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Modeling the Demand for Renting Electric Vehicles in Canada: A Stated Preference Choice Approach

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Summary

The introduction of electric vehicles (EV) is considered by many as an effective solution to alleviate petroleum dependency; however, the number of EVs in the current market remains scarce despite of its potential benefits. Many studies have been conducted to identify and assess various factors that significantly affect EV ownership. In contrary, little has been done regarding the potential EV adoption for commercial fleets. This paper addresses this limitation by focusing on rental vehicles. It is found that rental cost, vehicle attributes (e.g. maximum range and recharging time), and attitudinal statements have significant effect on EV rental choice.

Keywords: Canada, commercial, data acquisition, fleet, modeling

1. Introduction

Continuous increase in population size coupled with rapid urban expansion has generated high demand for personal travel and longer commutes. Increased travel activities place significant pressure on transportation systems and the environment. In 2012, Environment Canada [*1*] estimated that Canada produced 699 megatonnes of carbon dioxide equivalent, which was driven primarily by oil and gas industries (25%), as well as the transportation sector (24%). This burden, along with reliance on petroleum, a non-sustainable form of energy, emphasizes the need for more practical solutions in the future. Consequently, certain transportation policies have been geared towards alleviating automobile dependency. However, shifts to modes consuming less energy, such as walking and cycling, have a marginal effect given the current nature of urban form and considering that transportation energy consumption will continue to increase at a rapid rate in the future [*2*]. Hence, the introduction of alternative fuel vehicles (AFVs) is seen as one of the more viable solutions in overcoming oil dependency and reducing greenhouse gas (GHG) emissions from the transportation sector.

To date, many studies have been conducted to evaluate the adoption rate of new vehicle technologies, but the methods, scope and assumptions vary among AFV penetration rate studies. For example, Potoglou and Kanaroglou [*3*] focused on different disaggregate automobile demand models such as car ownership and vehicle type choice models. The authors also compared major advantages and disadvantages of revealed preference (RP) and stated preference (SP) data for AFV demand analysis. Similarly, Al-Alawi and Bradley [*4*] reviewed studies that have used consumer choice and market diffusion models to evaluate their strengths and weaknesses. They also provided recommendations for improving the effectiveness of the reviewed studies to help stakeholders with their decision making.

This paper strives to strengthen areas that had not been discussed extensively, and to provide a more recent analysis concerning the topic. While the majority of the studies found in the literature have been concerned with understanding household vehicle ownership behavior, little has been done to explore the potential of adopting these emerging vehicle technologies by commercial fleets. This study addresses this limitation in the literature by focusing on the demand for rental vehicles, which constitute approximately 70% of the total commercial passenger vehicles in Canada [*5*]. An online SP survey is developed to identify and evaluate the significant factors influencing the demand of consumers for renting specific types of vehicles (i.e. hybrid electric, plug-in hybrid electric, and battery electric vehicles) relative to internal combustion engine (ICE) vehicles. The rationale for this is that rental companies will normally invest in acquiring vehicle types that are in great demand by their clients. On the other hand, if their clients (i.e. consumers) are not willing to rent specific types of vehicles, then rental companies are less likely to own such vehicles.

Included in this paper is a literature review section, which provides an account of the current state of knowledge on AFVs and vehicle choice modeling. This is followed by another section that describes the development of the online survey used to collect the dataset that will be utilized in the analysis. Next, the econometric methods that will be employed to model the collected data are highlighted. Moreover, results are discussed. The final section provides a conclusion to the study and proposes direction for future research.

2. Literature Review

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. However, given the scarcity of studies on rental vehicle preference towards different types of AFVs, the remainder of this section will highlight the efforts that have been done to understand private vehicle type choice. Typically, there are two types of data used to assess individuals' vehicle type preference behavior: RP and SP data. RP data are often used to explain consumers' actual choice behaviors towards distinct alternatives; thus, there are studies that strived to understand factors affecting their purchase motivations. By comparison, SP data are frequently used to forecast the demand of products that are new or yet to exist in the current market; therefore, the usage of SP data has been the standard practice of many studies for evaluating the potential demand for new vehicle technologies [*6*].

On the RP side, the work reported by Haan et al. [*7*] surveyed current hybrid electric vehicle (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. Ozaki and Sevastyanova [*8*] 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. [*9*] 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).

