CONSUMER HETEROGENEITY IN ADOPTING ELECTRIC VEHICLES: A LATENT CLASS APPROACH

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Abstract

While alternative fuel vehicles have strong potential advantages in reaching energy security, environmental and climate goals, their adoption is yet slow. In this paper, we use data from an SP experiment among ca. 3,000 Dutch drivers to elicit individual preferences for full electric vehicles. We estimate a panel latent class model based on the *total costs of ownership* approach that includes monetary and non- monetary costs, and sketch psychological profiles of potential car user types. We identify 4 classes with distinctly different preferences for EVs and their attributes that are largely determined by individual knowledge, attitudes and environmental identity. Further we find that one of the important barriers for EV adoption is time spent on fast (station) charging. Implications for policy and practice are discussed.

Introduction

Electric mobility possessing strong potential in decreasing energy dependency and improvement in environmental conditions such as reduction in particulate matter and CO2 emissions is in its initial stage to penetrate the automobile markets as a step towards a more sustainable mobility. Various studies on full electric vehicle adoption (Struben and Sterman 2008, Scierzcula et al. 2013) suggest that such a transition – from fossil fuel fleet to electric fleet – would expectedly take long, and would need to be accompanied with various long-term stimuli. In this paper, we address the issue of consumer heterogeneity in the process of electric vehicle (EV) adoption, and related to this the issue of policy instrument heterogeneity that is necessary in order to stimulate the various consumer groups during EV adoption pace.

The data

We use SP data collected in 2012 in the Netherlands among a representative sample of approx. 3,000 car drivers. The experiment included a choice between 3 types of engines: conventional gasoline engine, full electric engine and a hybrid engine for a particular vehicle assumed to be pre selected by a respondent. The alternatives were described by 10 attributes: purchasing price, expected repurchasing price, operational costs, max range, min range, the amount of CO2 emissions and the possibility for a tow hitch. In addition, the vehicle with full electric engine contained information on slow (regular) charging time, detour and waiting time, and charging time at a fast charging facility. Each respondent has filled out 6 choice cards, in addition to some other questions related to current car, travel behavior, perceptions of and attitudes towards alternative fuel vehicles, purchasing preferences and some personal and household demographic data.

Methodology

Following the observations during the pilot phase, choice heuristics was identified consistent with the notion of total cost of ownership. In particular, respondents tended to cluster presented attributes in groups representing (yearly) costs associated with vehicle ownership (consisting of fuel/charging costs and depreciation), vehicle environmental impact given the yearly mileage travelled, vehicle towing potential, and for the EV option – frequency of and time spent on charging. To meet these heuristics, utility function specification was chosen so that it reflected what can be called generalized total costs of ownership: costs in money, time and environmental impact that were assumedly associated with each vehicle. Using the Biogeme software (Bierlaire 2003, 2008), a basic choice model was estimated as mixed logit (constants were assumed to be normally distributed).While the mixed logit model offered an improved log likelihood compared to its multinomial counterpart and revealed the presence of taste heterogeneity, it does not shed light on its sources. As a consequence, we have estimated a number of latent class models, LC (see for example Greene and Hensher 2003). Direct advantages of these models are that they account for unobserved heterogeneity in taste among respondents, take account of the panel structure of the data, as well as allow identifying separate groups/classes of respondents with similar tastes. Results of an LC model with 4 classes are reported in Table 2.

Results

Four classes of potential EV consumers are identified (corresponding to Table 2). They can be characterized as follows (1) alert pro-environmentalists; (2) young consumers with strong EV attitude; (3) young high-educated consumers with weak EV attitude; (4) low-educated consumers with weak EV attitude. Group membership was mostly determined by the psychographic variables (such as environmental identity, subjective knowledge about AFV technology, and own attitude towards EVs) rather than by socio-demographic variables (where age and education were significant determinants, while gender and income were not).

In modeling individual preferences, all choice coefficients were assumed to be group-specific. The monetary attribute and the station charge attribute stayed significant for all groups. Alert Pro-Environmentalists (20%) value reductions in CO_2 emissions, time spent on station charging and a hybrid vehicle the highest of all groups, while attach no positive value to a tow hitch or to EV relative to a conventional vehicle. Young Pro-EV consumers (28%) value both EV and hybrid vehicles significantly positively in comparison to a conventional car; CO_2 emissions per se do not seem to affect their choice. Young Anti-EV consumers (41%) have a negative valuation of EV and a positive valuation of a hybrid vehicle; they also attach a positive WTP to a tow hitch and to the time spent on slow and station charging. Finally, Low-Educated Anti-EV consumers (11%) have a highly negative valuation of both EV and hybrid vehicles, while their WTP for towing potential is the highest among all groups.

