MODELOS DE CLASES LATENTES PARA CAPTURAR HETEROGENEIDAD EN LA ELECCIÓN DE VEHÍCULOS ELÉCTRICOS

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RESUMEN
We characterize heterogeneity in preferences regarding plug-in electric vehicles (PEVs), including plug-in hybrids (PHEVs) and electric vehicles (EVs). Using survey data collected from 1,754 new-vehicle buying households in Canada in 2013, we segment respondents using latent-class analysis. Potential PEV were split into “PEV-enthusiasts” (8% of sample) with extremely high valuation of PEVs, while a broader segment of “PHEV-oriented” respondents (25%) expresses moderately positive valuation of PHEVs. Preference-based segments also vary by respondents’ valuation of specific attributes. Results suggest that PHEVs are the most likely PEV to have broad market appeal and that car buyers have high degrees of heterogeneity.

Palabras claves: Elecciones discretas, Heterogeneidad, Vehículos eléctricos

1. INTRODUCTION

It is intuitive that consumers vary in their tastes and preferences for new products and technologies. One consumer might be wildly enthusiastic about electric vehicles, a second consumer shows cautious interest, while a third completely rejects the concept. Consumers can be segmented according to these stated or revealed preferences for new technology, where these preferences are often quantified in terms of willingness-to-pay. Similarly, consumer segmentation can be based on the actual or likely timing of their purchase of a new technology, e.g. where a given consumer is either an “innovator”, “early adopter” or part of the “early” or “late” majority (Rogers, 2003). Economic approaches to consumer heterogeneity tend to focus on these differences in overall preference.

However, in addition to preference and timing of purchase, consumers also vary in the motivations that underlie their preferences. For example, two consumers might demonstrate the same enthusiasm (and willingness-to-pay) for an electric vehicle, but one wants to drive a pro-environmental symbol while the other is excited about owning a cutting-edge technology (Heffner et al., 2007). Arguably, effective characterization of consumer heterogeneity should address variations in consumer motivations as well as overall preferences. This study aims to explore both aspects of heterogeneity, using survey data collected from a representative sample of 1754 Canadian new vehicle buying households, which included a stated choice experiment, design space exercises and questions on personal values and lifestyle engagement.

Understanding heterogeneity can be important in the anticipation of demand for emerging technologies with potentially pro-environmental attributes, such as alternatively-fuelled vehicles, solar panels, and energy efficient appliances. Such products are complex in that they can offer a mix of private, symbolic and pro-societal benefits to the consumer (Brown, 2001; Heffner et al., 2007). Consumer preference for such technologies might be motivated by one or multiple benefits—which can vary greatly across the market. We focus on the case of plug-in electric vehicles (PEVs)—an emerging set of technologies that may play a key role in a societal transition toward deep greenhouse-house (GHG) emissions reductions (Williams et al., 2012). Our definition of PEVs includes plug-in hybrid electric vehicles (PHEVs) that can be powered by gasoline or grid electricity, as well as “pure” electric vehicles (EVs) that can only use grid electricity.

Most previous research into consumer demand for alternative-fuel vehicles has focused on preferences, typically estimating some form of discrete-choice model using empirical consumer data to quantify consumer valuation of technology (e.g. a PEV), or its attributes (e.g. one extra km of electric battery range). In that vein, we apply a latent-class discrete choice model as a way to identify consumer segments that primarily differ according to overall preferences (Swait, 1994). Latent-class choice modeling is an approach that has infrequently been applied to PEV demand, other than a few recent studies (e.g., Hidrue et al., 2011).

Section 2 provides background on theories of consumer preferences and lifestyle. Section 3 explains our data collection method and sample. Section 4 presents the method and results for our preference-based segmentation approach. Section 5 summarizes and discusses our findings and concludes with implications for research and policy.

2 BACKGROUND: TWO PERSPECTIVES ON CONSUMER BEHAVIOUR

There are a wide variety of models of consumer behaviour, and each model provides different explanations for the adoption or rejection of pro-environmental technologies and behaviours (Jackson, 2005; Peattie, 2010; Wilson and Dowlatabadi, 2007). Inevitably, the selected model will influence research results and the presumed implications for policy (Shove, 2010). Given our present objective of better understanding heterogeneity in consumer preferences and motivations, the selection of a model is important. This section reviews the two models that we draw from in this paper, with implications for the representation of heterogeneity. First is the preference-based approach that has dominated research on alternative fueled vehicles to date, and second is our lifestyle-based approach that explains consumer motivations according to the need to express and trial self-identity through engagement in meaningful activities, such as vehicle purchase and usage.