Although RP data provide realistic vehicle type choice information, they are highly influenced by personal tastes, multicollinearity among variables, and analyses are constraint by limited characteristics found in the current market. SP by design overcomes some of these problems (e.g. multicollinearity or limited characteristics). However, SP data requires use of certain types of discrete choice models. For example, early pioneering efforts of Ewing and Sarigöllü [*10*] were based on the multinomial logit (MNL) model to analyzed the determinants affecting the adoption of clean fuel vehicles in Montréal, Québec. Purchase cost, government subsidies and vehicle performance were crucial when purchasing a new AFV. However, a key issue with the MNL model is the potential violation of the independence of irrelevant alternatives (IIA) property.

To avoid potential restrictions of the IIA property, there are studies that utilized the nested multinomial logit (NMNL) model to identify and examine various factors that are most likely to affect households' adoption for

AFVs. For example, Potoglou and Kanaroglou [*11*] found that vehicle attributes (e.g. purchase price) and socio-economic characteristics (e.g. high level of education and household income) have significant effects on AFVs preference in Hamilton, Ontario. Similarly, Caulfield et al. [*12*] suggested that monetary attributes (e.g. purchase price and fuel costs) are highly regarded by Irish consumers, while reductions in vehicle registration tax and GHG emissions are insignificant.

The mixed logit (MXL) model has also emerged as a more robust alternative to the MNL model given its ability to account for unobserved heterogeneity in personal taste among the modeled observations [*13*]. Hence, it has been used as another way to estimate the propensity of AFV adoption, specifically in the European market [*14–16*]. It is found that German [*14*] and Dutch [*15*] households are very reluctant towards AFVs, primarily electric vehicles (EV) due to their limited driving range and long recharging time. However, government incentives (though more influential on German than Dutch consumers), alongside with improved driving range and charging infrastructures, would positively affect AFV preference. On the other hand, Danes are more inclined to own AFVs than conventional vehicles, other things being equal [*16*]. It is also suggested that AFV market share would significantly increase through purchase price and tax reductions for such vehicles. In addition, Tanaka et al. [*17*] utilized SP data and MXL model to evaluate the acceptance of 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.

It is also worth mentioning that Hidrue et al. [*18*] estimated a latent class model to assess the significance of specific EV attributes like vehicle range and charging time on the American market. The latent class model captures preference heterogeneity, and allows different choice orders, with some classes being more susceptible to choosing certain alternatives over others [*19*]. Other advance techniques, such as probit model, multiple discrete-continuous extreme value model [*20*], energy-economy model [*21*], and agent-based model [*22*], are also becoming more common in recent years.

This study is built on the extensive works regarding the demand for AFVs and extends their analyses on consumer rental context. Vehicle attributes common among the aforementioned studies 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 more realistically understand consumers' vehicle preferences.

3. Survey Development

Traditional methods of collecting research data are often through mail, telephone and face-to-face surveys. However, it is known that these methods can be too costly, very time consuming, restricted by limited design options, and requires the effort of more personnel. However, administration of online surveys has gained significant popularity in the past decade. With the growing number of individuals with Internet access, losing potential respondents has been less problematic. Like other methods, a web survey could also suffer from low response rates. Fan and Yan [*23*] suggest that response rates are influenced by various characteristics of the web survey design itself, such as topics, length, ordering and formatting. In addition, Potoglou et al. [*24*] found that recruitment method and sampling methods significantly affect non-response rates.

Fortunately, there are a number of world-wide renowned market research companies maintaining large panels of respondents who are more likely to complete online surveys. One such company is *Research Now* (http://www.researchnow.com/en-CA.aspx). This company retains a large panel of Canadian respondents who receive incentives from Research Now to participate in their online surveys. Research Now is hired to recruit respondents to participate in the online survey that was developed for this research and to ensure complete feedback from a total of 1000 respondents. A pilot to collect data from 100 respondents was performed on February 16, 2016, which was followed by a full launch on February 18 and 19, 2016 to collect data from the remaining 900 respondents.