Conclusions and policy implications

Our analyses show that the LC model is highly useful for analyzing consumer preferences for alternative fuel vehicles. Furthermore, we find that psychographic constructs such as knowledge about alternative fuel technologies, personal environmental identity and the attitude towards EVs determine by far the way that preferences for alternative vehicles are formed. This calls for more research into the factors underlying the psychological constructs that can be of use for policy and practice. Furthermore, we find that among estimated WTP indicators, value of time associated with station charging is, depending on the group, 5 to 10 times higher than the value of time found in the broader literature of transportation research (Knockaert et al. 2012, Bockarjova et al. 2012). This points at high disutility associated with long charging times (on average, 40min including expected detour and waiting), and the necessity for fast charging infrastructure that is able to meet this insistent need. Further research into the sources of disutility associated with station charging is called for (splitting into detour, waiting and charging itself). Finally, given the findings of current research on the role of charging time valuation as well as those of Sierzchula et al. (2013), it appears that the effectiveness of monetary incentives strongly depends on the presence of charging infrastructure. Further research into this matter may shed light on the reasons why current policies have failed to achieve desirable results so far in stimulating large-scale EV adoption (Chandra et al. 2010; Beresteanu and Li 2011), and how this can effectively be addressed in the future.

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Table 1. Estimation results of latent class logit model with panel structure (# classes=4) with respective WTP estimates

	Class 1		**Class 2**		**Class 3**		**Class 4**	
Group size:	*20%*		*28%*		*41%*		*11%*	
Group membership param.:								
Class const.			-1.570	**	5.320	***	5.610	***
			(0.596)		(0.523)		(0.658)	
Age			-0.035	***	-0.029	***	-0.008	
			(0.006)		(0.006)		(0.007)	
Male			0.065		-0.028	..	0.304	
			(0.154)		(0.155)		(0.187)	
College educ.ation			0.169		0.325	**	-0.648	***
			(0.146)		(0.145)		(0.203)	
High income			0.107		0.344	*	0.043	
			(0.186)		(0.182)		(0.232)	
No income info			-0.060		-0.108	..	-0.146	
			(0.162)		(0.162)		(0.197)	
Subj. knowledge			-0.130	**	-0.235	***	-0.267	***
			(0.058)		(0.058)		(0.070)	
Environmental ID			0.068		-0.179	**	-0.224	**
			(0.077)		(0.075)		(0.089)	
High range anxiety			-0.328		-0.086	..	0.194	
			(0.233)		(0.226)		(0.255)	
Descriptive norm			-0.051		0.037	..	0.086	
			(0.104)		(0.108)		(0.131)	
Own attitude to EV			0.841	***	-0.471	***	-1.060	***
			(0.129)		(0.123)		(0.144)	
Utility specification param.:								
Hybrid const.	2.750	***	0.997	***	0.458	***	-2.500	***
	(0.246)		(0.091)		(0.061)		(0.248)	
EV const.	0.539		1.820	***	-1.710	***	-3.020	***
	(0.334)		(0.098)		(0.142)		(0.283)	
Tot.Mon.Costs (€/year)	-0.635	***	-0.671	***	-1.100	***	-0.488	***
	(0.128)		(0.049)		(0.049)		(0.101)	
Slow charge (h/year)	-0.917	**	-0.461	***	-1.120	***	-0.623	
	(0.343)		(0.117)		(0.252)		(0.393)	
Station charge (h/year)	-0.067	***	-0.020	***	-0.045	***	-0.015	**
	(0.015)		(0.002)		(0.008)		(0.007)	
Tow hitch	0.003		0.255	***	0.453	***	0.863	***
	(0.116)		(0.052)		(0.057)		(0.205)	
CO2 emissions (t/year)	-0.637	**	-0.005		-0.122	***	-0.146	**
	(0.243)		(0.043)		(0.030)		(0.058)	
WTP:								
Hybrid const. (€/year)	**€ 4,331**		**€ 1,486**		**€ 416**		**-€ 5,123**	
EV const. (€/year)	**€ 849**	n.s.	**€ 2,712**		**-€ 1,555**		**-€ 6,189**	
VOT-slow charging (€/h)	**€ 1.44**		**€ 0.69**		**€ 1.02**		**€ 1.28**	n.s.
VOT-station charging (€/h)	**€ 105**		**€ 30**		**€ 41**		**€ 31**	
tow hitch (€/year)	**€ 4.50**	n.s.	**€ 380**		**€ 412**		**€ 1,768**	
CO2 emissions (€/t)	**€ 1,003**		**€ 6.83**	n.s.	**€ 111**		**€ 299**	
Estimation report:								
N estimated parameters:	*61*							
Sample size:	*17,862*							
Init log-likelihood:	*-17,635*							
Final log-likelihood:	*-14,847*							

, * - statistical significance at 5% and 1% level, respectively.