Transport Policy 135 (2023) 21–32

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Preferences for zero-emission vehicle attributes: Comparing early adopters with mainstream consumers in California

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ARTICLE INFO

Keywords:
Electric vehicle
Stated preference
Choice experiment
Early adopters
Mainstream consumers

ABSTRACT

Ambitious zero-emission vehicle (ZEV) adoption goals have been proposed to decarbonize the transportation sector, while the current market share pales in comparison. Although the distinct socio-economic characteristics of ZEV early adopters relative to mainstream car buyers are well understood, the two groups' preferences for ZEV attributes are not clear. This knowledge gap hinders the development of effective policies to achieve mass ZEV penetration goals. This paper examines consumers' preferences and willingness to pay for ZEV attributes based on 755 early adopters and 3493 mainstream consumers from the 2019 California vehicle survey data. Results show that early adopters are more sensitive to battery range, acceleration performance, home charging availability, and high occupancy vehicle lane access, while mainstream consumers attach greater importance to cost attributes (e.g., fuel and maintenance costs) and charging time. Moreover, the effects of monetary incentives are found to be significant for both groups, whereas neither early adopters nor mainstream consumers value the availability of public charging stations. The findings of this study inform targeted ZEV policymaking and marketing strategies in different adoption stages.

1. Introduction

Vehicle electrification represents one of the revolutions in the transportation sector and features prominently in global goals on climate change. Three types of zero-emission vehicles (ZEVs) have entered the market to replace internal combustion engine vehicles (ICEVs), including plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and fuel cell electric vehicles (FCEVs). PHEVs can be recharged from an external electricity source and produce zero tailpipe emissions when they are driven in all-electric mode. The PHEVs and BEVs are referred to as plug-in electric vehicles (PEVs) collectively. As California aims for a carbon-free electricity system by 2045, the PEVs can be zero-emissions at a well-to-wheel basis (CA.GOV, 2018). FCEVs use hydrogen as the fuel to generate electricity to power an electric motor. As a result, they produce only water when driving. While currently hydrogen is mainly produced from natural gas, the FCEVs can be promising when renewable power is used to produce green hydrogen (Lane et al., 2017). Therefore, the adoption of the three types of ZEVs, in combination with decarbonized electricity and green hydrogen production, can significantly reduce greenhouse gas (GHG) emissions in the transportation sector, which contributes to 27% of GHG emissions in the U.S. in 2020 (EPA, 2022).

Governments worldwide have announced ambitious ZEV adoption goals. In Europe, Norway aims for a 100% ZEV market share for passenger cars by 2025. Netherlands, Sweden, Denmark, and Iceland have set targets for phasing out all new sales of passenger ICEVs by 2030 (ICCT, 2020). China announced that ZEVs would represent 25% of overall vehicle sales by 2025 (State Council of the PRC, 2020). In North America, California has mandated that all new light-duty vehicles sold in the state be ZEVs by 2035 (CA.GOV, 2020), and British Columbia by 2040 (GOV.BC.CA, 2020). In contrast to the ambitious goals, ZEVs are still in the early stages of adoption in most parts of the world. Norway is the leading country in ZEV adoption with a 86% market share in 2021. The 2021 ZEV market share in China, the U.S., and Japan pale in comparison, which was 16%, 5%, and 1%, respectively (IEA, 2022).

To bridge the gap between the current low market share and ambitious targets, ZEVs must move beyond early adoption to achieve mainstream market penetration, and early adopters need to continue to choose ZEVs in subsequent purchases (Hardman and Tal, 2021). Based on the diffusion of innovation theory (Rogers, 2003), existing research

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https://doi.org/10.1016/j.tranpol.2023.03.002
Received 5 September 2022; Received in revised form 1 February 2023; Accepted 4 March 2023

has shown the differences in socio-economic characteristics, household traits, and travel patterns between ZEV early adopters and mainstream consumers (e.g., Hardman et al., 2016; Hardman and Tal, 2018). The different characteristics of the two consumer groups imply their unique preferences for ZEV attributes, which informs targeted policy measures of ZEV adoption. However, few studies compared the influential factors of ZEV purchase decisions between the two consumer groups. This paper fills this gap by comparing early adopters' and mainstream consumers' preferences for a comprehensive list of ZEV attributes (e.g., battery range, home charging, workplace charging, public charging, hydrogen refueling stations, acceleration performance, costs, and incentives) based on the 2019 California vehicle survey (CVS) dataset (TSDC, 2020). The 2019 CVS dataset records the results of choice experiments which involve eight vehicle fuel types: gasoline vehicles (GVs), hybrid electric vehicles (HEVs), PHEVs, diesel vehicles (DVs), BEVs, FCEVs, plug-in FCEVs (PFCEVs), and flexible fuel vehicles. Note that a PFCEV refers to a FCEV with the capability of a plug-in battery electric range (Lane et al., 2017).

This paper contributes to existing ZEV adoption literature in two ways. Theoretically, this paper moves beyond the socio-economic characteristics and dives into the influential factors of ZEV purchase decisions for early adopters and mainstream buyers, respectively. Practically, the findings of this paper provide insights for policymakers and ZEV manufacturers to develop targeted ZEV policies and marketing strategies for attracting ZEV early adopters and achieving mass market penetration. In the sections to follow, related prior studies are reviewed in Section 2. Section 3 introduces the methodology, including data collection, consumer segmentation, and modeling approach. Results are presented in Section 4 while Section 5 discusses the implications of these results. Concluding remarks are presented in the last section.

2. Literature review

Prior literature examines characteristics of ZEV early adopters from a variety of regions, such as Norway (Nayum et al., 2016), Sweden (Vassileva and Campillo, 2017; Westin et al., 2018; Haustein and Jensen, 2018), Switzerland (Brückmann et al., 2021), California (Hardman and Tal, 2016, 2018; Hardman et al., 2016, 2017; Javid and Nejat, 2017; Nazari et al., 2019), Canada (Axsen et al., 2018), and China (Sun et al., 2017; Chu et al., 2019). These studies demonstrate the distinct characteristics of early adopters relative to mainstream car buyers. For example, the early adopters are more likely to be males, wealthy, well-educated, and from larger households with multiple cars and better parking garage access. Given the significant differences in socio-economic characteristics between early adopters and mainstream consumers, the two groups' preferences for ZEV attributes (e.g., technical, infrastructural, cost, and incentives) are expected to vary. For effective ZEV policies and strategies targeted at different adoption stages, it is necessary to investigate how early adopters' preferences and willingness-to-pay (WTP) for ZEV attributes vary from mainstream consumers.

There have been numerous studies focusing on mainstream consumers' ZEV preferences (see the literature review papers by Coffman et al., 2017; Liao et al., 2017; Singh et al., 2020; Wicki et al., 2022). These studies often conduct stated preference surveys with choice experiments that include several vehicle alternatives (e.g., ICEVs, PHEVs, BEVs, and FCEVs). Each alternative is described with a variety of attributes, such as driving range, charging/refueling infrastructure availability, charging/refueling time, purchase price, fuel cost, and incentives (Higgins et al., 2017; Wang et al., 2017; Ferguson et al., 2018; Kormos et al., 2019; Khan et al., 2020). Discrete choice models are used to analyze the outcomes of respondents' choices. The estimated model coefficients represent respondents' preferences or tastes for those attributes and can be used for evaluating consumers' WTP for the attributes (Hackbarth and Madlener, 2016; Kim et al., 2019; Ma et al., 2019; Li et al., 2020a; Bansal et al., 2021).

