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Assessing drivers' preferences for hybrid electric vehicles (HEV) in Spain

Djamel Rahmani[1] and Maria Loureiro[2]*

Abstract

With the aim of analyzing preferences for hybrid electric vehicles (HEVs), two stated preference methods (a contingent valuation exercise and a discrete choice experiment (DCE) were used in a survey conducted in a representative sample of Spanish drivers. Overall, our findings show robustness between the willingness to pay (WTP) estimates elicited via a latent class model (LCM) and those from a payment card question, leading to an average positive WTP, although in general insufficient to cover the extra cost of HEVs. Furthermore, drivers who buy HEVs do not always do so for environmental reasons, but rather for reputational issues related to their self-image. Moreover, the lack of interest for HEVs may be motivated by different reasons, including the low level of information related to this technology. Thus, in order to increase the market share for HEV vehicles in the Spanish market, informative campaigns and additional economic incentives may be designed.

Keywords: Hybrid electric vehicles, Latent class model, Willingness to pay, Discrete choice Experiment.

Classification codes: D, H, M, O, Q

[1] CREDA-UPC-IRTA, Castelldefels, Barcelona, Spain.

[2]. Department of Economic Analysis, University of Santiago de Compostela, Spain.[*] Maria Loureiro is the corresponding author. Email: maria.loureiro@usc.es (ML).

1. Introduction

Global warming and air pollution are global problems caused by an increase in the world's total greenhouse gases (GHG) and pollution. The degradation of air quality has harmful implications for human health and wellbeing, biodiversity, and the environment. Although it is a global problem requiring international solutions, it also needs the existence of local initiatives adapted to the specific sectorial characteristics of each country and pollution problems (European Environment Agency, 2008).

The total GHG emissions of European Union (EU) has decreased by 22% between 1990 and 2015, due in large part to the economic recession in EU and its member countries' policies (Eurostat, 2017). Despite the reduction of the EU's total GHG emissions, the transport sector has increased its contribution significantly since 1990. In fact, transport emitted 23% of the EU's GHG emissions in 2015 (Eurostat, 2017). For this reason, decarbonizing the transport sector, especially road transport which contributes about two thirds of the transport sector GHG emissions (European Commission, 2017), will be the EU's great challenge for the next years.

Despite the seriousness of pollution, the market share of environmentally friendly vehicles or alternative fuel vehicles (AFVs) (see definition in Hackbarth and Madlener, 2013) in many countries is still very small. In the first quarter of 2017, 212,945 units of AFVs have been sold in the EU, showing a growth rate of 37.6%, compared to the same period in 2016 (ACEA, 2017).

Confounding earlier findings, regarding the capability of AFVs to keep gaining market share in the future justify the need to conduct a study where preferences towards environmental and economic attributes were assessed simultaneously. In this research paper, two stated preference methods, a discrete choice experiment (DCE) (Louviere et al., 2010), and a payment card format were used to elicit drivers' preferences towards vehicle type and attributes. The DCE makes it possible to disaggregate the individual's welfare assigned to a given vehicle into marginal utilities (and respective marginal valuations) corresponding to each one of the different attributes. In fact, DCEs are commonly used to elicit preferences for hybrid electric vehicles (HEVs) [Beck et al., 2013; Caulfield et al., 2010; Potoglou and Kanaroglou, 2007). Most of the studies were carried out in North America (Hidrue et al., 2011; Kahn, 2007; Klein, 2007; Lin et al., 2012; Partridge, 2013; Thatchenkery and Beresteanu, 2008), or in Australia (Abdoolakhan, 2010; Beck et al., 2013; Chua et al., 2010), while their penetration rate in these geographical areas is significantly higher than in Europe (Achtnicht, 2012; Hackbarth and Madlener, 2013; Hackbarth and Madlener, 2016; Ziegler, 2012). The general interest of the present work is to identify the most important factors that drive preferences for specific types of vehicles, especially HEVs; while testing the robustness of our findings.

The present research provides innovative results that contribute towards improving our understanding of the nature of the choice of vehicles. Significant preference heterogeneity with regards to automobiles is found. In particular, drivers who buy HEVs do not always do so for environmental reasons, but more for reputational issues. Moreover, lack of interest for HEVs may be motivated by other reasons, or may be due to mistrust or misconceptions about this technology. Although conventional vehicles still dominate the market, HEVs and flexible-fuel vehicles (FFV) will be able to gain a market share in the future, at least among certain segments. Willingness to pay (WTP) estimates elicited via LCM and via a payment card WTP question, show that both methods lead to a positive WTP for HEVs.

2. Literature review

Previous literature (see the review by Al-Alawi and Bradley 2013; Liao et al., 2017) analyzed preferences for alternative fuel vehicles using a wide range of vehicle types (including gasoline, diesel, natural gas, HEV…) vehicle attributes (price, fuel costs, maintenance cost, CO2 emissions...) and individual characteristics (gender, age, income, level of education, etc.). The latter variables are very important for market segmentation which is the focus of the present research.