2.1 The rational actor model and heterogeneous preferences

Neoclassical economics describes consumer behaviour according to the rational actor model, where consumers choose to buy products that maximize their individual utility or well-being (Hanley et al., 2013). Consumers are represented as having established preferences, or like and dislikes, for different products and their various attributes. The consumer's total valuation of a product is the sum of their valuation of its attributes. Preferences are assumed to be pre-existing and stable, where the consumer has perfect information about the products available (Jackson, 2005). Within neoclassical economics, consumer preference is typically quantified as willingness-to-pay (WTP), which is what a consumer (or in aggregate, the market) is willing to pay for one extra unit of a positive attribute (e.g. electric driving range), or for an electric vehicle relative to a conventional vehicle (comparing two packages of attributes). Preference theory, or neoclassical economic theory more generally, is silent on the motivations of consumer behaviour—preferences are assumed to exist, but generally not further explored or explained by the researcher (Jackson, 2005).

Discrete-choice modeling has emerged as the dominant method used to quantify consumer WTP for products and their attributes (Ben-Akiva and Lerman, 1985; McFadden, 1974; Train, 1980), particularly for alternative-fuel vehicles—see Hidrue et al. (2011) for a review. Discrete choice models can be estimated from empirical data, either stated (hypothetical) or revealed (actual market data). These models estimate coefficients that represent the utility that consumers associate with different products and their attributes, and WTP can be calculated as the ratio of a coefficient estimated for one attribute (or for the technology in general) to the coefficient estimated for purchase price.

While simple discrete choice models estimate a single WTP value for an entire sample, more recent discrete choice modeling studies attempt to incorporate degrees of heterogeneity through a variety methods. The most common method is the inclusion of interaction terms that estimate different WTP values based on socio-demographic variables such as gender, household size, education and commute distance (Brownstone et al., 2000; Bunch et al., 1993), for example how WTP for an alternative-fuel vehicle may vary by household income (Potoglou and Kanaroglou, 2007). Other discrete choice model studies have borrowed from behavioural theories beyond economics to interact preference estimates with constructs such as attitudes. Alternative fuel vehicle studies have frequently included variables representing environmental attitudes, where WTP is higher for respondents that are actively concerned about the environment (Ewing and Sarigollu, 2000) or that have higher environmental awareness (Hackbarth and Madlener, 2013; Ziegler, 2012).

A more sophisticated technique used to quantify preference heterogeneity is latent-class modeling, which identifies unique segments or "classes" of respondents and estimates different preference coefficients for each class (Swait, 1994). This approach has been applied infrequently to alternative-fuel vehicle demand. One example is the Hidrue et al. (2011) study that estimated consumer WTP for electric vehicles (and their attributes) and identified two different classes of respondents: conventional vehicle-oriented versus EV-oriented. Respondent membership in these classes was primarily determined by their overall preference for EV technology—EV-oriented respondents had an overall positive valuation of EVs relative to conventional vehicles. Membership in the EV-oriented class was also associated with being younger, more educated, and more likely to have transitioned towards a pro-environmental lifestyle in the past 5 years.

A third approach to quantifying preference heterogeneity is the random-parameters logit model (also sometimes called a mixed-logit), which estimates a standard deviation for an attribute coefficient in addition to estimating the mean value (Yoo and Ready, 2014). Although this approach can be statistically powerful, with r-square values that exceed those of similar latent-class models, results can be difficult to interpret—providing very little insight into the consumer characteristics or motivations that explain the observed differences in WTP (Yoo and Ready, 2014).

There is also a "hybrid" choice modeling approach that seeks to more directly integrate discrete choice modeling with modeling of other consumer characteristics, such as consumer context, perceptions, attitudes, and information processing (Ben-Akiva et al., 2002). This hybrid approach includes latent-class models that construct consumer classes based on both preferences and additional socio-demographic information or other characteristics. Such models have been applied to the exploration of a number of topics and theories in a variety of contexts, such as: the role of social interactions in teenager walking preferences (Kamargianni et al., 2014); linking psychometric data to general travel preferences (Hurtubia et al., 2014); relating lifestyle and life stage to housing choices (Walker and Li, 2007); and the role of social influence in PEV interest (Kim et al., 2014). However, Ben-Akiva et al. (2002, p173) note that while hybrid choice models can improve how discrete choice models fit consumer data, there is often "no clear behavioural interpretation" to the estimated coefficients—similar to some random parameters based approaches. Arguably, while the "hybrid" modeling approach provides a framework to help researchers to directly link behavioural theories to discrete choice models—the strength of the resulting insights ultimately depend on the appropriateness of the selected theories.

In summary, while preference-based approaches have been used frequently to describe consumer preferences for alternative-fuel vehicles, they tend to provide little insight into consumer motivations. Some discrete choice modeling approaches do capture a degree of consumer heterogeneity, i.e. where consumer interest in the technology varies according to certain demographics and environmental concern. However, none of these approaches has focused explicitly on heterogeneity in consumer preferences and motivations relating to alternative-fuel vehicles. We next turn to "lifestyle theory" as a perspective that we use to help fill this gap in the literature on motivation heterogeneity.