However, few studies compare ZEV preferences between early adopters and mainstream consumers, possibly due to the limited number of ZEV early adopters in the real world. One exception is Axsen et al. (2016) which conducted stated choice experiments for both early adopters (n = 94) and mainstream consumers (n = 1754) in Canada. Axsen et al. (2016) found that, compared to mainstream consumers, early adopters showed a much higher WTP for battery range and placed five times more value on renewable energy for electricity generation. However, the number of sampled ZEV owners (n = 94) and examined ZEV-specific attributes (i.e., battery range and home charging availability) are limited in Axsen et al. (2016). Moreover, the BEV battery range in their choice experiments is relatively small (ranging from 75 miles to 150 miles) which represents early generations of BEV models. In contrast, this paper is based on the 2019 California vehicle survey which includes 755 ZEV early adopters. The choice experiments in the survey include a comprehensive list of ZEV-specific attributes whose levels are designed to represent more recent ZEV technologies. The preferences of early adopters are compared with mainstream consumers for various ZEV attributes, including battery range, charging/refueling infrastructure availability (at home, workplace, and public places), regular and fast charging time, incentive policies, etc. The comparison results will inform ZEV policymaking for key issues on electric mobility in different stages of ZEV adoption.

3. Methodology

3.1. Survey data

This study is based on the publicly available 2019 CVS dataset. The CVS has been conducted at regular intervals for the past two decades. It aims to understand consumers' preferences for various vehicle attributes and forecast the light-duty vehicle demand for different fuel types. The latest 2019 CVS includes a residential survey and a commercial survey. This paper focuses only on the residential survey which consists of two modules: 1) the revealed preference (RP) part which collects respondents' socio-economic information, current household vehicle inventory, and vehicle usage behavior; 2) the stated preference (SP) part which includes a stated vehicle choice experiment. Despite the hypothetical bias, the stated choice experiment is a powerful approach to examine consumer preferences for alternatives that are not widely available in the real world. Numerous ZEV adoption studies have adopted this approach (see the literature review by Liao et al., 2017) since RP data on ZEV adoption is still limited.

Each survey respondent was asked to complete eight choice tasks. In each choice task, respondents selected their most preferred option from four vehicle alternatives. These vehicle alternatives are described by 21 attributes, as shown in Table 1. Some attributes are only applicable to certain fuel types. For example, the electric range attribute is only applied to PHEVs, BEVs, and plug-in FCEVs (PFCEVs). For each attribute, the detailed applicable fuel types and attribute levels are listed in Table 1.

3.2. Consumer segmentation

The residential survey of the 2019 CVS includes a total of 4248 respondents. In addition to surveying conventional vehicle owners in California (n = 3493), the 2019 CVS dataset features an add-on survey of ZEV owners (n = 755). For both respondent pools, the survey participants were randomly invited from the vehicle owners in the California Department of Motor Vehicles (DMV) registration database.

Table 2 compares the socio-economic characteristics of ZEV adopters, mainstream consumers, and the California Census population. The owners of all three types of ZEVs are dominated by males, while the gender ratio of mainstream consumers is close to the California population (50%). The age distribution of PHEV owners is similar to mainstream consumers, where the middle-aged group (35–64 years old)

Table 1
Attribute levels for choice experiment design.

Attributes	Applicable fuel types	Levels
Vehicle body type	All	Subcompact car, compact car, midsize car, large car, sports car, subcompact cross-over, compact cross-over/SUV; midsize cross-over/SUV; full-size/large SUV; small van; full-size/large van; small pickup truck; full-size/large pickup truck
Fuel type	–	Gasoline; HEV; PHEV; Diesel; BEV; FCEV; PFCEV [a]; Flex [b]
Brand type	All	Standard; premium
Model year	All	Used 6 years old (2015); used 3 years old (2018); used 6 years old (2019); new (2021); used 3 years old (2022); new (2025)
Purchase price ($)	All	Continuous
Fuel range (miles)	All but BEV	Continuous
Electric range (miles)	PHEV, BEV, PFCEV	Continuous
Availability of regular charging stations	PHEV, BEV, PFCEV	10%, 20%, and 30% of public parking facilities have regular charging stations
Availability of fast charging stations	BEV	10%, 20%, and 30% of public parking facilities have fast charging stations
Workplace charging	PHEV, BEV, PFCEV	Not available; regular charging available; fast charging available; free regular charging; free fast charging
Home charging	PHEV, BEV, PFCEV	Not available; regular charging available
MPGe	All	Continuous
Electric MPGe	PHEV, PFCEV	Continuous
Fuel cost per 100 miles	All but BEV	Continuous
Electricity cost per 100 miles	PHEV, BEV, PFCEV	Continuous
Refueling time	Gasoline, HEV, Diesel, FCEV, Flex	5 min
Regular charging time	PHEV, PFCEV	20, 30, and 40 min for 10 miles
	BEV	2, 4, and 6 h for 100 miles
Fast charging time	BEV	5, 15, and 25 min for 100 miles
Availability of Fuel Stations	Gasoline, HEV, PHEV, Flex	Gasoline stations (at today's locations)
	Diesel	30%, 50%, and 70% of today
	FCEV, PFCEV	1, 5, 10, 20, and 30 miles to station from home/work
Purchase incentive	Gasoline, HEV, Diesel, Flex	None
	PHEV, BEV	None; HOV lane access for 3 years; $1000 rebate; $1500 rebate; $2500 rebate; $2500 tax credit; $5000 tax credit; $7500 tax credit
	FCEV, PFCEV	None; HOV lane access for 3 years; $1000 rebate; $1500 rebate; $2500 rebate; $5000 rebate; $10,000 rebate; $2500 tax credit; $5000 tax credit; $7500 tax credit
Annual maintenance cost ($)	All	Continuous
Acceleration (seconds from 0 to 60 mph)	All	Continuous

Note:
[a] PFCEV is a FCEV with the capability of a plug-in battery range.
[b] Flexible fuel.

accounts for about 50%. In contrast, BEV and FCEV owners share similar age distributions, where middle-aged respondents account for about 70%. ZEV adopters are more likely to have higher income and higher educational attainments, and to be from larger households. Also, more than 80% of the ZEV adopters are from multi-car households, compared to 58% of mainstream consumers. For residential types, early adopters show a higher percentage of living in single-family homes than mainstream consumers. Overall, the sample of ZEV adopters tend to be males, middle-aged, with a higher level of income and educational attainment, from larger households with multiple cars, and living in single-family houses.

3.3. Modeling approach

Mixed logit (MXL) models with error components are used to analyze the outcomes of vehicle choice experiments. This model specification obviates the restrictive independence of irrelevant alternatives (IIA) assumptions of standard multinomial logit (MNL) models. Moreover, it allows for the dependence of unobserved factors over the repeated choice of the same respondent (Train, 2009). Note that the latent class choice models were not used since there are many attributes included in choice experiments. The number of estimated coefficients would be too large for a latent class model which hardly converges.

