MODELING THE DEMAND FOR ELECTRIC VEHICLES IN THE CANADIAN RENTAL MARKET: A STATED PREFERENCE APPROACH

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Introduction

Increase in daily travel activities coupled with reliance on conventional vehicles, places a significant pressure on the environment through tailpipe emissions. Fortunately, current advancements in battery technology along with the introduction of electric vehicles (EVs) is often considered as one of the more viable solutions to combating climate change and promoting sustainable energy. Due to the scarcity of EVs in the current market, many studies have utilized stated preference (SP) analysis along with estimating different forms of econometric model to identify and to understand factors affecting consumers' choice decisions regarding new vehicle technologies (for example: *Hackbarth & Madlener, 2016*; *Hoen & Koetse, 2014*; *Qian & Soopramanien, 2011*). In addition, Potoglou and Kanaroglou (*2008*) provided a comprehensive literature review on various research methods regarding alternative fueled vehicle demand, focusing on SP analysis and different discrete choice models. Moreover, Rezvani, Jansson, & Bodin (*2015*) focused primarily on empirical studies evaluating various consumer behaviors towards plug-in electric vehicle adoption

While most the existing studies have 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, Orsato, & Kemp, 2013*) and high average annual mileage (*Gnann, Plötz, Funke, & Wietschel, 2015*), making them ideal EV adopters; thus, it is important to understand the motivations behind their EV acquisition decisions. Some of these motivations are firm-specific; government agency's 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 on this study is built on the extensive works regarding new vehicle technology ownership and extends their analyses on consumer rental context. As of 2015, the rental industry accounts for about 69% of all car registrations and approximately 47% of all light truck registrations, which are the highest in both categories (*Canadian Automotive Fleet, 2016*). The focus of this study is to determine and evaluate the preferences and motivations of Canadian consumers towards renting certain vehicle types using a SP survey.

Survey Development

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: hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), and battery electric vehicle (BEV). A world-renowned market research company, Research Now Inc. (*2016*), was hired to recruit Canadian consumers to participate in the survey, and guarantee complete feedback from them. 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.

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 survey was divided into four main parts: (a) background questions regarding their most recent rented vehicle plan and travel pattern; (b) preference of various vehicle characteristics; (c) SP exercise; and (d) a series of attitudinal, socio-economic, and demographic questions.

The focal point of this survey is the SP exercise, which represents the rental choice in given hypothetical scenarios among four different powertrain technologies: internal combustion engine vehicle (ICEV), HEV, PHEV, and BEV. Respondents were presented with educational materials on vehicle technologies and their attributes to provide them with clear ideas about the differences of each alternative.

The choice experiment was based on the vehicle class/size categories that the respondent had recently rented. There were eight categories to choose from: economy/compact, intermediate, full-size, luxury, minivan, sport utility vehicle (SUV), pick-up, and cargo trucks (e.g. U-Haul). Twelve attributes (Figure 1) with varying levels 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 EV adoption studies. Most of these attributes are also self-explanatory and capture what factors were of importance to consumers when renting a vehicle.

Scenario 1 of 6

Based on your recent rental for **Leisure**, 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	$55	$38
Fueling/Charging Cost (CAN$ per 100km)	$9.33	$6.53	$7.00	$2.33
Monetary Incentives				
Discounts/Promotions	None	None	None	No Rental Tax
Hand-held GPS Navigation Device	Full Price	Full Price	Free	Free
Non-monetary Incentives				
Access to HOV, Bus Lanes, or Free Parking	None	None	Free Parking	Eligible for HOV and Bus Lanes
Performance				
Range per Refuel/Recharge (km)	600	700	550	250
Reduction in Tailpipe Emissions	No Reduction	20% Reduction	60% Reduction	100% Reduction
Acceleration from 0 to 100 km/h (sec)	8.9	8.5	10.7	9.3
Convenience				
Refueling Time	5 mins	10 mins	10 mins	N/A
Recharging Time	N/A	N/A	6 hrs	8 hrs
Number of available refueling/recharging stations in a TYPICAL 5km radius	5	1	3	3
Size of Storage Space (i.e. trunk)	1 Suitcase and 1 Carry-on	1 Suitcase	1 Suitcase	2 Suitcases
Which vehicle would you choose?	○	○	○	○

Figure 1: Sample Stated Preference Profile

Experimental Design

Once the appropriate attributes and their levels were determined, 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, Hensher, & Swait, 2000*). However, it typically generates a large number of choice profiles and can exponentially increase when additional attributes and/or levels are introduced. Fractional factorial design (FFD) is commonly used to overcome this barrier.