3.1 Survey Layout

The target respondents of this study are those who have rented a vehicle within the past 12 months. The first section comprised of questions regarding their rented vehicle plan and travel pattern, such as why, where and for how long they rented a vehicle. Respondents' attitudes towards the importance of certain vehicle characteristics were examined in the following section. They were then asked to choose what vehicle type they have rented based on eight vehicle classes: economy/compact, intermediate, full-size, luxury, minivan, sports utility vehicle (SUV), pickup truck and cargo truck. The following section presented respondents with a number of SP scenarios, where they were asked to choose among renting an internal combustion engine vehicle (ICEV) (i.e. conventional vehicle), an HEV, plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV). Next, their views regarding rental behaviors and electric mobility were noted. Lastly, respondents were asked about their demographic and socio-economic details.

3.2 Attributes

Findings from the reviewed literature on AFV preferences suggest that the most significant vehicle attributes can be classified into two categories: monetary and non-monetary. Monetary attributes, such as purchase price, fuel and maintenance costs, and potential financial subsidies, are typically considered to be the most important. On the other hand, non-monetary attributes include fuel/station availability, performance (e.g. acceleration), refueling and recharging time, maximum range, and emission reduction.

In accordance with existing literature, a set of attributes with varying levels are used to create choice games (i.e. scenarios) describing HEVs, PHEVs, and BEVs with respect to ICEVs. Respondents were also presented with descriptions of each vehicle fuel type to give them general but explicit idea about the difference among each alternative. In addition, attribute values depend on the vehicle class chosen by the respondent. Attributes and their levels used in this study are presented in Table 1. It is important to note that the focus of this study is on consumer vehicle rental context; thus, attributes such as purchase price, taxes and registration fees, maintenance and other annual costs are irrelevant.

Daily rental price for each vehicle class is estimated using average of lowest rental cost from major rental companies (e.g. Hertz®, Budget®, Enterprise®, etc.) in major Canadian cities with international airports (e.g. Toronto, Vancouver, Montreal, etc.) during off-peak times (e.g. Tuesday and Wednesday), excluding additional fees and taxes [*25*]. With these specific constraints, it is assumed that this will lead to competitive prices, in which rational individuals would highly consider.

Fueling and charging cost is defined as the amount spent on gasoline (excluding BEVs) and/or electricity (excluding ICEVs and HEVs) to power the rented vehicle every 100 km. The five-year average cost per litre of regular unleaded gasoline from August, 2011 to August 2015 is approximately $1.27 per litre [*26*]. Similarly, the five-year average of electricity prices from April, 2011 to April, 2015 for residential customers in major Canadian cities is calculated to be about $0.11 per kWh [*27*]. Moreover, estimated combined mileage (i.e. 55% city and 45% highway drive) for each available rental vehicle brand is determined from 2015 Fuel Economy Guide [*28*]. Average mileage for each vehicle class is then estimated in terms of gasoline cost. For example, the fuel cost for a conventional economy sedan is $9.33 per 100 km. Assuming PHEV uses 80% gasoline and 20% electricity (ratio varies), the cost to power the PHEV is $7.93 per 100 km, which is 15% less the base cost. Similarly, an economy BEV uses $2.31 worth of electricity per 100 km, which is 75% less the base cost.

The selection of incentives in this experiment is similar with reviewed AFV preference studies. Monetary subsidies such as free vehicle upgrade, exclusion from rental tax, and discounted rental price are used to promote EV alternatives. Additionally, discount in daily rental of navigation systems (e.g. 50% and 100%) is used in favor of PHEV and BEV preference. This form of incentive is deemed important, especially for those individuals travelling to unfamiliar locations. Non-monetary incentives like free parking and access to high-occupancy vehicle and bus lanes are also considered in this study.

Table 1: Attributes and number of levels of the discrete choice experiments

Variable	ICEV	HEV	PHEV	BEV
Daily rental price (CAN$)	Base case	+50% +30% +10% -10% -30% -50%	+50% +30% +10% -10% -30% -50%	+50% +30% +10% -10% -30% -50%
Fuel/charge cost per 100km (CAN$)	Base case	Same as base -10% -20% -30% None	-15% -25% -35% -45% None	-65% -70% -75% -80% None
Monetary incentives	None	Free vehicle upgrade No rental tax Discounted rental price	Free vehicle upgrade No rental tax Discounted rental price	Free vehicle upgrade No rental tax Discounted rental price
GPS rental discount	None	None	50% off Free	50% off Free
Non-monetary incentives	None	None Free Parking HOV or bus lane access	None Free Parking HOV or bus lane access	None Free Parking HOV or bus lane access
Maximum range (km)	300 400 500 600	400 500 600 700	550 600 650 700	250 400 550 700
Emission reduction	No reduction	-10% -20% -30% -40%	-50% -60% -70% -80%	100% reduction
Acceleration (sec)	Base case	20% slower 5% slower 5% faster 20% faster	20% slower 5% slower 5% faster 20% faster	20% slower 5% slower 5% faster 20% faster
Refueling time	5 mins 10 mins	5 mins 10 mins	5 mins 10 mins	N/A
Recharging time	N/A	N/A	30 mins 1 hr 4 hrs 6 hrs	10 mins 30 mins 4 hrs 8 hrs
Number of available stations	1 2 3 5	1 2 3 5	0 1 3 5	0 1 3 5
Size of storage	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