Let the utility from alternative j in choice situation t by individual n be U_{njt}:

$$U_{njt}=\beta_n X_{njt}+\varepsilon_{njt}$$

Where X_{njt} is a vector of attributes related to alternative j for respondent n in choice scenario t; β_n is a vector of unobserved preference coefficients associated with X_{njt}; ε_{njt} are independent and identically distributed (iid) extreme values over choice tasks, individuals, and alternatives. The coefficients β_n are allowed to be randomly distributed across individuals with density $f(\beta|\Omega)$, where Ω refers collectively to the parameters of this distribution (such as the mean and covariance of β).

Conditional on the β, the probability that individual n makes a sequence of choices $i_n^*=\{i_{n1}^*,i_{n2}^*,\dots,i_{nT}^*\}$ is the product of standard MNL probability over the T choice experiments:

$$P_n\left(i_n^*|\beta\right)=\prod_{t=1}^{T}\frac{\exp\left(\beta X_{ni_{nt}^*t}\right)}{\sum_{j=1}^{J}\exp\left(\beta X_{njt}\right)}$$

Where $T=8$ since each respondent takes eight choice tasks; $J=4$ since each respondent is presented with four alternatives in a choice task.

The unconditional choice probability $P_n(i_n^*|\Omega)$ for respondent n's choice results is the integral of $P_n(i_n^*|\beta)$ over the density of β:

$$P_n\left(i_n^*|\Omega\right)=\int_\beta P_n\left(i_n^*|\beta\right)f(\beta|\Omega)d\beta$$

The unconditional probability $P_n(i_n^*|\Omega)$ does not have a closed form so that it is approximated through simulation. The parameters Ω are estimated using maximum simulated likelihood, with 1000 Modified Latin Hypercube Sampling (MLHS) draws (Hess et al., 2006). Model estimation is implemented in the R package "Apollo" using the default Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization algorithm (Hess and Palma, 2019).

The MXL models require analysts to specify which elements in the β vector should be randomly distributed and which random distribution should be used. In this paper, the coefficients for fuel types serve as alternative-specific constants and are specified to be random. Considering the underlying correlations between vehicle fuel types, flexible substitution patterns across fuel types are captured with a full variance-covariance structure among the random fuel type coefficients. For other attributes, the coefficients are specified to be fixed because: 1) this paper aims not to examine the preference heterogeneity within a group; 2) having too many random coefficients makes the model difficult to converge. Then, a normal distribution is used for the random coefficients considering that different respondents can have positive or negative tastes for a vehicle fuel type. Note that other two-sided distributions (such as a triangular or uniform distribution) have been used occasionally in choice modeling. These distributions, however, are less commonly used than the normal distribution due to their restricted distribution shape.

Table 2
Descriptive statistics of respondents' socio-economics characteristics.

Socio-economic characteristics	Levels	PHEV users (N = 173)	BEV users (N = 278)	FCEV users (N = 304)	Mainstream consumers (N = 3493)	California population
		%	%	%	%	%
Gender	Male	60	70	75	49	50
	Female	40	30	25	51	50
Age	18–34	13	10	6	13	25
	35–64	56	69	72	50	33
	65+	31	21	22	37	14
Income	less than $24,999	1	0	1	8	18
	$25,000-$49,999	5	2	4	16	19
	$50,000-$99,999	20	20	13	31	28
	$100,000-$199,999	36	32	36	27	25
	$200,000 or over	38	46	47	18	11
Education	Associate degree or lower	18	18	15	39	66
	Bachelor degree	34	36	33	30	21
	Graduate degree or higher	48	46	52	31	13
Employment	Full-time employment	50	60	66	40	49
Household Size	1	12	12	15	28	24
	2	43	43	41	44	30
	3 or more	45	45	44	27	46
Household Vehicle Number	1	18	14	17	42	31
	2 or more	82	86	83	58	69
Residential Type	Single family	87	87	83	73	66
	Apartment	13	13	16	23	30
	Mobile home or other type of housing	0	0	1	4	4

The MXL models are estimated for early adopters and mainstream consumers, respectively. Due to the scale differences, the estimated model coefficients cannot be directly compared between early adopters and mainstream consumers. Instead, the WTP measure, which is derived from the coefficient estimates of choice models, is often used to compare the ZEV preferences between consumer groups. Thus, this paper mainly compares the two groups' marginal WTP for an attribute, which is calculated using the formula below:

$$WTP_k = \frac{\partial U}{\partial k} \bigg/ \frac{\partial U}{\partial p}$$

Where WTP_k is the calculated WTP measure for attribute k, $\frac{\partial U}{\partial k}$ and $\frac{\partial U}{\partial p}$ refer to the derivatives of the utility function with respect to attribute k and purchase price, respectively.

4. Results

Table 3 shows the MXL model results for early adopters and mainstream consumers. This section mainly presents consumers' preferences and WTP for EV technical attributes, charging/refueling infrastructure, incentives, cost attributes, and fuel types. Additionally, the MXL models control for the effects of vehicle age, body type, and alternative presentation order in choice experiments. Coefficient estimates for these controlled variables are attached in Table A-1 in the Appendix.

4.1. *Technical attributes*

4.1.1. *Battery range*

The effects of battery range are specified to be specific to vehicle fuel type. Mainstream consumers appear to be indifferent to the battery range of plug-in hybrid vehicles (PHEVs and PFCEVs), but value the battery range of BEVs significantly. Differently, early adopters place a significant value on the battery range of both BEVs and plug-in hybrid vehicles.

Fig. 1 (a) and (b) show the derived WTP for the battery range of BEVs and plug-in hybrid vehicles, respectively. For BEV battery range, early adopters show a greater marginal WTP than mainstream consumers: early adopters are willing to pay $242 for a one-mile increase from a base 300-mile BEV battery range,[1] which is about 60% higher than the marginal WTP of mainstream consumers ($152). Similarly, for the battery range of plug-in hybrid vehicles, the marginal WTP is higher for early adopters than for mainstream consumers: early adopters are willing to pay $386 for a one-mile increase from a base level of 30 miles, compared to the $44 of mainstream consumers.

4.1.2. *Acceleration performance*

As expected, both early adopters and mainstream consumers prefer vehicles with better acceleration performance, especially early adopters. As shown in Fig. 2, early adopters are willing to pay $3056 for a 1-s reduction in 0–60 mph acceleration time, which is about 4 times the WTP of mainstream consumers ($777).

4.2. *Charging/refueling infrastructure availability*

A variety of charging infrastructure types are examined, including public charging (regular and fast), workplace charging (regular and fast), and home charging. The availability of public and workplace charging shows a minor role for both consumer groups. In contrast, home charging availability exerts a significant effect on the utility of BEVs for early adopters, but not for mainstream consumers. As shown in Fig. 3 (a), early adopters are willing to pay $29145 for access to home charging for BEVs.

The availability of hydrogen refueling stations is represented by the distance from home/work to a hydrogen station. The effect of hydrogen refueling station availability on the utility of PFCEVs and FCEVs is specified to be different. Model results show that this effect is only significant for PFCEVs, but not for FCEVs. Furthermore, the significant

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[1] The battery range enters the utility function in a logarithmic form to represent a decreasing marginal utility (Daziano 2013; Hackbarth and Madlener, 2016; Noel et al., 2019). Due to this non-linear specification, the marginal WTP for battery range is dependent on the level of battery range.