2.2 Lifestyle theory and heterogeneity in motivation

Lifestyle theory provides one perspective on consumer motivation. "Lifestyle" is a concept that has been defined and applied inconsistently across disciplines, varying by context. It can be loosely defined as a "way of living" or as an indication of an individual's character (Walker and Li, 2007). In transportation and economics research, lifestyle has been operationally defined according to demographic characteristics such as income and travel accessibility (Krizek and Waddell, 2002), transportation patterns (Choo and Mokhtarian, 2004), and interests in housing types (Walker and Li, 2007). Within sustainable consumption literature, "pro-environmental" lifestyle is typically defined as some set of pro-environmental activities (Gatersleben et al., 2010), which can be split by various categories of consumption (Barr and Gilg, 2006; Sanquist et al., 2012; Shui and Dowlatabadi, 2005). Some studies investigate barriers to consumer engagement in pro-environmental lifestyles, searching for actions that might "empower" consumers such as product labelling and education programs (Thøgersen, 2005). However, most of this lifestyle research does not address the role of consumer motivations in pro-environmental lifestyle engagement or the heterogeneity therein.

In contrast, what we are calling "lifestyle theory" is based on Giddens' (1991) notion that lifestyles are collections of related practices that reflexively relate to an individual's self-concept. Giddens' (1991) postulates that in a modern world lacking the clear expectations previously provided by tradition, consumers must actively create their identity through the activities or practices they engage in. Identity is reflected, maintained and created through engagement in lifestyle. An individual is likely to engage in a number of different lifestyles concurrently (Giddens, 1991). For example, an individual might engage in different packages of activities relating to family, career, and, say, outdoor recreation—with each lifestyle representing different aspects of their self-concept. Giddens (1991) describes lifestyle construction as a fluid and ongoing process; new lifestyles and aspects of identify are created as individuals enter new stages in life, engage with new social groups, and receive different feedback relating to their present lifestyle. Further, an individual might be open to trying or engaging in new activities and lifestyles, and perhaps buying different types of products, when their life is in some state of transition, or liminality (Turner, 1969).

Spaargen (2003) applies aspects of Giddens' theory to the case of sustainable consumption, arguing the engagement in pro-environmental activities is a function of the individual's self-concept as well as their overall context. Axsen et al. (2012) further develop and apply "lifestyle theory" to the case of consumer interest in pro-environmental technologies, analyzing empirical data collected from car buyers in San Diego, California to find that pro-environmental technologies can be attractive to consumers engaging in a pro-environmental lifestyle, a technology-orientated lifestyle, or some combination of the two. For example, a pro-environmental lifestyle might include regular engagement in activities such as recycling and composting, while a technology-oriented lifestyle might include activities relating to researching and purchasing new technologies. In each case, the package of activities reflects aspects of the individual’s self-concept, and engagement in those activities serves to reinforce that concept. Lifestyle theory can thus help to describe heterogeneity in consumer motivations; a consumer that has a high preference or WTP for a PEV could see the vehicle as supporting their technology-orientated lifestyle, environment-oriented lifestyle, or potentially both. Or, relating this concept back to preference-theory, consumers with the same preferences might be driven by different motivations.

While lifestyle theory originates from the field of sociology, it is consistent with some research from psychology. For example, individuals subscribing to a pro-environmental identity report higher engagement in some types of pro-environmental behaviours, such as waste reduction and “eco” shopping and eating (Whitmarsh and O'Neill, 2010). Pro-environmental self-concept or identity is closely related to the concept of biospheric values, which also predicts engagement in pro-environmental behaviour (van der Werff et al., 2013). But as noted in the previous paragraph, pro-environmental identity or values are not the only motivations for interest in pro-environmental technology—there may be several sets of identities, values and lifestyles that support the purchase and use of PEVs, solar panels, and other pro-environmental technologies.

In summary, lifestyle theory provides a useful theoretical basis to quantify heterogeneity in consumer motivations. Giddens (1991) theorizes that processes of identify and lifestyle construction can be unique for each individual. Some engage in pro-environmental lifestyles, and others develop self-concepts that reject pro-environmental motives. Because there is little previous research to work from, the present study is largely exploratory in seeking to identify which combinations of lifestyles and motivations might exist among a given sample. We use cluster analysis to facilitate this process, as this method can identify groups of respondents that are similar to each other and different from respondents in other groups, based on the variables specified by the researcher (SPSS Inc., 2004). We presently use a similar approach as Axsen et al.’s (2012) quantitative exploration of lifestyle theory: performing cluster analysis of survey data to identify five unique segments of new vehicle buyers, based on pro-environmental and technology-oriented lifestyle engagement, as well as lifestyle openness (liminality) and overall environmental concern.

3. DATA COLLECTION

3.1 Survey sample

The target population for our survey is new vehicle buyers in English-speaking Canada (Quebec was excluded due to the extra costs required for language translation). We define “new vehicle buyers” as households who have purchased a new vehicle in the past five years and use a vehicle regularly. A market research company (Sentis Market Research) recruited a representative sample. We oversampled the provinces of British Columbia (n=363) and Alberta (n=189) to facilitate regional comparison of PEV demand and potential energy impacts for the broader survey project—though that regional comparison is not a focus for our present research. The survey included three distinct parts. Initially, 3179 respondents completed Part 1, with 1823 completing Part 2, of which 1754 finished Part 3 of the survey. Table 1 compares our full sample (n = 1754) to Canadian Census data. As expected, our sample is generally older, more highly educated, and more likely to own a home relative to the general population, as has been found in previous studies of new vehicle buying households (Axsen and Kurani, 2010; Harris-Decima, 2013).