In a very recent literature review, Liao et al (2017) summarized the individual characteristics found to contribute to taste heterogeneity for AFV into six groups: socio-economic and demographic variables (gender, age, income, education level, household composition); psychological factors (pro-environmental attitude, concern for battery, innovativeness, status symbol); mobility and car-related condition (current car condition, expected car condition, current mobility habit); spatial variables (charging capability, living in urban area, countries and regions); experience (trial period), and social influence (market share, market share in social network, positive reviews). Belgiawan et al., (2017) found that symbolic affective increased the students' purchase intention of expensive vehicles while it made them less eager to buy more environmentally friendly cars (HEV or electric vehicles). They also found that students with high awareness of environmentally socially problems of car use prefer more environmentally AFVs. Bočkarjova et al., (2014) combined a dynamic innovation diffusion framework and stated preference data to analyze sources of heterogeneity in the adoption of HEVs and electric vehicles. They found significant preferences heterogeneity, demographic and psychological differences between 5 consumers' groups (innovators, early adopters, early, majority, late majority, and traditionalists). Cirillo et al. (2017) analyzed consumers' preferences for gasoline, HEV, and electric vehicles in a dynamic marketplace. They showed that women with a high education level were the most attracted by HEVs, while young people or men with a high education level were more likely to opt for electric vehicles. In a multi-country analysis, McLeay et al. (2018) examined risks perceptions of hybrid car adoption focusing on heterogeneity behavior due to self-image and cultural dimension. Based on risks perceptions they distinguished four different groups (pessimists, realists, optimists, and casualists) that also differ in terms of environmental self-image, and underlying cultural values.

According to Liao et al. (2017), modelling techniques used in vehicle choice analysis have evolved from the basic McFadden multinomial logit (McFadden, 1974) (MNL) model, to nested logit models (Potoglo and Kanaroglou, 2007; Qian and Soopramanien, 2011) accommodating for the correlation between alternatives, and then to mixed logit model (Hackbarth and Madlener, 2013; Helveston et al., 2015), considering random taste heterogeneity across individuals (McFadden & Train, 2000), as well as more recent parametric and semiparametric logit models (Bansal et al., 2017) .

The source of taste heterogeneity may be assessed by interacting individual and alternative specific factors, or estimating a hybrid choice model (Jensen et al., 2013; Glerum et al., 2014); or a LCM (Abdoolakhan, 2010; Beck et al., 2013; Hackbarth and Madlener, 2016; Hidrue et al., 2011) which is the model selected for the present analysis.

LCM has been recently used to asses consumer preferences towards AFV around the world (see Abdoolakhan, 2010; Beck et al., 2013; Hackbarth and Madlener, 2016; Hidrue et al., 2011; among others). The present investigation compares the sample's WTP for HEVs estimated in two different ways: using a direct approach (asking drivers directly to indicate how much they would pay more for HEVs compared to the same conventional vehicle via a payment card question) and in an indirect way (using a DCE). This comparison makes possible to check the degree of consistency between the results obtained from both methods. Several approaches for measuring WTP have been applied in the literature (Breidert et al., 2006), but little is known about the correspondence of their results. Asking drivers to indicate their WTPs for HEVs is an approach which focuses on price and ignores the importance of other attributes, while in a DCE, drivers are asked to select their most preferred alternative among hypothetical vehicles defined by various attributes. Therefore, it is interesting to test the robustness of both methods in terms of generating WTP estimates for HEVs. The present research tests the external validity (convergent validity) of the DCE using the same sample of individuals (within-subject design).

There exist studies (Breidert et al., 2006; Ryan and Watson, 2009) which compare the WTP estimates derived from both methods in other sectors and the findings are mixed. Jin et al. (2006) compared the welfare measures derived from the two methods in the case of studying preferences for alternative solid waste management policies, and found no significant differences between them. However, in an analysis conducted to elicit women's preferences for Chlamydia screening, Ryan and Watson (2009) compared welfare estimates from the two methods and found significant differences between the WTP estimates from both approaches. The present study provides evidence towards coherent results across methodologies.

3. Methods

3.1 DCE

In a DCE, individuals face a sequence of choices where they are asked to choose their preferred alternative in each choice set. The set of options includes a limited number of different alternatives (Hensher, et al., 2015). Also, as the alternatives are defined by the same attributes but with different levels, when individuals are making a tradeoff between different alternatives, they are also doing it between different attributes (importance ranking) and different attribute levels.

Focusing on the existing literature (Potoglou and Kanaroglou, 2007), a total of five relevant vehicle attributes were included in the DCE, including vehicle type, price, fuel consumption, CO2 emissions and biofuels adaptation (see Fig 1). Fuel type, price, fuel consumption, and CO2 emissions are considered in several studies (Achtnicht, 2012; Zeigler, 2010; Hackbarth and Madlener, 2013). In some studies, more attributes (driving range, Fuel availability, Refueling time, Battery recharging time) were considered which are often specific to plug-in electrified cars (electric cars and plug-in hybrid cars).

However, HEVs have similar autonomy (range) and refueling time than conventional cars. Because the preferences that drivers assign to HEVs vs. regular vehicles are of interest for this research, the attribute ‘fuel type’ was selected with two possible levels (conventional fuel and HEV). Qian and Soopramanien (2011) found that Chinese were more likely to move from petrol fuel vehicles to HEVs than to electric vehicles.