Table 3
MXL model estimation results.

Attributes	Fuel type	Early adopters		Mainstream	
		Est.	Std. err	Est.	Std. err
Technical attributes					
Logarithm of fuel range	All but BEV	0.68	0.20	0.62	0.10
Logarithm of battery range	PHEV, PFCEV	0.30	0.08	0.02	0.04
Logarithm of battery range	BEV	1.88	0.22	0.65	0.14
Acceleration time from 0 to 60mph	All	−0.79	0.16	−0.11	0.07
Charging/refueling infrastructure availability					
Density of public regular charging station	PHEV, PFCEV	−0.09	0.07	−0.01	0.03
Density of public regular charging station	BEV	−0.05	0.09	0.01	0.05
Density of public fast charging station	BEV	−0.04	0.08	0.04	0.04
Workplace charging not available	PHEV, PFCEV	–	–	–	–
Access to workplace regular charging	PHEV, PFCEV	0.19	0.16	0.03	0.07
Access to workplace fast charging	PHEV, PFCEV	0.18	0.15	−0.03	0.07
Workplace charging not available	BEV	–	–	–	–
Access to workplace regular charging	BEV	−0.04	0.19	−0.12	0.10
Access to workplace fast charging	BEV	0.14	0.19	−0.05	0.10
Home charging not available	PHEV, PFCEV	–	–	–	–
Access to home regular charging	PHEV, PFCEV	0.08	0.14	0.09	0.05
Home charging not available	BEV	–	–	–	–
Access to home regular charging	BEV	0.75	0.21	0.02	0.07
Distance to hydrogen refueling station	PFCEV	−0.25	0.08	−0.05	0.05
Distance to hydrogen refueling station	FCEV	−0.11	0.07	0.00	0.05
Charging time					
Regular charging time	PHEV, PFCEV	−0.21	0.43	0.13	0.23
Regular charging time	BEV	−0.38	0.24	−0.27	0.17
Fast charging time	BEV	−0.17	0.05	−0.12	0.03
Cost					
Purchase price	All	−0.26	0.03	−0.14	0.02
Fuel cost per 100 miles	All but BEV	−0.01	0.08	−0.07	0.03
Electricity cost per 100 miles	PHEV, BEV, PFCEV	0.05	0.05	0.10	0.02
MPG-e	All	0.09	0.03	0.10	0.02
Electric MPG-e	PHEV, PFCEV	0.06	0.03	0.08	0.02
Annual maintenance cost	All	−0.03	0.01	−0.03	0.00
Incentives					
HOV lane access for 3 years	PHEV, BEV, FCEV, PFCEV	0.28	0.08	0.02	0.05
Monetary incentive	PHEV, BEV, FCEV, PFCEV	0.08	0.01	0.05	0.01

effect of hydrogen refueling stations on PFCEVs is only found for early adopters, not for mainstream consumers. On average, early adopters are willing to pay $955 for a one-mile reduction in the distance from home/work to a hydrogen refueling station, as shown in Fig. 3 (b).

4.3. *Charging time*

The coefficient of charging time is specified to be specific to vehicle fuel types. Neither early adopters nor mainstream consumers value the reduction in the charging time of plug-in hybrid vehicles. In contrast, the effect of charging time of BEVs is found to be significant, with nuanced results depending on consumer groups and charger types. As shown in Fig. 4, mainstream consumers are more sensitive to BEV regular charging time than early adopters: mainstream consumers show a WTP of $1927 for a 1-h reduction in 100-mile regular charging time, which is roughly 32% higher than the WTP of early adopters ($1461). Similarly, for BEV fast charging time, mainstream consumers are willing to pay $861 for a 1-min reduction in 100-mile fast charging time, which is about 31% higher than the WTP of early adopters ($657).

4.4. *Incentives*

The effects of monetary incentives are found to be significant for both groups, especially for mainstream consumers. For non-monetary incentives, granting access to HOV lanes is found to be effective only for early adopters, not for mainstream consumers. Early adopters show a WTP of $10979 for accessing HOV lanes, as shown in Fig. 5.

4.5. *Cost attributes*

Mainstream consumers are more sensitive to the cost attributes (e.g., fuel cost per 100 miles, miles per gallon, and annual maintenance cost) than early adopters. As shown in Fig. 6 (a), mainstream consumers are willing to pay $462 for a one-dollar reduction in fuel cost per 100 miles, while early adopters appear to be indifferent to the reduction in fuel cost. The electricity cost per 100 miles (applicable to PHEVs, BEVs, and PFCEVs) is not significant for early adopters too, but it shows a surprisingly positive correlation with vehicle utilities for mainstream consumers.

Miles per gallon-equivalent (MPG-e) is used in choice experiments for different vehicle fuel types. The average MPG-e in choice experiments for an ICEV, HEV, PHEV (gasoline mode), BEV, FCEV, and PFCEV (hydrogen mode) are 27, 41, 41, 107, 61, and 60, respectively. For the plug-in hybrid powertrains (PHEVs and PFCEVs), the choice experiments also present the electric MPG-e which refers to the MPG-e when the vehicle is operating in electric mode. Fig. 6 (b) shows the marginal WTP for improving one MPG-e for both groups. Mainstream consumers are willing to pay $722 for one MPG-e increase, which is 108% higher than the WTP of early adopters. Similarly, for one unit increase in electric MPG-e, mainstream consumers show a marginal WTP of $574, which is 170% higher than early adopters, as shown in Fig. 6 (c).

The WTP for a reduction in annual maintenance cost is shown in Fig. 6 (d). Mainstream consumers are willing to pay $2358 for a $100 reduction in annual maintenance cost, which is about twice the WTP of early adopters.

4.6. *Fuel type*

The coefficients for vehicle fuel types are specified to be random. The random effects are allowed to be correlated using a full variance-covariance structure to capture flexible substitution patterns across vehicle fuel types. The estimated Choleski factors (attached in Table A-2 in the Appendix) are used to calculate correlation coefficients between fuel types. As shown in Fig. 7, there are positive substitution effects among the non-ICEV fuel types. In particular, when early adopters prefer PHEVs to ICEVs, they tend to prefer HEVs over ICEVs. When early adopters show positive preferences for FCEVs compared to ICEVs, they tend to prefer PFCEVs to ICEVs. For mainstream consumers, HEVs and PHEVs, PHEVs and BEVs, BEVs and PFCEVs, and PFCEVs and FCEVs are strongly positive substitutes compared to ICEVs.

5. Discussion

This section discusses the implications of results that are critical to electric mobility, including battery range, charging infrastructure deployment, costs and incentives. Limitations of this study and avenues for future research are also discussed.