Table 1: Demographic comparison of our sample with the Canadian census data

	All respondents	Census (Canada)
Sample Size	1,754	33,476,688
Household Size		
1	13.1%	27.6%
2	40.0%	34.1%
>2	47.0%	38.3%
Female (respondent)	58.4%	51.0%
Age (respondent)		
<35	30.0%	25.9%
35-44	18.2%	13.4%
45-54	19.5%	15.9%
55-64	19.2%	13.1%
>64	13.1%	14.8%
Highest level of education completed (respondent)		
High school or less	18.4%	49.3%
Some university, college, trade, diploma	43.0%	32.6%
University degree (Bachelor)	26.2%	13.5%
Graduate or professional degree	12.4%	4.6%
Household income (gross)		
Less than $40,000	14.8%	24.9%
$40,000 to $59,999	20.5%	19.3%
$60,000 to $89,999	27.8%	24.3%
$90,000 to $124,999	24.6%	16.8%
Greater than $125,000	12.3%	14.7%
Own residence	77.9%	68.7%
Residence type		
Detached House	66.7%	61.9%
Attached House	15.3%	17.0%
Apartment	16.4%	14.0%
Mobile Home	1.6%	1.2%

Note: Data on household size, sex, age, and residence type are from the 2011 Canada Census. Data on work status, education, and income are from the 2006 Canada Census. Data on home ownership are from the Canadian Mortgage and Housing Corporation

3.2 Overview of survey instrument

The three-part web-based survey instrument was implemented in 2013. Although web-based surveys can result in a recruited sample that is disproportionately younger and of higher socioeconomic status than non-respondents (Couper et al., 2007), this concern is presently minimized because new vehicle buying households tend to have these same differences relative to the general population. The overall flow of the survey instrument is as follows:

- Part 1 (25 minutes, completed in a single sitting): collected data on household characteristics, including lifestyle and socio-demographic information, as well as familiarity and perceptions regarding PEVs and other energy-using technologies.
- Part 2 (mail-out package completed at home, within a few weeks): elicited home recharge potential using a home recharge assessment, elicited driving patterns using a three-day driving and parking diary, and provided respondents with a short booklet to introduce them to PEV technologies as a primer for Part 3.
- Part 3 (30 minutes, completed in a single sitting): investigated consumer preferences regarding PEVs, including a PEV stated choice experiment and design space exercise.

The complete survey instrument is available online (Axsen et al., 2013). The next two sub-sections further discuss aspects of the survey that are relevant to both of our segmentation approaches.

3.3 Lifestyle and environmental concern

Part 1 of the survey elicited respondents' engagement in different lifestyles, asking their frequency of engagement in 47 different activities with 5-point response categories ranging from "never" to "very frequently." We presently focus only on responses to ten of these questions which relate to the two lifestyle types previously found to be associated with interest in pro-environmental technology: environment- and technology-oriented lifestyles (Axsen et al., 2012). The five environment-oriented activities included "engaging in environmental conservation activities," "attending environmental meetings" and "promoting environmental conservation (talking to people about the environment)", which together have a Cronbach's alpha of 0.85 (indicating a high degree of internal consistency). The five technology-oriented activities included "researching new technology," "shopping for new technology" and "working on or tinkering with technology," which together have a Cronbach's alpha of 0.92. For each lifestyle category, we create a single composite score by summing their responses to the five questions.

The survey also included a nine-item scale of respondent "liminality", which describes how open an individual is to engaging in a new lifestyle. As mentioned in Section 2.2, a person that is in a more "liminal" or transitional state might be more willing to consider purchasing a new technology as a way of trying out a new lifestyle—Axsen et al. (2012) used this same question scale and found an association between liminality and interest in pro-environmental activities. The five-point response categories ranged from "strongly disagree" to "strongly agree" regarding statements such as "I often try new activities" and "I am currently making a big transition in my life." Together, the nine questions have a Cronbach's alpha of 0.58 (when negative statements are reverse-coded), which suggests a moderate degree of internal consistency.

