PHEV, BEV	0.0517***	0.0515***	0.0516***
FCOST × *YESA10*	HEV, PHEV, BEV	0.0374***	0.0387***	0.0379***
MONET × *DISC* × *ONQC*	HEV, PHEV, BEV	0.1682***	0.1695***	0.1671***
GPS × *AIR* × *YOUNG*	PHEV, BEV	0.1952	0.2072	0.1960***
NMONET × *HINC*	HEV, PHEV, BEV	0.1054**	0.1053**	0.1056**
EMIS × *YOUNG*	HEV, PHEV, BEV	0.3615***	0.3474***	0.3506***
EMIS × *HEDU*	HEV	0.9970***	1.0133***	1.0113***
	PHEV, BEV	0.1641**	0.1633**	0.1650**
EMIS × *YESR5*	HEV, PHEV	0.5248***	0.5476***	0.5203***
EMIS × *YESR6* × *YESA10*	BEV	0.3599***	0.3434***	0.3543***
ACCEL × *SINGLE* × *MALE* × *YESR2*	HEV, PHEV	-0.1320***	-0.1337***	-0.1323***
	BEV	-0.2035***	-0.2047***	-0.2024***
*CTIME** × *YESA2*	PHEV, BEV	0.1552***	0.1556***	0.1534***
*CTIME** × *YESA12*	PHEV	-0.0843***	-0.0851***	-0.0834***
	BEV	-0.1187***	-0.1184***	-0.1178***
STAT × *LEI* × *LDIST*	HEV, PHEV	0.0393**	0.0398**	0.0396***
	BEV	0.0591***	0.0607***	0.0595**
*LUGG** × *HHL* × *MID*	HEV, PHEV, BEV	0.0116*	0.0122**	0.0118**
*LUGG** × *LEI*	HEV, PHEV, BEV	0.0060**	0.0062*	0.0059*
$L(C)$		-7,176.1962	-7,176.1962	-7,176.1962
$L(\beta)$		-6,126.8428	-6,125.6241	-6,126.5478

*Note(s): ***,**, and * indicate significance at 1%, 5%, and 10% level*

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