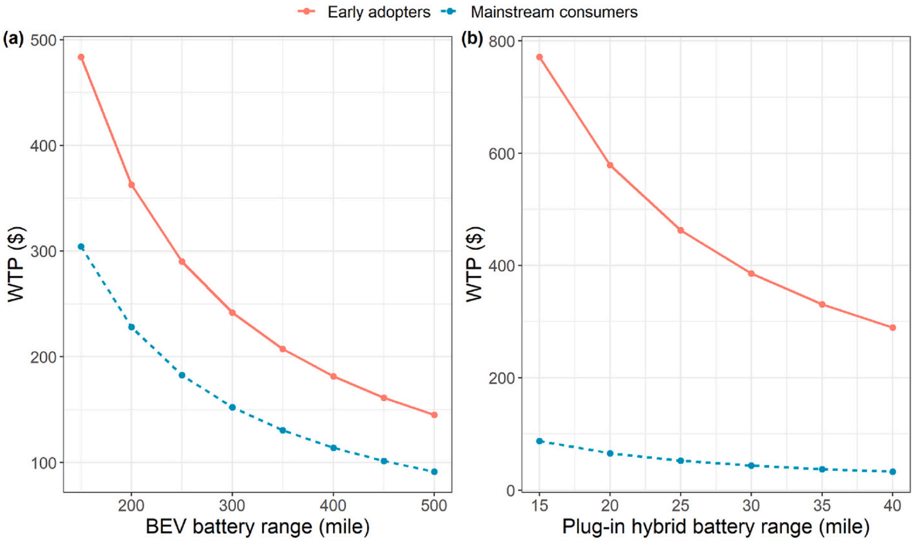

Fig. 1. Marginal WTP for battery range.

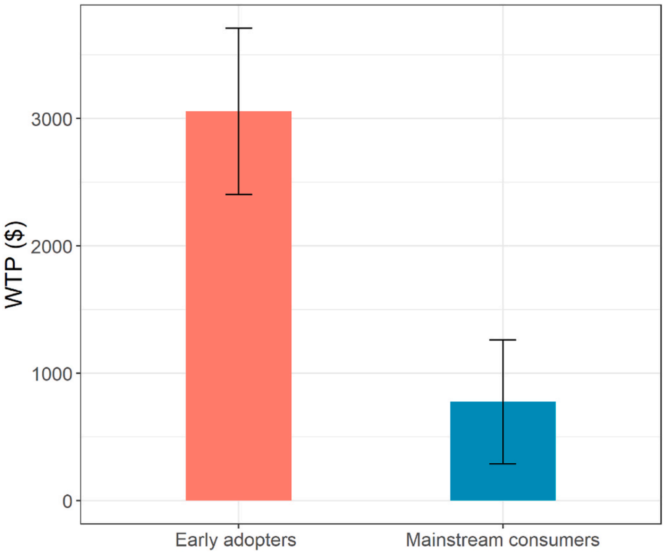

Fig. 2. Marginal WTP for a 1-s decrease in 0–60 mph acceleration time.

5.1. Battery range

This study finds that early adopters place a greater value on battery range than mainstream consumers. This finding is consistent with the results of Axsen et al. (2016) which compared PEV early adopters with mainstream consumers in Canada. The mainstream consumers' lower sensitivity to battery range may be related to ZEV knowledge and familiarity.[2] Mainstream consumers are found to show limited awareness of ZEVs, lack of ZEV experiences, and confusion about ZEV-specific attributes (Caperello and Kurani, 2012; Krause et al., 2013; Axsen et al., 2017; Long et al., 2019; MacInnis and Krosnick, 2020; Hardman et al., 2020). In Denmark, Jensen et al. (2013) compared participants' PEV preferences before and after a three-month trial with a BEV. Results showed that the importance of the BEV range doubled after the trial, with the WTP rising from 65 €/km to 134 €/km. Focusing on the Nordic countries, Noel et al. (2019) found that the WTP for BEV battery range in Norway and Iceland was approximately twice that of Finland. They attributed the lower WTP in Finland to a lack of consumer awareness and experiences with PEVs. Based on a SP survey among 2123 mainstream consumers in Canada, Kormos et al. (2019) found that battery range had no significant impact on PEV preferences. These findings together suggest that mainstream consumers' WTP for battery range might be underestimated in existing literature based on stated preference surveys due to the lack of experience and familiarity with ZEVs.

5.2. Charging infrastructure

Early adopters show high WTP for home charging. This result echoes Axsen et al. (2016) which reported that PEV early adopters in Canada were willing to pay $23,178 for access to Level-2 home charging. These high WTP values highlight the significant importance of home charging availability for early adopters. In contrast, mainstream consumers are found to show a much lower WTP for home charging availability. This is possibly because mainstream consumers attach greater importance to cost attributes (e.g., fuel and maintenance costs) instead of charging attributes in their vehicle purchase decisions.

Both early adopters and mainstream consumers are indifferent to the availability of public charging infrastructure. Note that existing literature on the effects of public charging infrastructure show mixed findings. While some studies highlight its significant impacts on ZEV preferences (Lieven, 2015; Mersky et al., 2016; Hackbarth and Madlener, 2016; Narassimhan and Johnson, 2018; Jia and Chen, 2021), several studies indicate a minor role of public charging infrastructure (Qian et al., 2019; Miele et al., 2020; Danielis et al., 2020; Hardman et al., 2020; Bansal et al., 2021).

These mixed findings on charging infrastructure might be related to the nature of SP choice experiments which often show inherent hypothetical bias (Train, 2009). The 2019 CVS includes an add-on survey on PEV owners about their actual availability of home charging, workplace charging, and public charging. Moreover, the add-on survey asked PEV owners to judge their overall experience with PEVs based on a seven-point Likert scale (i.e., I hate it, a failure, unsatisfactory, satisfactory, excellent, delightful, I love it). We then developed an ordered

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[2] Another possible explanation is that ZEV early adopters are more likely to be those driving more (Plötz et al., 2014) and thus value the battery range more. In this study, we test the interaction of battery range and household annual mileage per vehicle which is divided into three categories: lower than 5000 miles, between 5000 and 11500 miles, and greater than 11500 miles. Estimated coefficients for the interaction terms represent the effects of battery range for travelers in different mileage categories. Model results suggest no significant differences in battery range effects across different mileage categories.

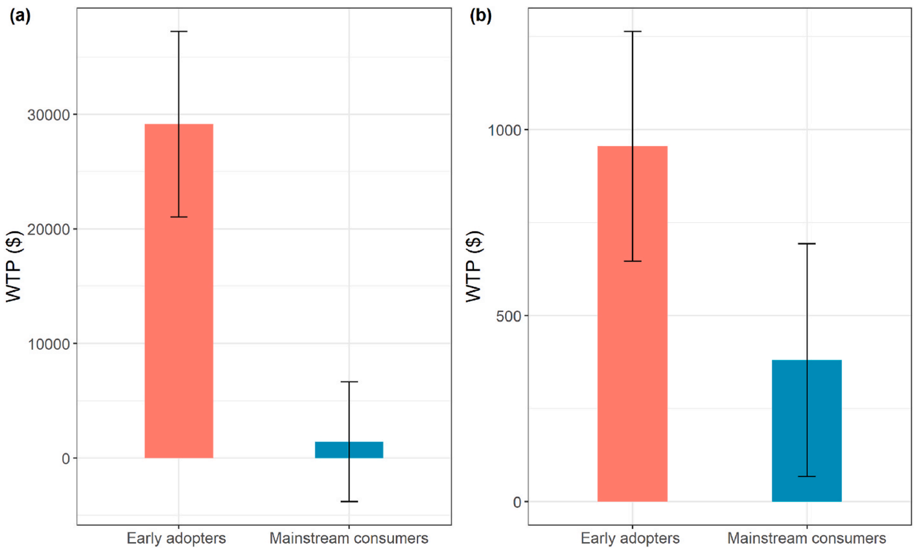

Fig. 3. Marginal WTP for: (a) Home charging availability for BEVs. (b) One-mile decrease in distance to hydrogen refueling station from home/work for PFCEVs.