The survey also included a measure of environmental concern. We used the "brief," eight-item version of the New Environmental Paradigm (NEP) scale (Cordano et al., 2003), which has been used extensively in environmental behaviour literature and is considered to be an effective measure of concern about environmental issues (Stern et al., 1995). Again, we calculated a single composite score of environmental concern for each respondent, after reverse coding negative statements, where the eight items have a Cronbach's alpha of 0.84

3.4 Informing respondents about PEVs

Research indicates that new vehicle buyers are generally unfamiliar with PEVs and tend to be confused about their attributes (Caperello and Kurani, 2012; Kurani et al., 1994). In our present research instrument we thus take care to educate our respondents before eliciting their PEV interests and preferences. Part 2 of the survey instrument included exercises that encourage the respondent to think through their potential usage of a PEV in a functional sense, including a home recharge assessment questionnaire and a three-day driving and parking diary. We also included a "PEV Buyers' Guide" document, which explained how the different PEV vehicle technologies function using language that is accessible to non-experts, as determined through extensive pre-testing and previous research (Axsen and Kurani, 2009, 2013b). These documents are also available in full online (Axsen et al., 2013).

4. CONSTRUCTING PREFERENCE-BASED RESPONDENT SEGMENTS

4.1 Method

Part 3 of the survey instrument included a stated choice experiment that we used to estimate a discrete choice model. Discrete choice models quantify consumer preferences and are based on random utility theory, assuming that overall consumer utility for a product is based on components that are observable and unobservable (Ben-Akiva and Lerman, 1985; McFadden, 1974; Train, 1980). The observable portion of utility is represented by a vector of coefficients weighted to the specified attributes of the product in question, e.g. purchase price and fuel costs for a PEV. The alternative specific constant represents the observable utility of each choice not captured by attributes specified in the model. The unobservable utility is specified with a random parameter, with the distribution varying by model type.

The most common choice modeling technique is the simple multinomial logit (MNL) which estimates a single set of coefficients for the entire sample. To quantify heterogeneity in consumer preferences, we estimate a latent-class choice model which divides the sample into some number of classes (or segments) and estimates separate sets of coefficients for each class (Greene and Hensher, 2003; Shen, 2009; Zito and Salvo, 2012). The latent-class model assumes that individual preferences can be discretely grouped according to different patterns of preferences. This approach can be designed to use individual characteristics to facilitate the formation and interpretation of class membership, e.g. demographic and psychographic characteristics (Strazzera et al., 2012). However, the determination of class membership tends to be determined more by consumer preferences, so latent-class models tend to provide more insights into preference heterogeneity rather than heterogeneity in motivations. The estimation of coefficients for a given class can use an MNL or something similar.

We estimate a latent class choice model using data collected via the stated choice experiments in the survey instrument (Part 3). Every respondent indicated the make, model, purchase price and fuels costs of their next anticipated new vehicle purchase (which initially we asked them to limit to being a conventional vehicle). This information was then used to present six customized vehicle choice sets to the respondent. Each choice set presented four different vehicles: a conventional vehicle (their next anticipated vehicle purchase), and a hybrid (HEV), plug-in hybrid (PHEV) and pure electric version (EV) of that vehicle.

The experimental design is detailed in Table 2 and included incremental purchase price increases, fuel cost differences, and electric-powered driving ranges that accommodate a range of potential PEV designs (e.g., Delucchi and Lipman, 2010; Kromer and Heywood, 2007). The choice set also specified the availability of slower (Level 1) or faster (Level 2) vehicle charging at the respondents' home. The four attributes (purchase price, weekly fuel cost, vehicle electric range and charge speed) were sufficient to address our heterogeneity-based research questions, and appear consistently in previous research—see Hidrue et al. (2011) and Tanaka et al. (2014)

for recent reviews. We did not include representation of public charging infrastructure; empirical research suggests that home charging infrastructure is more likely to be important among potential early mainstream buyers (Bailey et al., 2015). Aside from the drivetrain and the attributes depicted in Table 2, respondents were informed that all vehicles were identical, e.g. in terms of appearance, power and performance.

Table 2: PEV choice model experimental design (6 choice sets per respondent)

Attributes	Next anticipated conventional vehicle	Hybrid vehicle	Plug-in hybrid vehicle	Electric vehicle
Purchase Price	Selected by respondent	Conventional price 10% more 20% more 40% more	Conventional price 10% more 20% more 40% more	Conventional price 10% more 20% more 40% more
Weekly fuel cost	Selected by respondent	40% less 30% less 20% less 10% less	80% less 60% less 40% less 20% less	80% less 60% less 40% less 20% less
Electric-driving range	n/a	n/a	16 km 32 km 64 km	120 km 160 km 200 km 240 km
Home recharge access	n/a	n/a	Level 1 (1 kW) Level 2 (6 kW)	Level 1 (1 kW) Level 2 (6 kW)
Recharge time [a]	n/a	n/a	Calculated	Calculated

[a] The discrete choice experiment showed "recharge time" to respondents to help them understand the charging needs of the PHEV or EV. Recharge time was calculated as the time required for the respondent to fully recharge a depleted battery using their home charger. This time is a function of the vehicle's electric driving range, the base vehicle type (where larger vehicle bodies are assumed to require more electricity consumption or have a higher kWh/mile), and the speed of the home charger (Level 1 or Level 2).