As the aim was to assess the heterogeneity of drivers’ WTP for vehicles with different attributes, the price attribute is considered crucial when purchasing a new vehicle (Adler et al., 2003). Chowdhury et al. (2016) analyzed Swedish preferences for green vehicles’ attributes and found that price was the most important attributes for potential buyers. Previously, Klein (2007) showed that less than 3 out of 10 Prius hybrid vehicle buyers in the US during 2006 bought them for environmental reasons, reporting that the rest chose the vehicle for economic reasons. In order to use realistic values for price, information from the Spanish market for small and midsize vehicles was used to define three levels of the price attribute: a low level (€12,000), an intermediate level (€16,000) and a high level (€20,000). The intermediate level corresponds to the average price of passenger cars sold in Spain in 2012. The upper and lower limits have been established taking into account the fact that HEVs are offered at prices €3,000- €5,000 higher than their conventional models, and the fact that the majority of the passenger vehicles sold in Spain in the last few years cost less than €20,000.

Because the aim was to assess drivers’ preferences for fuel efficiency improvements in vehicles (Adler et al., 2003), the attribute ‘fuel consumption’ was included with two suitable levels: an efficient level (€5 per 100 kilometers) and a more inefficient level (€7 per 100 kilometers). The values were displayed in euros per 100 kilometers, in order to simplify the tradeoff between attributes (Achtnicht, 2012; Ziegler, 2012). Lower and upper limits comparable to values included in recently studies (Achtnicht, 2012; Ziegler, 2012) were used. In this line, Chowdhury et al. (2016) simulated positive shifts in market size and market share for vehicles with high fuel efficiency. Thatchenkery and Beresteanu (2008) suggested that greater fuel efficiency motivates individual preferences for HEVs.

In addition, two environmental attributes were included in the choice; in particular, carbon dioxide (CO2) emissions, and the option of biofuel adaptation. Similarly, focusing on small/midsize vehicles and recent studies (Achtnicht, 2012; Ziegler, 2012), two possible levels were set for the attribute 'CO2 emissions': an efficient level (100gr per kilometer) and an inefficient level (150gr per kilometer). In this context, Chowdhury et al. (2016) reported that the impact of CO2 emissions was higher than that of fuel efficiency. The attribute 'biofuels adaptation' was included due to the fact that interest in flexible-fuel vehicles is on the rise. Flexible fuel vehicles were introduced in the Spanish vehicle fleet from 2007, as a response to the European strategies (Directive 2003/30/EC) aimed at promoting the use of biofuels in the transport sector. A dichotomous variable of whether the vehicle is equipped or not with this option was considered. The EU is fighting to reduce its transport greenhouse gas emissions and energy dependence, developing new alternative technologies, and also making major efforts to promote the use of biofuels (Although the European Commission recently proposed the phasing-out of conventional biofuels by 2030, due to their impact on changes in land use (European Parliament, 2015). Through different policies, the EU encourages the use of biofuel as it is a clean energy, price-competitive with gasoline and diesel, and because it can be distributed using the existing infrastructure (Pacini and Silveira, 2011).

Fig 1. Attributes and levels

The combination of the five attributes and their levels provides $3*2^4= 48$ possible combinations. In order to reduce the number of combinations, the SPSS software was used to generate an optimal orthogonal design (OOD) with 8 choice sets. This number of choice sets is optimal to estimate the main effects with a very low level of attribute correlation within and among alternatives. Each of the 8 sets that were created contained one alternative, which was called the first alternative. Then, based on the procedure by Street and Burgess (2007), and using a vector of differences (12111), the second alternative was defined for each choice set, achieving a design efficiency of 98%. We did not consider any restrictions in our experimental design; therefore all attributes with their corresponding levels were freely combined across conventional vehicles or HEVs. Ziegler (2010) combined the same levels for the purchase price, fuel costs, and CO2 emissions across gasoline, diesel, and HEVs. Each respondent received a sequence of 8 choice sets, while they were asked to select their preferred alternative in each choice occasion. Each choice set was conformed by two automobiles and the no-choice alternative (neither alternative A nor B) (for more details see Rahmani and Loureiro, 2018). An example of the DCE card is shown in Fig 2.

Fig 2. Choice experiment question and Card example

3.2 WTP with Payment Card Format

In addition to the DCE, the survey included a payment card WTP question where drivers were asked to indicate how much (0%, 10%, 20%,…, 100%) they would pay at most for a HEV over the average price of a conventional vehicle of €15,000. To facility comprehension of the question, the numeral value of price premium was included in the question between parentheses. Participants responded the payment card WTP question first, and then the DCE was presented (See the framed question in Appendix 1).

4. Econometric model specification

The LCM captures preference heterogeneity between different groups of drivers, relaxing the IIA assumption. A LCM segments the sample into Q unobserved different groups, containing in each group drivers with high preference homogeneity while being significantly different from the other groups. In this way, attribute parameters are distributed discretely over the latent groups (Green and Hensher, 2003). The appropriate number of classes to be used is generally based on estimated criteria of goodness of fit (AIC, BIC). The probability (H_{iq}) that an individual i belongs to the class q, where $q \in [1,...,Q]$, is (Hensher et al., 2015):

$$H_{iq} = \frac{\exp(z_i^{'}\theta_q)}{\sum_{q=1}^{Q}\exp(z_i^{'}\theta_q)} \qquad (1)$$

where,

Z_i : is a vector of individual characteristics (covariates variables).

θ_q : is a vector of parameters associated with the covariate variables. The Q-th class is taken as a reference $\theta_Q=0$.