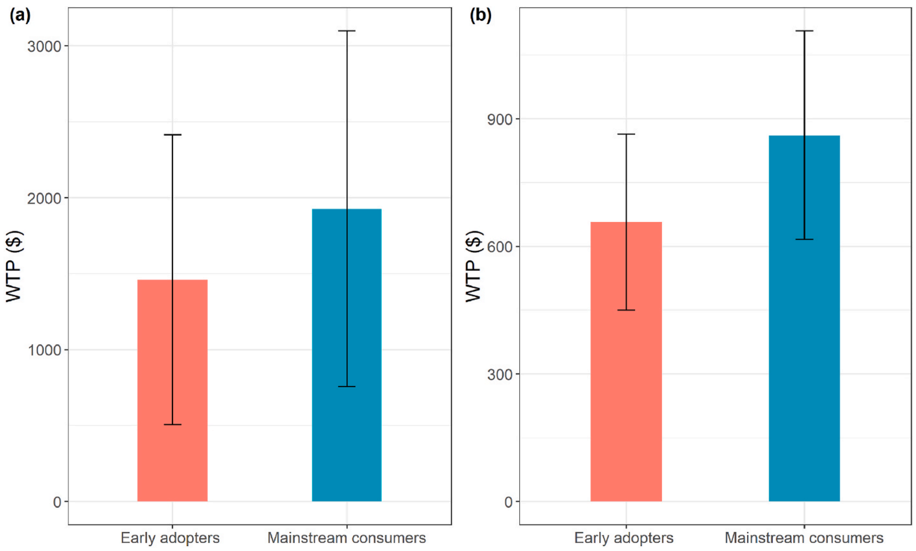

Fig. 4. Marginal WTP for: (a) 1-h reduction in BEV regular charging time for a 100-mile charge (b) 1-min reduction in BEV fast charging time for a 100-mile charge.

logit model to examine the impacts of actual charging availability on the PEV usage experience. The control variables for the ordered logit model include PEV owners' socio-economic characteristics, household characteristics, PEV vehicle attributes, and travel patterns. Model results are attached in Table A-3 in the appendix.

According to the ordered logit model results, home charging availability significantly correlates with BEV usage experiences while the role of workplace and public charging stations (regardless of regular or fast charging) is minor. These findings echo the results based on SP choice experiment data, which highlights the importance of home charging availability for BEV adoption. The public charging infrastructure results, however, should be interpreted cautiously. In this paper, the public charging availability is a generic measure without differentiating local destinations charging from long-distance travel charging. Considering the range anxiety of BEV users, travelers may show very different preferences for public charging infrastructure between the two traveling scenarios.

5.3. *Charging time*

Concerning charging time, the effects of fast charging time are more significant than regular charging time, which is consistent with Li et al. (2020b). Furthermore, mainstream consumers are found to be more sensitive to charging time than early adopters. Mainstream consumers' WTP for fast charging time is about $861 for a 1-min reduction in 100-mile charging time, which is 31% higher than the WTP of early adopters ($657). Comparing the WTP values across studies is difficult due to varying levels of the charging time attribute. For example, Danielis et al. (2020) reported that the WTP for 1 min reduction in fast charging time is 87 €, which is much lower than our estimates. In Danielis et al. (2020), the fast charging time is designed with three levels (25, 40, and 55 min), while the three fast charging time levels for this study are 5, 15, and 25 min, respectively. Qian et al. (2019) reported a WTP value that lies between the estimates of Danielis et al. (2020) and this study: consumers are willing to pay 2424 RMB to save 1 min of fast charging time. The high marginal WTP for fast charging time (mainstream consumers in particular) highlights the necessity of fast charging technology research and development for EVs to gain mass market

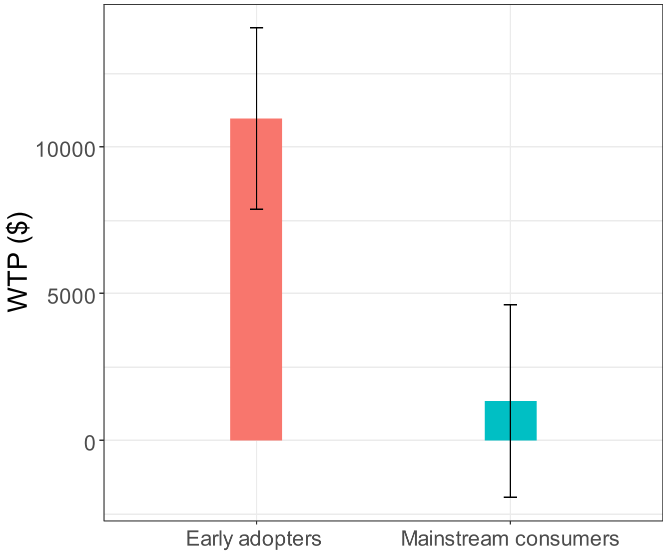

Fig. 5. WTP for HOV lane access.

penetration.

5.4. Incentives and costs

Monetary incentives (federal tax credits and state rebates) are found to significantly affect ZEV preferences, especially for mainstream consumers. However, the purchase subsidy is not sustainable and will be gradually phased out. The abolishment of purchase subsidies will significantly reduce consumers' ZEV purchase intention (Lu et al., 2020). Note that the negative effects of cancelling monetary incentives can be alleviated due to the gradually decreasing upfront costs of ZEVs. As Slowik et al. (2022) predict, the purchase price parity between ICEVs and BEVs with up to 300-mile of range will emerge before 2030.

Moreover, researchers and policymakers are considering shifting ZEV incentive measures from the purchase stage to the vehicle usage stage (Nunes et al., 2022; Lu et al., 2022). This paper finds that accessing HOV lanes significantly affects early adopters' preferences for ZEVs, with a WTP of $10979. Though not showing the specific WTP values for HOV lane access, Jenn et al. (2020) surveyed over 14000 PEV adopters and reported that HOV lane access is one of the top three reasons for consumers to adopt PEVs in California. Similarly, Bjerkan et al. (2016) found that HOV lane access was a core incentive for many BEV adopters in Norway. In contrast, the HOV lane access is not appreciated by mainstream consumers.[3] This result suggests that further innovative incentive policies targeted at vehicle usage stages should be explored to achieve mass ZEV market share.