The experimental design is based on the attribute levels in Table 2, resulting in a full factorial design of $4^7 \times 3^1 \times 2^2$. We used SAS's "MktEx macro" function to generate a main-effects fractional factorial version of this experimental design and set the number of choice sets to 48 (Kuhfeld, 2005). As part of the design generation we ensured that all choice sets were different and that unrealistic attribute combinations were not created. The final D-efficiency was 98%, where a "good" D-efficiency rating is 80% or greater, indicating that the design is balanced and orthogonal (Bliemer and Rose, 2011). This series of choice sets was then divided into 8 blocks of six choices and each respondent completed 1 randomly assigned block and 6 choice sets. Each choice set presented all four vehicle drivetrains.

We estimated the latent-class choice model with Latent Gold version 5.0 (Vermunt and Magidson, 2013). Although there are statistical diagnostics that are commonly used to determine the optimal number of classes, we emphasize that our present focus is on improving our understanding of heterogeneity in consumer preferences and motivations—not just maximizing the predictive performance of the model. Thus, we consider several criteria when selecting the number of classes to include in our model, ordered here from most important to least: 1) maximizing the interpretability of the solution, 2) avoiding solutions with proportionally large classes (e.g. greater than 50% of sample) or very small classes (e.g. less than 5% of sample), 3) avoiding solutions where two or more classes are essentially identical, and 4) if consistent with the above objectives, maximizing statistical measures of quality and parsimony, namely the Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Louviere et al., 2000). We calculate WTP values for each class using coefficient estimates that are statistically significant at a 95% confidence level.

4.2 Results

Table 3 summarizes latent-class model solutions based on the number of classes specified, which we characterize by the statistical and qualitative criteria summarized above. As the number of classes is increased, the models perform better according to statistical measures such as the pseudo R-square, the AIC and the BIC—the latter two being measures of model quality and parsimony. However, our non-statistical criteria—primarily interpretability—suggest that these solutions with 6 or more classes are not desirable because two or more classes are not unique from an interpretability standpoint. Further, solutions of eight or more classes include at least one "small" classe that represents less the 5% of the sample and solutions have several insignificant coefficient estimates. We select the five class solution as optimal because it reveals clear and interpretable differences in respondent classes according to alternative specific constants, attribute coefficients, and individual characteristics (Table 4).

Table 3: Latent-class model diagnostics for different numbers of classes (n=1754)

Number of classes	Number of parameters (k)	Log-likelihood (LL)	AIC[a]	BIC[b]	Pseudo R^2[c]	Classes are clearly different[d]	Includes "small" classes[e]
2	32	-10320	20704	20879	0.371	Yes	No
3	55	-9531	19171	19472	0.479	Yes	No
4	78	-9097	18350	18777	0.547	Yes	No
(selected) 5	101	-8794	17789	18342	0.586	Yes	No
6	124	-8653	17554	18232	0.616	No	No
7	147	-8520	17334	18138	0.638	No	No
8	170	-8429	17199	18129	0.651	No	Yes

Note: Number of Individuals = 1754, number of observations N = 10524

[a]Akaike information criterion = -2(LL - k).

[b]Bayesian Information criterion = -LL+[(k/2) Ln (N)]

[c]Pseudo R2 = 1- (LL/LL (0))

[d]We used our subjective judgment to determine if the identified classes are different in "meaningful" ways, e.g. with different preferences or lifestyles as indicated by the significant coefficients.

[e] We consider a class to be inappropriately small if it includes 5% or less of the total sample.

Table 4 depicts the coefficient estimates for the discrete choice model in each class, the calculations for WTP where coefficients are significant at a 95% confidence level, and the demographic and lifestyle characteristics that are associated with class membership. The probability of membership in each class can be interpreted as the proportion of the sample that is represented by that class. Across all five classes, all the vehicle price and fuel cost coefficient estimates are significant and of the expected sign. Most of the alternative specific constants are significant, and seem to be the primary determinant of class membership. Half of the PEV constant interactions with Level 2 access at home are significant, indicating that WTP for a PHEV or EV is higher if a faster charger speed is available at the respondent's home. Interestingly, only three of the 10 vehicle range coefficients are significant at a 95% confidence level, indicating that the stated range of the PHEV (16, 32 or 64km in the experimental design) or the EV (120, 160, 200, or 240km) did not systematically influence the respondents in most classes.

Respondent WTP is calculated for each class as the ratio of a given attribute or constant to the purchase price coefficient, where WTP for vehicle type corresponds to the alternative-specific constants. The “PEV-enthusiast” class (8% of sample) has extremely high WTP values for HEVs, PHEVs and EVs, indicating that even if fuel costs are equivalent to that of a conventional vehicle, the average respondent in this class would pay over $40,000 extra for an HEV, or pay more than $130,000 extra for a PHEV or an EV (and an extra $40,000 more for an EV if Level 2 charging were available at their home). These WTP values seem highly inflated and should not be interpreted in a literal sense—instead the values indicate that respondents in this class have very strong positive preferences for PEVs (hence the “PEV-enthusiast” label). The PHEV-oriented class (25% of sample) generally prefers PHEVs, and is on average willing to pay an extra $15,000 for such a design. The HEV-oriented (16%), HEV-leaning (28%), and CV-oriented (23%) classes have negative or non-significant WTP values for PHEVs and EVs.