The WTP of individual i, from class q, for a given attribute "A" may be calculated dividing the estimated parameter ($\hat{\beta}_{iA|q}$) for the attribute "A" by the "Price" coefficient ($\hat{\beta}_{iP|q}$) (Nguyen et al., 2015).

$$\mathrm{WTP}_{iA|q}=(\text{Attribute A}\,|\,q)=-\frac{\hat{\beta}_{iA|q}}{\hat{\beta}_{iP|q}} \tag{2}$$

For the effect coding attributes, the ratio in eq.(2) is multiplied by 2. The average WTP of the sample for the attribute "A" may be obtained by weighting (weighted mean) the class WTP means by the probabilities of the class membership [Kamakura and Russell, 1993; Nguyen et al., 2015] as shown in eq.(3).

$$\mathrm{WTP}_{iA}=(\text{Attribute A})=\sum_{q=1}^{Q} H_{iq}\mathrm{WTP}_{iA|q} \tag{3}$$

Based on the nature of the discrete variable, the results of the payment card WTP question are modeled using a tobit model whose corresponding utility function is (Wooldridge, 2002):

$$Y_i^*=X_i^{'}\beta+\varepsilon_i \tag{4}$$

where,

Y_i^* : is a latent variable.

$X_i^{'}$: is a set of independent variables; β : is a vector of parameters.

ε_i : is the error term and ε_i □ i.i.d. $N(0,\sigma^2)$.

The observable non-negative WTPs (Y_i) calculated using the payment card WTP question are defined as (Wooldridge, 2002):

$$y_i = \begin{cases} y_i^* & \text{if} \quad y_i^* > 0 \\ 0 & \text{if} \quad y_i^* \leq 0 \end{cases} \tag{5}$$

5. Data

In order to make the survey more realistic, two different DCE versions were designed, according to preferences for large or small-medium vehicles. Respondents who stated to prefer a small-medium vehicle, received automatically the corresponding DCE; whereas those who preferred a larger vehicle received a second version, with the only difference being the levels of the attributes (price, fuel consumption and CO2 emissions). While 875 respondents expressed their desire to buy in the future a small-medium vehicle, only 138 respondents opted for large vehicles. This paper focuses on the data referring to preferences for small-medium vehicles. In this line, Hahn et al. (2018) showed that preferences for green vehicles are heterogeneous across vehicle size.

The DCE was included in an online survey, presented in July 2013 to a representative sample (N=875 drivers) of residents over the age of eighteen in Spain, who previously expressed their desire to buy a small or midsize vehicle in the near future. In the sample, 92.46% of households have 1 or more cars. The weekly driving frequency of the sample (4 days) is comparable with the national frequency (5 days) (Spanish Observatory of Drivers, 2014). The drivers' current vehicles included a total of 33 different vehicle brands. The most popular brands are Renault (12.46%), followed by Ford (11.27%), Citroën (9.93%) and Seat (9.33%). Most of the drivers' actual vehicles are diesel (54.65%) or gasoline (44.85%), while only 3 drivers have a hybrid vehicle and only 1 driver has a biofuel vehicle.

The survey included a set of questions to capture the behavior, attitudes, socioeconomic and demographic characteristics of the drivers. The characteristics of the sample are shown in Table 1. In this sample, 51% of the drivers are male, with a mean age of 46 years, compared to the national average of 44 years (Spanish Observatory of Drivers, 2014). Unemployed drivers represent about 18% of the sample, and 24.6% of drivers are members of households with a monthly income under €1,200. Nearly half (46%) of the sample has university studies. In addition, 14% believe that HEVs are slower, while 18% consider that HEVs have less power, and about 16% report that they did not know what HEVs are like. Finally, 17% report that HEVs have limited autonomy, showing a clear misunderstanding of the difference between HEVs and EVs.

Table 1 Descriptive statistics

Variables	Description	Mean	Std. Dev
MALE (dummy)	1 for male, 0 for otherwise.	.513	.499
AGE (Continuous)	age of participants (years).	45.972	13.546

LHINC (dummy)	1 for monthly income under €1,200 and 0 otherwise.	.246	.431
MHINC (dummy)	1 for monthly income higher than €1,200 and equals or lower than €3,000, 0 otherwise.	.646	.477
UNIV (dummy)	1 for respondents with university studies, 0 for otherwise.	.457	.498
IMAGE (Continuous)	importance (score) attributed for the incentive "social image".	2.744	1.256