As expected, mainstream consumers are more sensitive to operating costs (e.g., fuel and maintenance). However, the challenge is that mainstream consumers tend to show misconceptions about the operating costs of PEVs, such as believing that PEVs have higher maintenance costs than ICEVs (MacInnis and Krosnick, 2020). Thus,

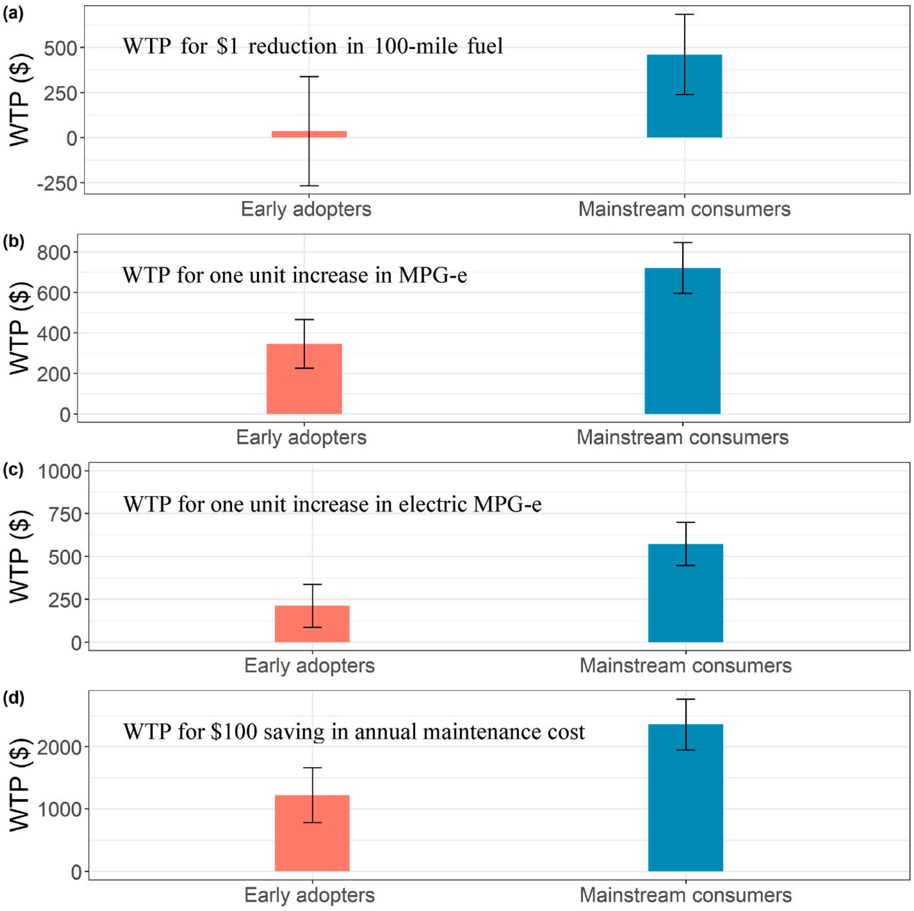

Fig. 6. Marginal WTP for cost-related attributes.

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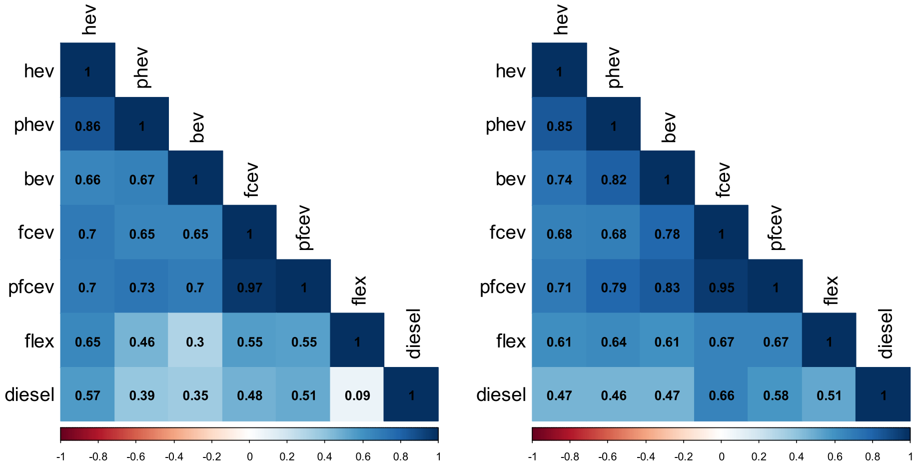
[3] Note that the interaction term of HOV lane access and household driving mileage is also tested. Results do not show any significant differences in the effects of HOV lane access for different driving mileage categories.



(a) (b)

Fig. 7. The correlation coefficient between fuel types for: (a) early adopters; (b) mainstream consumers.

educational campaigns on the operational cost-saving benefits compared to ICEVs can be beneficial for PEV mass market penetration. Lastly, the high sensitivity to operating costs indicates a challenge for the adoption of FCEVs which have higher fuel costs than ICEVs. As noted by Hardman et al. (2017) and Shin et al. (2019), the cost of hydrogen refueling is identified as one of the major barriers to FCEV adoption. Thus, it is essential to address the high fuel cost barrier to make FCEVs competitive among other vehicle powertrain types.

5.5. Limitations

The authors note several limitations of this study. As with prior ZEV adoption studies based on SP choice experiments, the results may have hypothetical bias, in which respondents' stated choices do not accurately reflect their real-world behaviors. The hypothetical bias is especially relevant to ZEV adoption studies that are based on the stated preferences of mainstream consumers who tend to show misconceptions about ZEVs (Axsen et al., 2017; Long et al., 2019, etc.). This informs future research avenues to consider the role of knowledge in ZEV preference modeling (Giansoldati et al., 2020; Rotaris et al., 2021).

Second, the choice experiments did not differentiate fast charging stations along freeways from local travel destinations. Future work should design choice experiments to examine whether the two traveling scenarios show different preferences for fast charging facilities, given the range anxiety of BEV users, especially for long-distance travel (Xu et al., 2020).

Third, this paper ignores preference heterogeneity within the group of mainstream consumers (Axsen et al., 2015, 2016; Hackbarth and Madlener, 2016; Ferguson et al., 2018; Kormos et al., 2019; Liao et al., 2019; Abotalebi et al., 2019; Gong et al., 2020) and within the group of early adopters (Hardman et al., 2016; Lee et al., 2019). In particular, we do not differentiate between PHEV, BEV, and FCEV adopters due to the low number of respondents for each ZEV type. The preference heterogeneity within the group of early adopters should be considered in future research when a sufficient sample size can be obtained for adopters of each ZEV type.

Lastly, this study only examines ZEV adopters in California. California is the leading state in ZEV adoption in the U.S., with its own specific characteristics such as ZEV incentive policies, charging/refueling infrastructure deployment, consumer demographics, and cultural and political contexts. The specific results (e.g., WTP values for ZEV attributes) may not hold for other study regions and should be generalized with caution. However, this study informs ZEV policies to consider the differences in ZEV preferences between early adopters and mainstream consumers. Future studies should aim to investigate whether and how early adopters' ZEV purchase decisions differ from mainstream consumers in other regions. The findings of these similar studies help policymakers better understand the role of ZEV attributes in encouraging ZEV adoption in different stages.