Performance of rental vehicles is assessed in terms of maximum range, reduction in tailpipe emissions and acceleration. 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 attribute values are in line with previous studies. AFV alternatives are assumed to have better range than conventional vehicles due to their improved fuel economy. It is also important to note that the BEV range is overestimated in order to capture the potential improvements in battery capacity in the future. Next, reduction in tailpipe emissions is the potential percent GHG reduction of EV alternatives. Finally, acceleration is described as the average time the rental vehicle takes in seconds to accelerate from a standing start to 100 km/h. The base value for each vehicle class is estimated using average acceleration of common vehicle brands according to Autos.com [*29*]. The attribute levels for all alternatives are based on the work of Hidrue et al. [*18*].

Refueling time (excluding BEVs) and recharging time (excluding ICEVs and HEVs) values are based on the literature and real-world observations. It is assumed that it takes from five to ten minutes to fully refuel a vehicle. On the other hand, recharging time of a PHEV or BEV greatly vary depending on charging method: about ten minutes for battery replacement (potential alternative) and thirty minutes (DC fast charging stations) to eight hours (Level 1 charging stations). Accordingly, it is assumed that there is always at least one gasoline station within any five kilometer radius, while there could be no recharging station within the same radius. Lastly, size of vehicle storage is important when renting a vehicle. Attribute values are presented in terms of number of luggage and carry-ons [*25*], with an exception for cargo trucks, which is in cubic feet.

3.3 Experimental Design

After settling on the attributes and their levels, SP scenarios were constructed. There are different methods to develop these SP experimental designs. The simplest but impractical way is through a full factorial design, where every possible choice situation (i.e. all combination of the attribute levels) is presented to the respondent. 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 in a factorial design is represented by the following equation [*30*]:

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

Therefore, adding more attributes and levels would result in a significantly large number of choice scenarios, which is unreasonable if presented to the respondents. Various methods have been used in the past to overcome this barrier. The most common way is developing an orthogonal fractional factorial design, which aims to minimize the correlation among attribute levels in choice situations [*12, 14, 31, 32*]. There are also studies that rely on default functions of different software packages such as SAS [*11, 18*] and Sawtooth [*15*] to generate different number of choice sets. Regardless of methods used, the primary goal is to present as minimum number of scenarios as possible to respondents, while simultaneously alleviating any potential bias in the design and reduce noticeable fatigue and rejection.

In this study, an online SP survey was constructed based on orthogonal fractional factorial design using Ngene software package, so that orthogonality holds both within and across the alternatives [*30*]. Blocking approach is also incorporated in the design; the purpose of blocking is to ensure that respondents are not always presented with primarily low or high attribute levels for a specific attribute (i.e. attribute level balance) [*30*]. In other words, a blocked design guarantees that respondents are exposed to different scenarios that offer top and bottom attribute levels. Ngene produced 144 choice games, which was grouped into 24 blocks (each containing six unique scenarios); respondents were then assigned with a block. A sampling procedure of blocks was conducted to ensure that all blocks, hence all scenarios, are presented in the experiment with equal frequencies.

4. Data Collection and Results

A pilot was conducted to collect data from 100 respondents, which was followed by a full launch to gather data from the remaining 900 respondents. In total, there were 1,007 respondents who completed the survey. Table 2 shows some characteristics of the sample of respondents who successfully completed the survey in comparison to the 2011 Census. Note that some information such as occupation and household income are collected but not presented. Most respondents are from Ontario (49%). In addition, the majority of the respondents (about 78%) rented a vehicle for business and leisure purpose, which supports the fact that almost 82% of the respondents rented a vehicle at an airport or nearby their residence. Next, the most preferred rental vehicle class is intermediate sedan (about 34%). Moreover, most respondents seem to be neutral towards most vehicle features, such as styling, roominess and performance, except for fuel economy. On the contrary, the majority of respondents are either concerned about the limited range of EVs, have limited knowledge of location of public recharging stations, or have never rented an EV before due to unavailability at their preferred rental companies. Therefore, this information supports why ICEVs remain the dominant vehicle choice (33%) and the BEV market share is quite low (19%).