An FFD maintains the main characteristic of a CFD (i.e. 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; practically, losing these effects is permissible as they only account for small portion of explained variance (*Louviere et al., 2000*). 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 or systematically constructed. 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.

In this study, the experimental design was generated using a software called Ngene (*Choice Metrics, 2014*). Ngene produced 144 unique choice profiles for each vehicle class/size category, which were divided into 24 blocks, such that each respondent only has to comprehend six scenarios in order to minimized fatigue and other nuisance effects, while simultaneously collecting a substantial number of observations per respondent. Each block was assigned to respondents sequentially depending on their 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 1 shows a sample choice profile.

The Latent Class Model

The main goal of this study is to identify significant factors influencing consumers' rental vehicle preferences, and to possibly capture any unobserved heterogeniety among rental consumers. Advancements in discrete choice modeling led to the development of the mixed logit (ML) (*Hensher & Greene, 2003*) and the latent class (LC) (*Greene & Hensher, 2003*) models. Both models extend the capabilities of the multinomial logit (MNL) model by allowing the analyst to capture impacts of unobserved heterogeneity among modeled observations. To do so, the ML model allows its random parameters to follow a continuous distribution (assumed by the analyst), while the LC model uses a discrete number of latent classes to explain potential heterogeneity. Although it is inconclusive which model is better than the other (*Greene & Hensher, 2003*), the LC model captures richer patterns of heterogeneity than the ML model by associating class allocation with socio-demographic, and latent (e.g. taste and attitude) factors (*Hess, Fowler, Adler, & Bahreinian, 2012*); hence, it is preferred for this study.

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*). Thus, the LC model is composed of two probabilistic models: a class utility model and a class assignment model. The class utility 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:

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

Since each respondent in this study was exposed in six consecutive choice tasks, panel effect should be 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:

$$P_{ri|s} = \prod_{t=1}^{T} P_{rti|s} \tag{2}$$

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:

$$H_{rs} = \frac{\exp(\theta_s Z_r)}{\sum_{s=1}^{S} \exp(\theta_s Z_r)} \tag{3}$$

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. (2) and eq. (3):

$$P_{ri} = \sum_{s=1}^{S} P_{ri|s} H_{rs} \tag{4}$$

Since the true number of classes S is usually unknown to the analyst, there are various statistical measures used to determine the optimal number of S (*Swait*, *2007*). Akaike Information Criterion (*AIC*) and Bayesian Information Criterion (*BIC*) were used to assess the quality and parsimony of the models estimated in this study:

$$AIC = -2(LL - k) \tag{5}$$

$$BIC = -LL + \frac{k \log N}{2} \tag{6}$$

These criteria utilize the log-likelihood at convergence (*LL*), number of parameters (*k*), and sample size (*N*) to select the appropriate *S*. Moreover, Axsen, Bailey, & Castro (*2015*) considered additional qualitative criteria to promote interpretability and usefulness of the model such as avoiding models with significantly large (greater than 50% of sample) or small (less than 5% of sample) classes, and avoiding those with identical segments. The LC model of this study was estimated over two to six classes. 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 2).

Table 2: Latent Class 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

Estimated Results

Although efforts have been made to maximize the performance of the model, it is important to emphasize that the main focus of this study is to improve the understanding of heterogeneity in rental vehicle preferences. When estimating the LC model, NLOGIT (*Greene*, *2007*) 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 3). In what follows, we discuss both submodels: class utility model and class assignment model, separately.

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 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 plug-in electric vehicles or PEVs (i.e. PHEVs *and* BEVs).

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 5 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 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.