In the specified utility function of the LCM, all five vehicle attributes considered in the DCE were included. The attribute PRICE represents the price (continuous variable) of the displayed conventional or HEV hypothetical alternatives. The attribute SAVINGFUEL is an effect coding variable which takes the value 1 if the fuel consumption of the displayed vehicle alternative is €5 per 100 kilometers (efficient vehicle), and -1 if it consumes €7 per 100 kilometers (inefficient vehicle). The attribute ABATEMENT-CO2 is an effect coding variable corresponding to the environmental efficiency of the displayed vehicle alternative, taking the value 1 if the vehicle emits 100 grams of CO2 per kilometer (efficient vehicle), and -1 if it emits 150 grams of CO2 per kilometer (inefficient vehicle). The attribute BIOFUEL is an effect coding variable indicating whether the vehicle alternative is equipped to run with biofuels, being 1 if yes and -1 if no. Two dummy variables were added, ASCc and ASCh which are alternative specific constants, the first of which represents conventional vehicles, and the second HEVs. The attributes' levels of the no-choice option were coded as a series of zeros; therefore the deterministic utility of the no-choice option was zero. In addition, a set of driver-specific characteristics (MALE, AGE, LHINC, UNIV, and IMAGE) was used to define the profile of the members who form each particular class. The variables MALE, LHINC, and UNIV are dummy variables respectively representing drivers, who are male, who earn less than €1,200 per month, and who have university studies. The variable AGE is continuous, representing the age of drivers in years (divided by 10). The variable IMAGE is continuous, and represents the importance (score) of a drivers' personal image when buying an efficient car. Earlier findings suggested that higher educational level, higher income level, higher environmental awareness (Erdemn et al., 2010; Liu, 2014; Thatchenkery and Beresteanu, 2008) and social status-seeking (Chua et al., 2010) motivate individual preferences for HEVs. In a recent study, Partridge (2013) showed the gain of utility obtained by selecting HEVs; however, a part of it was attributed to individual preferences towards seeking social image (Chua et al., 2010, Partridge, 2013).

6. Results and discussions

Our data base contains a total 8 observations for each individual (the number of choice tasks for each respondent) * 875 (number of respondents) =7000 observations. The percentage of respondents who selected the conventional car, a HEV, or the status quo option is 29.61%, 40.51%, and 29.87%, respectively. In the empirical exercise, the assumption of IIA is tested using the Hausman and MacFadden test. Results (see Rahmani and Loureiro, 2018) from this test reject the null hypothesis (IIA assumption), implying that the MNL model is not appropriate to fit our data.

In order to relax the IIA assumption and to assess driver preference heterogeneity, a LCM is estimated, accommodating correlated responses across observations (among the choices expressed by each individual) and making the class allocation as a function of socio-demographic variables (Table 1). In order to determine the appropriate number of classes to consider, LCMs with different number of classes (2 classes, 3 classes, 4 classes, 5 classes, and 6 classes) have been estimated. Various overall fit statistics were estimated for each LCM, and presented in Table 2. Considering the conditional (posterior) class probabilities, we identified the class each individual belongs to. Therefore, it was possible to summarize the mean WTPs obtained from the payment card WTP question by class. To this end, we estimated a tobit model for each class using the payment card WTP estimates as a dependent variable and only the constant as independent variable. Moreover, we estimated a tobit model where the dependent variable is the individual WTP of the members of the whole sample and the independent variables were the same sociodemographic variables included in the LCM.

The results show that all the statistics are improving from 2 classes to 5 classes, indicating that the 5-class model has the best fit. The Bayesian information criterion (BIC) is the most appropriate to use in this case, as it penalizes for the number of parameters in the model (Roeder et al., 1999). The lowest (best) value of the Bayesian information criterion (BIC) is achieved by the 5-class model. However, some authors (Greene, 2014; Hensher et al., 2015) have suggested that the existence of potential overspecification should also be assessed when determining the number of classes. In our empirical modeling, the 5-class, and 6-class models are over-specified containing very small groups of individuals (less than 1% of the sample), with un-meaningful estimated parameters (imprecise and insignificant parameters, large standard errors). Therefore, the 4-class model was selected. The predictive power was calculated (Hensher et al., 2015) as the overall proportion of correct predictions (number of correct predictions/number of observations). As reported at the bottom of Table 2, the correct prediction rate of the 4-class model is 70.79%. Table 3 shows the final results of the MNL and the 4-class LCM.

Table 2 Overall fit of the MNL and the LCMs with sociodemographic variables

	MNL MODEL	2 CLASS MODEL	3 CLASS MODEL	4 CLASS MODEL	5 CLASS MODEL	6 CLASS MODEL
LL	-6,578.013	-5,590.762	-5,263.936	-5,136.378	-4,989.743	-5,370.491
K	6	18	30	42	54	66
N	7,000	7,000	7,000	7,000	7,000	7,000
R-SQRD	.136	.273	.315	.332	.351	.302
R2ADJ	.135	.272	.314	.330	.348	.298
AIC	13,168.0	11,217.5	10,587.9	10,356.8	10,087.5	10,873.0
BIC	13,209.1	11,340.9	10,793.5	10,644.6	10,457.6	11,325.3
Correct predictions	43.66%	60.69%	67.39%	70.79%	77.86%	70.29%

L.L: Log-likelihood; K: Number of factors; N: Number of observations; R-SQRD: r squared; R2ADJ: adjusted r squared; AIC: Akaike information criterion; BIC: Bayesian information criterion.