Table 4: Latent-class results for 5-class solutions (n=1754)

Class label	PEV-enthusiast	PHEV-oriented	HEV-oriented	HEV-leaning	CV-oriented
Probability of Membership	0.080	0.254	0.159	0.277	0.230
Discrete choice model					
HEV constant	0.64**	2.30***	2.65***	0.88***	-2.91***
PHEV constant	2.09***	3.22***	-1.37***	-0.11	-4.72***
EV constant	2.14***	-1.16**	-5.07	-3.10***	-2.15
Vehicle price (CAD$)	-0.00002***	-0.0002***	-0.0002***	-0.0006***	-0.0003***
Fuel cost (CAD$/week)	0.0002	-0.0407***	-0.0079***	-0.0387***	-0.0197***
PHEV range (km)	-0.0035	-0.0033	0.0118**	0.0065**	0.0039
EV range (km)	-0.0017	0.0038	0.0003	0.0057**	-0.0195
PHEV x Level 2 charging at home	0.11	0.51***	1.04***	0.51***	-0.20
EV x Level 2 charging at home	0.62***	1.20***	3.67	0.26	-1.08
Implied willingness-to-pay[a]					
Saving $1000/year in fuel		$3,781	$670	$1,258	$1,126
HEV	$41,245	$11,090	$11,692	$1,493	-$8,637
PHEV[b]	$135,026	$15,568	-$6,028		-$14,021
EV[b]	$137,794	-$5,612		-$5,246	
PHEV with Level 2 charging		$2,444	$4,602	$856	
EV with Level 2 charging	$39,981	$5,805	$670	$1,258	
Class membership model [relative to base]					
Constant	-6.0***	-1.9***	-0.5	[Base]	1.2***
Household size (number of people)	0.17*	0.10	-0.15**		-0.22***
$50,000 to $99,999 [Base = “<$50,000]	0.18	-0.28*	-0.29*		-0.20
$100,000 to $150,999 [Base = “<$50,000]	0.36	-0.21	0.15		0.15
$150,000 or more [Base = “<$50,000]	-0.05	-0.28	0.15		0.12
Bachelor’s degree [Base = “less than Bachelor’s]	0.43	0.15	-0.30*		-0.54***
Graduate degree [Base = “less than Bachelor’s]	0.12	-0.03	-0.38*		-0.94***
Live in Alberta [Base = “rest of Canada”]	1.14**	0.28	0.45*		-0.17
Live in British Columbia [Base = “rest of Canada”]	1.42***	0.42**	0.59**		-0.11
Live in Ontario [Base = “rest of Canada”]	0.75*	-0.04	0.03		-0.23
Technology-oriented lifestyle score	0.10***	0.02	-0.01		-0.04**
Environment-oriented lifestyle score	0.10***	0.09***	0.02		0.02
Environmental concern (NEP score)	0.06***	0.04***	0.03*		-0.04***
Liminality score	0.02	0.00	0.04**		0.03*

*Significant at 90% confidence level
**Significant at 95% confidence level
***Significant at 99% confidence level
[a] We only depict willingness-to-pay calculations where the coefficient estimates are significant at a 95% confidence level or greater. As of February 12, 2015, $1.00 CDN is equivalent to $0.80 USD and €0.70 EUR
[b] Because the coefficient estimate for PHEV and EV range are not statistically significant, our willingness-to-pay calculations for PHEV and EV are not based on the range of a given PHEV or EV (e.g. PHEV-16 vs. PHEV-32).

Respondents in most classes have a positive and significant WTP associated with having Level 2 charging at home, though these values vary by magnitude and association with PHEV versus EV purchase. The classes also differ by sensitivity to fuel costs—for example, the PHEV-oriented class places the highest value on fuel cost savings (more than five times that of the HEV-oriented class). Interestingly, the fuel cost coefficient is not significant for the PEV-enthusiast class, suggesting that those respondents' PEV interest is not financially motivated.

The class membership model in the lower half of Table 4 further describes respondent characteristics for each class, using the HEV-leaning class is used as the "base" or reference point. PEV-enthusiast and PEV-oriented respondents are the most likely to engage in environment-oriented lifestyles and to have high levels of environmental concern. PEV-enthusiast respondents are unique as the most likely to also engage in technology-oriented lifestyles. In summary, while this latent class choice model approach does provide some insight into how different lifestyle patterns and motivates are associated with PEV interest, class membership (and thus heterogeneity) is primarily determined by preference. We now turn to our second segmentation approach to explicitly quantify consumer heterogeneity according to lifestyle as an indicator of motivation.