The Class Assignment Model

Various demographic and socio-economic characteristics of each respondent were collected through the survey. Information regarding their rental vehicle pattern, such as the main reason for renting a vehicle and the location of their last rental, were also gathered. In addition, a number of attitudinal statements

Table 3: Estimated Results of Latent Class Model

Variable	Alternative	MNL Model	LC Model Class 1: ICEV-oriented	LC Model Class 2: EV-curious	LC Model Class 3: HEV-leaning	LC Model Class 4: PEV-oriented
Class Probability			*0.218*	*0.336*	*0.245*	*0.201*
Class Utility Model						
HEV constant	HEV	–3.4542***	–13.7519***	–2.9975***	–2.8943	0.5619
PHEV constant	PHEV	–3.6672***	–13.5688***	–4.3382***	–2.1295	2.4634
BEV constant	BEV	–4.2157***	–13.9814***	–6.3427***	–2.7886	2.6709
Daily rental price (CAN $)	All	–0.0348***	–0.0383***	–0.0389***	–0.1510***	–0.0175***
Fuel/charging cost per 100km (CAN $)	All	–0.0689***	–0.0732	–0.0550*	–0.2316***	–0.0131
Number of stations within a 5 km radius	All	0.0208**	–0.1065	0.0442**	0.0552	–0.0113
Size of storage space (ft^3)	All	0.0402***	0.1346**	–0.0027	0.0145	0.0912***
Acceleration time from 0 to 100km/h (sec)	ICEV	–0.3047***	–1.0142***	–0.3334***	–0.3225	0.0024
1 if monetary incentive is offered, 0 otherwise	HEV	0.2389***	1.6685	0.0678	0.6505**	0.5286
Maximum range per refuel/recharge (100 km)	HEV, PHEV, BEV	0.0629***	0.1937	0.1045**	0.0072	0.0683*
Tailpipe emission reduction (%)	HEV, PHEV, BEV	0.0043**	–0.0155	0.0102***	0.0024	–0.0036
Recharging time (hr)	PHEV, BEV	–0.0251***	0.0172	–0.0296	–0.1214***	–0.0364*
Class Assignment Model						
Constant			–2.9216***	–1.5462***	BASE	–1.5584***
1 if respondent's preferred vehicle is either SUV or minivan; 0, otherwise			0.7161**	0.9984***		1.6223***
1 if respondent is 18 to 34 years old; 0 otherwise			–0.6595*	0.1952		0.4380
1 if respondent has household income of less than $50,000			1.3596***	0.7644*		1.2625***
1 if respondent has household income from $50,000 to $99,999			0.8635***	0.3832		0.5401*
1 if respondent owns an old vehicle (i.e. 2005 or older); 0, otherwise			–0.6175*	–0.6214**		–0.9635**
1 if respondent finds reduced tailpipe emissions important; 0, otherwise			0.4417	0.9457***		0.8182**
1 if respondent is willing to tolerate charging inconvenience for benefits of an EV; 0, otherwise			–2.7371***	–1.3348***		0.1065
1 if respondent is willing to spend more money to rent an EV; 0, otherwise			0.9815	0.9237*		1.9090***
1 if respondent like to rent a vehicle with same features as his/her own vehicle; 0, otherwise			0.5577**	0.3766		0.0365
1 if respondent like to reflect his/her personal image through the rented vehicle; 0, otherwise			0.4417	-0.0078		0.5529*
1 if respondent would modify my travel patterns to rent an EV; 0, otherwise			–0.8509**	–0.5098*		0.2702
1 if respondent thinks it's his/her responsibility to protect the environment through his/her decisions, including renting a vehicle; 0, otherwise			0.1330	0.2973		0.5920*
1 if respondent thinks plugging in a rented EV is not practical; 0, otherwise			0.3441	0.3327		–0.6639**
1 if respondent thinks rental vehicle is about travelling from A to B			–0.4756	–0.4994		–0.7452**

*Note(s): ***, **, and * indicate significance at 1%, 5%, and 10% level* were presented to the respondents to potentially capture their views on electric mobility in the rental market. 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 other segments are interpreted in relation to base group. 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 are less likely to be young 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 same features as their own vehicles. In addition, they are not willing to tolerate charging inconvenience and modify their travel patterns just to be rent an EV. These information support the preliminary assumption that members in class 1 are ICEV-oriented inviduals. Respondents in class 2 share similar features with class 1 in terms of vehicle ownership and prefered rental vehicle class. They also share the disinterest of renting EV due to its 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 implies 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, thinks 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 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.

Conclusion and Future Work

The conducted analysis in this paper is novel and makes a direct contribution to policies geared towards promoting sustainable transportation in Canada. According to the achieved results, future policies could 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. This result suggests that advancing the knowledge in battery technology and investing to facilitate its commercialization are crucial in the advancement of EVs in the rental market. Moreover, pushing policies towards the 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.

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. 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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