If we consider the results from the LCM with 4 classes (column 2 of Table 3), we find significant heterogeneity in terms of preferences for the attributes across the sample, resulting in important differences in all the parameters among the 4 classes. Furthermore, the number of attributes that significantly affect drivers' choices is different across classes. The attributes that significantly affect (at least at 5% level of significance) the vehicle choice in all classes are the price variable (PRICE), and the type of car (regular or HEV). In all the classes, price carries a negative and highly significant impact on the vehicle choices, which is in line with previous literature (Liao et al., 2017). Furthermore, it is possible to identify a group (third class) that is much more environmentally friendly than the rest, as in this class, vehicle choices are strongly affected (at least at 1% level of significance) by environmental efficiency, biofuel adaptation and preferences towards HEVs (compared to conventional cars). Regarding the significance and the sign of the sociodemographic variables, the gender variable (MALE) is negative and highly significant (at 1% level) in class 3 but it is not significant either in class 1 or class 2, while age (AGE/10) is positive and significant in class 2 (at 5% level) and in class 3 (at 1% level). Low income (LHINC) is negative and significant (at 5% level) in class 1, but it is not significant in class 2 and class 3. University studies (UNIV) is statistically significant in any of the classes. The self-image (IMAGE) is positive and significant in class 1 (at 1% level) and negative and statistically significant in class 2 (at 5% level).

Looking at the results in greater detail, the first class contains a group of drivers who are less sensitive (the second less sensitive) to price (PRICE) in comparison with the rest of the classes. The effect of energy efficiency on the group members' vehicle choice is highly significant, although its magnitude is half that of the third class. Also, the environmental efficiency (ABATEMENT_CO2) and biofuel adaptation (BIOFUEL) have a significant (at least at 5% level of significance) impact on vehicle choices. With respect to the type of vehicle, drivers prefer an HEV to conventional vehicles (ASCh is statistically larger [Mean (diff) = 1.108; z=7.70, p-value = .000] than ASCc) in *ceteris paribus* conditions. The members of this class are less likely to earn a monthly income below €1,200 than drivers in the fourth reference class. Current findings correspond with previous literature showing that individuals with good economic conditions are less sensitive to price (Achtnicht et al., 2012; Hackbarth and Madlener, 2013) and fuel efficiency (Helveston et al., 2015). In line with previous findings (Erdemn, 2010; Liu, 2014), these drivers are also more likely to be 'image seekers' than the members of the fourth class. The drivers who belong to this first class are designated as "enthusiastic about HEV, but mainly for aspirational reasons".

The second class contains drivers who are the least sensitive to price (PRICE). In addition, neither energy efficiency (SAVING_FUEL) nor biofuel adaptation (BIOFUEL) affect their vehicle choices, while environmental efficiency (ABATEMENT_CO2) has an intermediate impact on vehicle choices, compared to the rest of the classes. These drivers prefer conventional cars over HEVs (ASCh is statistically lower [Mean (diff) = -.924; z=-3.82, p-value = .000] than ASCc) in *ceteris paribus* conditions. They are older than the drivers in the fourth class, and in comparison, are less likely to be image seekers. The members of this second class may be considered as the “skeptical HEV buyers”. In this context, Beck et al. (2013) found that people who prefer petrol vehicles over HEVs were older, less sensitive to any additional emission charges of using a motor vehicle.

The third class includes drivers with the strongest preferences for energy efficiency (SAVING_FUEL), environmental efficiency (ABATEMENT_CO2) and biofuel adaptation (BIOFUEL). They have stronger preferences than others for HEVs in comparison to conventional vehicles (ASCh is statistically larger [Mean (diff) = 1.218; z=10.62, p-value = .000] than ASCc), in *ceteris paribus* conditions. This class contains individuals who worry at the same time about vehicle emissions, biofuel adaptation, and who are HEV-oriented but less affected by price. This result is comparable with the findings of previous studies (Hackbarth and Madlener, 2016) and implies that price is relatively less important for the more pro-environmental groups. In line with previous studies (Abdoolakhan, 2010; Cirillo et al., 2017; Hidrue et al., 2011), members of this class are less likely to be men, and more likely to be older than drivers in the fourth reference class. The members of this third class are called “HEV-oriented and aware drivers”.

The fourth class consists of drivers with the highest sensitivity towards price (PRICE) compared to other classes. In addition, energy efficiency (SAVING_FUEL) has a significant influence on their vehicle choices. In contrast, environmental efficiency (ABATEMENT_CO2) has the lowest impact (at 10% level of significance) on their vehicle choices, compared to the rest of the classes. Together with the second class, these are the only two groups that do not worry about biofuel adaptation. It is the only class where drivers do not have special preferences for any vehicle type (ASCh is not statistically different [Mean (diff) = .048; z=.30, p-value = .765] to ASCc), in *ceteris paribus* conditions. These can be denoted as “good deal seekers.”

Table 3 Results of the MNL and the LCM (4 classes)

	MNL	LCM			
	Sample	**Class 1**	**Class 2**	**Class 3**	**Class 4**
Parameters in utility functions					
PRICE	-2.056***	-.657***	-.450**	-3.066***	-5.361***
	(.055)	(.153)	(.193)	(.220)	(.299)
SAVING_FUEL	.281***	.382***	.027	.728***	.438***
	(.017)	(.063)	(.080)	(.051)	(.089)
ABATEMENT_CO2	.255***	.139**	.447***	.773***	.123*
	(.017)	(.055)	(.075)	(.055)	(.066)
BIOFUEL	.100***	.112**	.075	.377***	.026
	(.017)	(.055)	(.098)	(.046)	(.065)
ASC_c	2.980***	3.640***	2.854***	2.257***	10.096***
	(.084)	(.513)	(.473)	(.242)	(.547)
ASC_h	3.402***	4.748***	1.929***	3.476***	10.145***
	(.086)	(.520)	(.538)	(.309)	(.490)
Class assignment parameters					
Constant	.	-1.780***	-2.589***	-.234	0.0
		(.626)	(.710)	(.348)	(Fixed)
MALE	.	-.112	-.098	-.527***	0.0
		(.272)	(.349)	(.183)	(Fixed)
AGE/10	.	.094	.264**	.179***	0.0
		(.103)	(.124)	(.068)	(Fixed)
LHINC	.	-.930**	.066	-.095	0.0
		(.366)	(.430)	(.199)	(Fixed)
UNIV		-.132	.097	-.010	0.0
		(.265)	(.363)	(.179)	(Fixed)
IMAGE		.336***	-.001**	-.0004	0.0
		(.096)	(.0005)	(.0003)	(Fixed)
Goodness of fit					
LL	-6,578.013	-5,136.378			
K	6	42			
N	7,000	7,000			
R-SQRD	.136	.332			
R2ADJ	.135	.330			
AIC	13,168.0	10,356.8			
BIC	13,209.1	10,644.6			
Correct predictions	43.66%	70.79%			