Table 2: Demographic characteristics of the respondents

		Respondents (%)	**2011 Census (%)**
Gender	Female	47.77	51.54
	Male	50.94	48.46
	Prefer not to say	0.99	-
Marital Status	Married or Common Law	70.80	57.72
	Never Married	18.37	28.02
	Other (Widowed / Divorced / Separated)	8.64	14.25
	Prefer not to say	2.18	-
Age Range	18 to 24	5.66	11.56
	25 to 34	20.06	16.29
	35 to 44	24.13	16.92
	45 to 54	19.96	20.07
	55 to 64	18.37	16.54
	65 and up	11.52	18.63
Household Size	1	13.80	27.58
	2	40.22	34.14
	3	20.66	15.63
	4	16.98	14.29
	5 or more	8.04	8.37
Number of Dependent	0	59.88	40.00
	1	16.78	27.02
	2	14.20	23.29
	3	5.76	9.70
	4 or more	1.29	
	Prefer not to say	2.09	-
Education	High school or equivalent	15.29	26.76
	Apprenticeship or trades	5.66	11.33
	College	24.33	19.08
	University at bachelor level	31.18	13.95
	University above bachelor level	20.95	7.87
	No certificate, diploma or degree	0.99	21.01
	Prefer not to say	1.59	-

Initial estimation of parameters was conducted using the multinomial logit model (Eq. 2), where the choice probability P_{ir} of choosing an alternative rental vehicle r, and V_{ir} is a linear function that depends on observed factors characterizing alternatives r chosen by individual i.

$$P_{ir} = \frac{\exp(V_{ir})}{\sum_j \exp(V_{jh})} \tag{2}$$

In this exercise, vehicle attributes used in the SP experiment, respondents' socio-economic characteristics, and their attitudinal statements towards vehicle rental and electric mobility, were introduced in the model. Interactions among the variables were also considered in the estimation. Respondents who completed the entire survey in less than 5 minutes were dropped in the analysis, which resulted in the final total of 873 respondents or 5,238 observations. The rationale being that it would be improbable to complete the survey diligently in less than 5 minutes, and excluding these respondents means removing some unwanted noise in the results. Table 3 shows estimated parameters of the MNL model. Note that from this point forward, EV refers to HEV, PHEV, and BEV together.

Table 3: Parameter estimates of the multinomial logit model

Variable	**Alternative**	**β (t-stats)**
Constant	HEV	-1.681(-5.04)
	PHEV	-1.854 (-4.92)
	BEV	-2.090 (-5.24)
SP Experiment Variables		
Daily rental cost ($CAN)	EV	-0.035 (-32.20)
Fuel cost per 100 km ($CAN)	ICEV	-0.245 (-10.07)
	HEV	-0.055 (-2.81)
	PHEV	-0.054 (-2.47)
Monetary incentives (1 if an incentive is offered; 0 otherwise)	HEV	0.250 (3.11)
Maximum range on a full tank of gas /fully charged battery (km)	EV	0.065 (3.77)
Emission reduction (%)	EV	0.485 (2.19)
Recharging time (hr)	PH/BEV	-0.033 (-3.38)
Number of available refilling / recharging stations within 5 km radius	All	0.024 (2.28)
Number of luggage (1 if vehicle can carry at least 3 luggage; 0 otherwise)	EV	0.136 (1.96)
Midsize (1 if vehicle is intermediate sedan or SUV; 0 otherwise)	HEV	0.694 (7.75)
	PHEV	0.568 (6.01)
	BEV	0.355 (3.64)
Demographic and Socio-economic Variables		
Province of residence (1 if respondent is from QC, ON, or BC; 0 otherwise)	HEV	0.204 (2.35)
	PHEV	0.292 (3.08)
	BEV	0.177 (1.79)
Age (1 if respondent is 18-34 years old; 0 otherwise)	HEV	0.548 (5.15)
	PHEV	0.451 (4.03)
	BEV	0.613 (5.37)
Household size (1 if household has at least 3 members; 0 otherwise)	EV	0.535 (4.37)
Number of dependents (1 if household has at least 1 child; 0 otherwise)	EV	-0.552 (-4.25)
Retired (1 if respondent is retired; 0 otherwise)	EV	-0.169 (-1.89)
Preferred Vehicle Characteristics		
Vehicle brand (1 if respondent wants foreign brand; 0 otherwise)	EV	0.226 (2.62)
Fuel economy (1 if respondent wants excellent fuel economy; 0 otherwise)	HEV	0.464 (5.16)
	PHEV	0.517 (5.31)
	BEV	0.485 (4.76)