5. DISCUSSION AND CONCLUSIONS

5.1 Overall PEV interest

Although our focus is on characterizing heterogeneity in preference and motivation among potential PEV buyers, we start by highlighting some overall trends in PEV preference or interest. First, throughout our analysis we see that PHEV designs tend to be more popular among survey respondents than pure EV designs—regardless of the electric driving range—as indicated by stated interest and calculated WTP measures. Specifically, PHEV designs were valued more highly than EV designs in the PEV-oriented preference-based segment, and were selected more often than EVs and valued more highly than EVs. This pattern of relatively high PHEV interest in our Canadian sample replicates findings from previous studies of U.S. car buyers (Axsen and Kurani, 2009, 2013a, b).

Second, we find that most respondent segments are more attracted to a PEV if they can have a Level 2 vehicle charger at home—which can recharge a battery six times faster than a regular Level 1 outlet (110/120-volt). The Level 2 charger tends to be perceived as more valuable for operating an EV than for a PHEV; willingness-to-pay (WTP) for a PHEV increases by about \$1000 to \$3000 with a Level 2 charger, whereas the WTP for an EV increases by about \$3000 to \$6000. However, some segments did not indicate a statistically significant valuation of Level 2 charging for an EV or PHEV—suggesting that the installation of special at-home charging infrastructure is not necessary for all potential PEV buyers.

Surprisingly, coefficient estimates for PHEV and EV driving range are not significant in most of our segments, which contrasts with previous choice models (e.g., Hidrue et al., 2011). While one explanation may be that there is a flaw in our experimental design, e.g. if we did not include a wide enough variety of range levels, this finding may alternatively be an accurate indication that new vehicle buyers with little or no previous PEV experience find it difficult to place a value on a unit of electric-powered driving range. The latter explanation is consistent with findings by Kurani et al. (1994) that California households have difficulty articulating what driving range they would "need" for a pure electric vehicle. Further, more recent evidence suggests that consumer perceptions of driving range can change after they purchase a PEV and drive it for several months and gain experience with recharging, electric driving and reflection on their actual driving range needs (Turrentine et al., 2011).

5.2 Preference-based heterogeneity

Overall preferences for PEVs and their attributes vary substantially across the sample. Our preference-based approach to quantifying consumer heterogeneity utilized a latent-class analysis. The five identified classes differ substantially according to their interest in vehicle types, valuation of fuel savings, lifestyle, environmental concern, and education. Interestingly, household income did not significantly differ across the classes. The largest differences are overall vehicle preferences: one class prefers a conventional vehicle (23% of sample), two classes place higher value on an HEV (44% of sample), and two classes have greater interest in a PHEV or an EV (33% of sample).

The PEV-enthusiast class (8% of sample) is particularly extreme—respondents express very high WTP values for HEV, PHEV and EV designs, and do not significantly value fuel savings. Members of this class have the highest levels of technology- and environment-oriented lifestyle engagement. This "PEV-enthusiast" class may be indicative of the extreme nature of "very early" PEV buyers in North America who generally have very different characteristics, preferences and motivations relative to later buyers. In contrast, the PHEV-oriented class (25% of sample) positively values PHEVs and HEVs, but not EVs, values fuel cost savings more highly than any other class, while also exhibiting higher environmental concern and lifestyle engagement than the HEV- or CV-oriented classes. These findings support the notion that PEV (and HEV) interest is generally associated with higher degree of environmental concern and lifestyle as indicated by previous choice modeling studies (e.g., Ewing and Sarigollu, 2000; Hidrue et al., 2011) and also supports exploratory research suggesting that PEV interest can be associated with engagement in a technology-oriented lifestyle (Axsen et al., 2012). However, this (preference-based) latent-class approach did not yield much insight into how consumer motivations may differ independently of preferences.

5.3 Implications for research, markets and policy

For research efforts that seek to understand consumer motivations regarding pro-environmental technologies such as PEVs, we provide evidence that heterogeneity can be substantial and important. We also demonstrate that a given approach to heterogeneity will shape the insights that can be discovered. Our preference-based approach identified segments with very different preferences for HEVs, PHEV and EVs, and their attributes. This preference-based approach also suggests that PEV interest is generally associated with engagement in certain lifestyles and environmental concern.

Although consumer interest in PEVs can be associated with particular motives in aggregate, such as high valuation of fuel cost savings, high environmental concern or engagement in environment- or technology-oriented lifestyles—it is a mistake for marketing efforts to focus only on these aggregate patterns. If the intent is to engage with the full potential early PEV mainstream market that we identify in this research, automakers, electric utilities, governments and other PEV-stakeholders ought to consider the full suite of consumer motivations and their different combinations. Following a "one size fits all" approach to marketing, information campaigns, or policy design may backfire with some consumer segments; for example, marketing efforts relating to an environmental benefits may connect well with some consumers (e.g. "Strong Pro-environmental" or "Tech-enviro"), but might also conflict with the motivations of other potential buyers. Further, PEV incentives, e.g. subsidies, high-occupancy vehicle lane access, or reduced electricity rates, will be valued differently by various consumers. In short, PEV marketing and policy efforts ought to identify and consider the differing motivations and preferences across potential buyers.

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