- ***, **, *: Significance at 1%, 5%, 10% level; (): Standard Error; L.L: Log-likelihood; K: Number of factors; N: Number of observations; R-SQRD: r squared; R2ADJ: adjusted r squared; AIC: Akaike information criterion; BIC: Bayesian information criterion.

Based on the posterior class membership probabilities, the model allocates 15.5% of the sample in the “enthusiastic about HEV but mainly due to aspirational aspects” group (first class), 9.2% in the “skeptical HEV buyers” group (second class), 43.4% in the “HEV oriented and aware drivers” group (third class), and 31.9% in the “good deal seekers” group (fourth class). Therefore, from the entire sample, 58.9% (first class + third class) prefer HEVs over conventional vehicles, *ceteris paribus*, although 15.5% (first class) are willing to buy them for reputational purposes. This result sheds quite an optimistic light on the future of the HEV market in Spain. Although the rest of the sample do not appreciate HEVs compared to conventional vehicles, *ceteris paribus*, they positively value savings in fuel consumption and reductions in CO2 emissions which are two enhancements included in HEVs. We also observe that most of respondents who prefer small or midsize vehicles (43.4% + 31.9%) present high price sensitivity, as described in previous findings (Jensen et al., 2013).

Table 4 summarizes WTP results derived from the LCM. The average WTP of the sample in order to update a vehicle, from regular to HEV, considering a HEV with specific attributes evaluated at (€20,200; 3.6l/100km; 75gr of CO2/1km) and a conventional model (€18,550; 5l/100km; 112gr of CO2/1km) is estimated as €1,348.27, within the range found by Liu ($963-$1,718) (Liu, 2014). In spite of being statically significant, this price premium is still insufficient to cover the market price difference of HEVs. The members of the “HEV-oriented and aware drivers” group (Class 3) have the highest WTP (€1,659.32) for HEVs, whereas individuals belonging to Class 2 have the lowest WTP. In fact, sample respondents belonging to this class have to be compensated in order to move from a conventional vehicle to a HEV.

Table 4 Mean WTP for the alternatives and their attributes across class

Mean WTP	Class 1	Class 2	Class 3	Class 4	Sample
€2 saved in fuel consumption per 100km.	1.164*** (.306)	.123 (.351)	.475*** (.030)	.163*** (.029)	.439*** (.050)
50g of CO2 reduced in emissions per 1km.	.425** (.202)	1.990** (.926)	.504*** (.031)	.046* (.024)	.482*** (.089)
the car is adapted to run with biofuels.	.343* (.192)	.334 (.485)	.246*** (.024)	.009 (.024)	.159*** (.032)
To move from regular to HEV	1,657.12*** (3.670)	-1,688.97*** (17.982)	1,659.32*** (.585)	1,650.97*** (.456)	1,348.27*** (1.808)

(): Standard error; ***, **, *: significance at 1%, 5%, and 10% level, respectively.

Table 5 presents results obtained from a payment card WTP. Compared to the previous LCM, the results are similar in some aspects, although with substantial differences as well. In line with the LCM, the WTPs are positive.

In order to provide a direct comparison, we summarize the WTPs obtained from the payment card WTP question by the classes previously identified by the LCM. Table 5 presents the mean WTPs by class computed from a tobit model without socio-economic variables (tobit with only a constant term). The sample mean WTP elicited via LCM and with the payment card WTP question are €1,348.27 (Std. Err.= 1.808) and €3,597.08 (Std. Err.= 28.776), respectively. However, like in the LCM estimates, members of Class 1 (€3,962.06) and class 3 (€3,853.45) have the highest WTPs for HEVs.

Table 5: The averages of willingness to pay (WTP) by class (Tobit with constant)

		Coefficient	Std. Err.	T	P>|t|
Class 1	Constant	3,962.069	71.526	55.39	.000
Class 2	Constant	3,625.984	72.202	50.22	.000
Class 3	Constant	3,853.448	52.591	73.27	.000
Class 4	Constant	3,097.328	44.129	70.19	.000
Sample	Constant	3,597.087	28.776	125	.000

We also estimate a Tobit model to predict the WTPs obtained from the payment card WTP question controlling for the same sociodemographic variables (MALE, AGE, LHINC, UNIV, and IMAGE) included in the LCM. Results are reported in Table 6. Compared to those found in the LCM, the results are mixed. In line with the LCM, the WTP increases with image awareness (IMAGE). However, WTP increases between men (MALE), with low income (LHINC) and decreases with age. These estimates should be taken with caution, given that in the LCM, people who pay the biggest premium for HEVs (Class 3) are older and more likely to be female.