Variable	Alternative	β (t-stats)
Emission (1 if respondent wants *reduced* tailpipe emission; 0 otherwise)	PHEV	0.286 (3.84)
Trunk space (1 if respondent wants ample cargo space; 0 otherwise)	HEV	-0.374 (-4.14)
	PHEV	-0.263 (-2.73)
	BEV	-0.269 (-2.71)
Add-ons (1 if respondent wants new technology add-ons; 0 otherwise)	EV	0.243 (2.32)
Luxury (1 if respondent wants luxury styling; 0 otherwise)	EV	-0.396 (-3.74)
Attitudinal Statements		
Willing to tolerate battery charging inconvenience (1 if yes; 0 otherwise)	PHEV	0.764 (8.36)
	BEV	0.951 (9.96)
NOT willing to spend more money to rent an EV (1 if yes, 0 otherwise)	HEV	-0.433 (-4.19)
	PHEV	-0.625 (-5.79)
	BEV	-0.549 (-4.91)
Rent a vehicle with same features as owned vehicle (1 if yes, 0 otherwise)	PHEV	-0.184 (-2.31)
	BEV	-0.442 (-5.28)
Will NOT modify personal travel to rent an EV (1 if yes, 0 otherwise)	HEV	-0.499 (-5.02)
	PHEV	-0.801 (-7.62)
	BEV	-0.819 (-7.48)
EV driving range is NOT a concern (1 if yes, 0 otherwise)	BEV	0.215 (2.37)
Charging a rented EV is NOT practical (1 if yes, 0 otherwise)	PHEV	-0.394 (-5.00)
	BEV	-0.614 (-7.26)
Interaction effects		
High income (≥$75,000) × High education (College or higher)	HEV	0.280 (3.35)
	PHEV	0.349 (3.92)
	BEV	0.274 (2.95)
High income × Will soon purchase an EV	EV	0.359 (2.60)
Like to rent vehicle with new and innovative features that owned vehicle does not have × Owned vehicle year is 2011 or later	EV	0.263 (2.13)
Rent for leisure purposes × Midsize vehicle × Room for ≥ 3 passengers	EV	0.378 (3.20)
Spent $20-$60 per day on rental vehicle × Consider rental discounts	EV	0.271 (3.87)
Young single males × rapid acceleration	EV	-1.080 (-2.85)

All estimates are intuitive and consistent with a priori theoretical expectations. Specifically, coefficient of rental cost was found to have negative significant impact on rental decision, implying that all things being equal, respondents are rational decision makers and would choice low-cost vehicles. It is supported by the fact that individuals who were not willing to spend more money just to rent EVs were less likely to rent EVs in general. In contrary, individuals with high income and high level of education, and those who stated that they will soon purchase an EV were more inclined in renting EV because price is less likely to be an impending factor, and they are tend to be knowledgeable of EVs' potential benefits.

With regards to fuel cost, the parameter estimate is intuitive; respondents were less likely to rent an ICEV when fuel cost increased. HEV and PHEV choices were also affected, though not as much as ICEV due to their better fuel economy. Similarly, individuals who greatly value fuel economy were more willing to rent EVs, especially PHEV and BEV. People on a budget (i.e. spend less than $60 per day and always consider rental discounts) also tend to rent EVs due to the potential savings in fuel costs.