6. Conclusion and policy implications

This paper compares preferences for ZEV attributes between early adopters and mainstream consumers. Mixed logit models with error components are developed based on vehicle fuel type SP choice experiment data in California, U.S. Model results demonstrate the high correlation between alternative fuel vehicle types, which should be explicitly considered in future research on ZEV adoption choice modeling. Furthermore, this study moves beyond the socio-economic characteristics and dives into the influential factors of ZEV purchase decisions for early adopters and mainstream buyers, respectively. The varied preferences for ZEV attributes between the two consumer groups highlight that governments and manufacturers should develop tailored policies and marketing strategies in different ZEV adoption stages.

Mainstream consumers show high sensitivity to cost-related attributes in their ZEV purchase decision-making. First, monetary purchase incentives are critical for mainstream consumers to adopt ZEVs. As the purchase subsides gradually be phased out, ZEV manufacturers should devote particular attention to decrease battery costs to mitigate the cost disparity between ZEVs and conventional gasoline vehicles. Second, educational and marketing campaigns on the operational cost-saving benefits can be effective for mass market penetration. Additionally, research and development for PEV fast charging technology are needed since mainstream consumers show high WTP for a reduction in fast charging time.

For early adopters, different measures are needed to ensure that those who have adopted ZEVs do not abandon them in subsequent vehicle purchases. Home charging infrastructure installation cost discounts and maintenance service, and HOV lane access can be effective to encourage early adopters to choose ZEVs. Moreover, the battery range and vehicle acceleration performance should be underlined in the marketing strategies targeted at early adopters.

Declaration of interest

None.

Funding

This work is supported by the Fundamental Research Funds for the

Central Universities, CHD [grant number 300102342108].

CRediT authorship contribution statement

Wenjian Jia: Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition. Zhiqiu Jiang: Formal analysis, Visualization, Writing – original draft, Writing – review & editing. Qian Wang: Formal analysis, Visualization, Writing – original draft, Writing – review & editing. Bin Xu: Formal analysis, Writing – review & editing. Mei Xiao: Formal analysis, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix

Table A-1
Estimated coefficients for the controlled variables

Attributes	Early adopters		Mainstream Consumers	
	Est.	Std. err	Est.	Std. err
Model year: new	–	–	–	–
Model year: used 3 years old	−1.20	0.13	−0.64	0.06
Model year: used 6 years old	−1.49	0.18	−0.76	0.08
Subcompact car	–	–	–	–
Compact car	0.53	0.16	0.69	0.07
Midsize car	0.81	0.17	0.80	0.08
Large car	−0.12	0.22	−0.30	0.10
Sports car	−0.04	0.22	0.11	0.10
Subcompact cross-over	0.01	0.18	−0.02	0.09
Compact cross-over/SUV	0.78	0.17	0.71	0.08
Midsize cross-over/SUV	1.04	0.18	0.75	0.09
Full-size/large SUV	0.25	0.24	−0.19	0.13
Small van	−0.27	0.22	−0.94	0.11
Full-size/large van	−1.25	0.25	−1.06	0.12
Small pickup truck	−0.56	0.23	−0.53	0.10
Full-size/large pickup truck	−0.57	0.27	−0.34	0.12
Brand type: standard	–	–	–	–
Brand type: premium	0.31	0.14	−0.35	0.07
Alternative order 1	–	–	–	–
Alternative order 2	0.02	0.06	0.07	0.03
Alternative order 3	−0.04	0.07	−0.09	0.03
Alternative order 4	−0.12	0.06	−0.27	0.03

Table A-2
Choleski factorization of the full variance-covariance matrix of the random coefficients for the fuel type

Coefficient estimates	Early adopters		Mainstream Consumers	
	Est.	Std.err	Est.	Std.err
Mean: gas	–	–	–	–
Mean: hev	1.31	0.26	−0.61	0.07
Mean: phev	0.28	0.77	−2.29	0.37
Mean: diesel	−1.45	0.53	−2.80	0.17
Mean: bev	−4.84	1.72	−2.54	0.96
Mean: fcev	0.98	0.33	−2.74	0.15
Mean: pfcev	−0.15	0.88	−4.15	0.42
Mean: flex	−0.41	0.32	−1.16	0.07
Sigma: hev	1.82	0.23	1.94	0.08
Sigma: phev_hev	1.83	0.29	2.17	0.10
Sigma: phev	1.10	0.22	1.35	0.08
Sigma: diesel_hev	1.64	0.34	1.24	0.16
Sigma: diesel_phev	−0.56	0.59	0.34	0.18
Sigma: diesel	2.32	0.45	2.32	0.14
Sigma: bev_hev	2.11	0.37	2.39	0.13
Sigma: bev_phev	0.67	0.59	1.17	0.14
Sigma: bev_diesel	0.08	0.30	0.28	0.17
Sigma: bev	2.33	0.16	1.82	0.08
Sigma: fcev_hev	2.40	0.35	2.06	0.16
Sigma: fcev_phev	0.33	0.34	0.64	0.19
Sigma: fcev_diesel	0.42	0.26	1.11	0.14
Sigma: fcev_bev	0.80	0.25	0.95	0.14
Sigma: fcev	2.24	0.20	1.57	0.12
Sigma: pfcev_hev	2.47	0.37	2.33	0.14
Sigma: pfcev_phev	0.90	0.37	1.15	0.16
Sigma: pfcev_diesel	0.71	0.24	0.77	0.14

(*continued on next page*)

Table A-2 (*continued*)

Coefficient estimates	Early adopters		Mainstream Consumers	
	Est.	Std.err	Est.	Std.err
Sigma: pfcev_bev	0.89	0.24	0.93	0.12
Sigma: pfcev_fcev	2.02	0.20	1.42	0.11
Sigma: pfcev	0.58	0.32	0.74	0.15
Sigma: flex_hev	1.19	0.31	1.24	0.10
Sigma: flex_phev	−0.34	0.39	0.45	0.11
Sigma: flex_diesel	−0.73	0.34	0.46	0.10
Sigma: flex_bev	−0.19	0.32	0.20	0.10
Sigma: flex_fcev	0.52	0.26	0.36	0.11
Sigma: flex_pfcev	0.95	0.38	−0.05	0.23
Sigma: flex	−0.32	0.43	1.40	0.07

Table A-3

Ordered logit model results for the PEV usage experiences.

	BEV model			PHEV model		
Variables	Est.	Std. error	T value	Est.	Std. error	T value
Male	0.02	0.29	0.05	0.24	0.31	0.76
Age: 18–34	−0.71	0.42	−1.69	−0.68	0.45	−1.50
Age: 65 or older	0.01	0.38	0.02	0.26	0.39	0.68
Graduate degree	0.08	0.28	0.28	0.19	0.31	0.61
Household income: $200k or more	0.65	0.30	2.13	−0.52	0.35	−1.47
Multi-car (2+) households	−0.60	0.43	−1.39	−0.45	0.43	−1.05
Solar panel installation	0.63	0.32	1.99	0.84	0.37	2.28
Battery range	0.85	0.23	3.71	0.74	0.26	2.88
Drive every day	0.33	0.41	0.80	1.18	0.59	2.01
Home L2 charge access	0.56	0.30	1.87	−0.20	0.41	−0.49
Workplace charge access	−0.07	0.29	−0.25	0.10	0.35	0.28
Public charge access	0.01	0.42	0.01	0.15	0.39	0.39
Public fast charge access	0.07	0.34	0.19	0.32	0.66	0.48

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