Table 6: Tobit model with the same sociodemographic characteristics used for class assignment

	Coefficient	Std. Err.	T	P>|t|
MALE	305.246	61.161	4.99	.000
AGE/10	-140.435	22.950	-6.12	.000
LHINC	422.247	70.391	6	.000
UNIV	77.222	60.814	1.27	.204
IMAGE	65.342	23.713	2.76	.006
Constant	3,751.432	139.370	26.92	.000

7. Conclusions and implications

Assessing the heterogeneity of drivers' preferences in the context of vehicle choices is important for public decision-makers in order to understand market segmentation. In this way, more appropriate policies can be developed to promote HEV, and address them to the corresponding target population segment. In order to assess these issues, a DCE was conducted and administered in a structured online survey. The findings reveal significant heterogeneity in terms of preferences over four latent classes labeled as "enthusiastic about HEV but mainly for aspirational reasons", "skeptical HEV buyers", "HEV-oriented and aware drivers" and the "good deal seekers" groups. In line with previous literature (Liao et al., 2017), all the groups are affected negatively and highly significantly by price. There are clear differences in the drivers' preferences over these 4 classes. The first and the third groups are clearly pro-environmental and HEV-oriented; however the second and the fourth groups are conventional vehicle and price-oriented, respectively, and not at all interested in biofuels. In particular, drivers from the “enthusiastic about HEV but mainly for aspirational reasons” class represent 15.5% of the sample, are not very sensitive to price, and are more likely to be wealthy image seekers, compared to the members of the last class “good deal seekers”. The “skeptical HEV buyers” are the least sensitive to monetary attributes, and are not at all affected by energy efficiency (SAVING_FUEL) or biofuel adaptation (BIOFUEL). They are influenced by environmental attributes (ABATEMENT_CO2), and prefer conventional cars to HEVs. They comprise 9.2% of the sample, and are more likely to be older drivers and less likely to be image seekers, compared to the members of the fourth class. The “HEV-oriented and aware drivers” are the most affected by energy efficiency (SAVING_FUEL), environmental efficiency (ABATEMENT_CO2) and biofuel adaptation (BIOFUEL) and strongly prefer HEVs to conventional vehicles. They represent 43.4% of the sample, and are less likely to be men, and more likely to be older than the reference class members. The “good deal seekers” are the most sensitive to price (PRICE), and are affected at all by environmental attributes (ABATEMENT_CO2, BIOFUEL). They do not have special preferences for any type of vehicle. They comprise 31.9% of the sample. Our results agree with previous findings (Jensen et al., 2013) showing that preferences for small or midsize vehicles s are associated with high price sensitivity. Moreover, our results correspond with previous literature, denoting that people with high income are less sensitive to price (Achtnicht et al., 2012; Hackbarth and Madlener, 2013) and to fuel efficiency (Helveston et al., 2015). Regarding people who prefer conventional vehicles over HEVs, our results are in line with Beck et al. (2013) who found that people who prefer petrol cars over HEVs were older, less sensitive to any additional emissions surcharge of using a motor vehicle. We also find that our results are in line with those of previous studies (Hackbarth and Madlener, 2016) with respect to the fact that more pro-environmental groups are less price sensitive. Regarding the profile of pro-environmental groups, we find that they are less likely to be men, and more likely to be older, in line with previous studies (Abdoolakhan, 2010; Cirillo et al. (2017; Hidrue et al., 2011). Compared to other studies, we have shown that Spanish car buyers are not only in one pro-environmental group and another group which does not care for the environment, but there is a variety of drivers classified into 4 groups. Moreover, we showed that HEV potential buyers are specifically of two types: those who buy HEVs for image reasons (class 1) and those who do it for environmental reasons (class 3). Methodologically, we have been able to compare the results of two methodologies of WTP values (DCE vs Payment Card question) not only in average terms but also in terms of class (within and between classes).

In total, more than half (first and third classes) of drivers prefer HEVs to conventional cars, *ceteris paribus*, even though some of them (first class) do so in part because of reputational reasons. This positive perception towards HEVs is quite optimistic with regards to the future of this technology in the market. However, it was also found that the sample's average WTP to move from conventional cars to HEVs is quite small compared to the price markup for these vehicles. This can be partially explained by drivers' limited information about HEVs.

In summary, increasing the attractiveness of the attributes of HEVs and emphasizing their 'green' image will result in greater demand for HEVs. However, as shown in this study, the effort that each group is willing to make in order to reduce air pollution is different, and so public policies aimed at promoting the use of efficient vehicles may be designed and adopted differently when targeting various groups. In particular, a mix of public incentives and nudging policies may be required. Our findings may serve as a guide for possible future public strategies or programs aimed at promoting AFVs. Finally, our findings show robustness between WTP estimates elicited via a LCM and those for a payment card WTP question. In particular, both approaches lead to positive WTP for HEVs.

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10. Appendix

Appendix 1: Payment card WTP question

Q. How much would you be willing to pay at the most for a HEV over a conventional car of 15,000 euros?