Similar to results found in the literature, increase in maximum range of EVs, and in number of refilling and recharging stations had significant effect on EV preferences, indicating that range anxiety remained a major concern for EV adoption. People who stated that they will not modify their personal travel just to rent an EV were less likely to choose EVs, especially PHEVs and BEVs. On the other hand, individuals who were supposedly not concern with EVs limited range were more susceptible in renting BEVs. Long recharging time of EVs was also found to hinder PHEV and BEV preferences. In line with this result, respondents who find charging a rental EV impractical were less likely to rent such vehicles, while those who were willing to tolerate potential inconvenience of long recharging time were likely to rent PHEVs and BEVs.

Offered monetary incentives in general were only significant on HEV rentals. Respondents possibly consider that these incentives were not enough to endure the potential inconvenience that comes with PHEV and BEV. Likewise, non-monetary incentives were found to have insignificant influence on EV preference in general. The tailpipe emission reduction variable tried to capture peoples' views toward the environmental impact of vehicles. All else being equal, reduced emissions of EVs increased the utility of these alternatives, especially when an individual values reduced tailpipe emissions.

Size of the vehicle is important when renting a vehicle; those individuals who prioritized ample cargo space were more hesitant in renting EVs, since typical EVs are small and compact. All things being equal, individuals were likely to rent an EV if it is an intermediate sedan or an SUV. Consequently, respondents who rented for leisure purposes and preferred a spacious vehicle (i.e. room for at least three passengers) were inclined to rent an EV if it is a medium size vehicle. Households with at least three members were more likely to rent an EV; however, when the household had at least one child, they tend to abstain from renting EVs.

With respect to demographic characteristics, people living in the provinces of Quebec, Ontario, and British Columbia were more inclined to rent EVs, which could be due to the significant number of EVs in these provinces [*33*], suggesting a neighbor effect. Neighbor effect means that certain things become more desirable as they become more common in the market [*31*]. Retired respondents were more hesitant to rent an EV, while young individuals in general were keener in driving EVs. This result suggests technology gap among the respondents. However, young single males who value rapid acceleration and individuals who prefer luxury vehicles would not rent an EV, due to its limited power and style. Moreover, people who own new vehicles (e.g. 2011 or later), and are fond of new and innovative features that their current vehicle does not have, were more likely to rent EVs; they could also be described as early adopters. In contrary, people who prefer to rent a vehicle with same features as their current vehicle were less inclined to rent PHEV and BEV, implying that they prefer vehicles mainly powered by gasoline. All things being equal, individuals who like foreign brands preferred to rent EVs, possibly due to most popular EVs are foreign made.

5. Conclusion and Future Work

There have been increasing interests in AFVs, particularly EVs, which encourage researchers to analyze and quantify the potential diffusion of these vehicle technologies. The paper aimed to identify and evaluate significant factors affecting AFV preference for commercial fleets, particularly on the rental sector. A nationwide web survey had been developed, in which respondents were presented with six choice scenarios (i.e. one block) drawn from a pool of 144 choice games. A total of 1,007 respondents have completed the survey, where the majority of them chose ICEVs as their preferred rental vehicle, while BEV had the lowest demand. This result is expected and sensible because it shows that the respondents do not reflect wishful thinking and are aware of the drawbacks (e.g. limited range) of BEVs. Among the entire sample, only 873 respondents were utilized to estimate the MNL model, which resulted to a decent goodness-of-fit ρ of 0.175. The results reinforce some of the previous findings from the literature. It is found that rental price, fuel cost, maximum range, emission reduction and recharging time have significant effect on EV rental preference. More interestingly, respondents' preferred vehicle attributes and stated attitudinal statements helped explained some of the variability in their rental decisions.

However, a prominent issue with estimating an MNL model using SP data is the violation of the IIA property. Since each sampled individual was presented with multiple choice responses, there is a possibility that these responses are correlated across observations. In order to relax the IIA property, more intricate models, such as

MXL and latent class models, will be estimated in the next steps of the study. These complex models could also identify and explain potential unobserved heterogeneity present in the observations. In general the results obtained from the MNL model provide an excellent benchmark in estimating MXL and latent class models. Willingness-to-pay for certain rental EV attributes will also be assessed to understand people's views towards EV technology and its potential benefits. Currently, there has been minimal information regarding EVs' rental demand across Canada, making it difficult for stakeholders to assess the potential environmental, social and economic benefits of such emerging vehicle technology. This research will help identify and examine the significant attributes that could potentially affect the rental demand for different types of EVs. In general, this paper strives to provide vital insights about the demand of EVs in the rental market.

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