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Alexandros Dimitropoulos

Faculty of Economics and Business Administration, VU University Amsterdam, and Tinbergen Institute, the Netherlands.

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Tel.: +31(0)20 525 8579

The influence of environmental concerns on drivers' preferences for electric cars

Alexandros Dimitropoulos*

Department of Spatial Economics, VU University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands

Abstract

We examine the influence of drivers' environmental concerns on their preferences for different types of plug-in electric vehicles (PEVs). Our empirical approach is built around the results of a large-scale survey among Dutch drivers, where preferences for electric vehicles are elicited through a choice experiment and environmental concerns are reflected in individual responses to Likert-type questions. On this basis, we develop advanced latent class models to study preference heterogeneity and its link to drivers' socio-demographic background and environmental concerns. We find that environmental concerns are an important predictor of class membership and that highly concerned drivers tend to cluster in classes with a positive stand towards PEVs. High environmental concerns are positively associated with driver's age and education, while negatively related to driver's household income.

Keywords: Latent class; Latent variable; Environmental concern; Electric vehicle; Plug-in hybrid.

JEL Classification codes: D12, O33, Q58, R41.

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* Tel.: +31(0)205982085; Fax: +31(0)205986004; E-mail: a.dimitropoulos@vu.nl. The author is also affiliated to the Tinbergen Institute, Amsterdam.

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1. Introduction

Plug-in electric vehicles (PEVs) have been enjoying the vigorous support of policy makers during the last decades, as their large-scale adoption is considered a promising means of confronting mounting concerns over environmental degradation, climate change, oil dependence and energy security.[1] This is reflected in recent attempts of the US and European governments to set ambitious goals for the penetration of PEVs in national car fleets. However, consumer adoption of PEVs, and especially full electric vehicles (FEVs), has long been hampered by relatively high acquisition costs, considerable uncertainty over developments in battery technologies, and drivers' reluctance to accept changes in their current refuelling behaviour.[2]

Aiming to partially address these concerns, car manufacturers have recently developed intermediate solutions based on the parallel use of internal combustion engines (ICE) and electric propulsion systems, broadly labelled as plug-in hybrid electric vehicles (PHEVs).[3] At the same time, new refuelling concepts aiming to bring the PEV charging time down to the levels of the refuelling time of ICE-propelled cars, such as fast-charging and battery-swapping, have been developed and implemented worldwide. These developments have created the need for a renewed look at consumer preferences for PEVs, especially focussed on relevant vehicle attributes. Concurrently, it is important to understand which consumer characteristics are more likely to be associated with the profiles of candidate adopters of PEVs and target fiscal policies, communication strategies and marketing activities to drivers matching those profiles.

In this paper, we study the influence of drivers' environmental concerns and sociodemographic background on their stated preferences for different types of PEVs and their attributes. To this end, we use a large-scale survey among Dutch drivers, where preferences for different vehicle technologies are elicited via a choice experiment and environmental concerns are reflected in drivers' responses to Likert-type questions. In contrast to previous stated preference (SP) studies in the field, we distinguish between plug-in hybrids and two types of full electric cars, an FEV with a built-in battery and one whose battery can be swapped at specialised stations. Data are analysed with advanced panel latent class models (see also Kamakura & Russell, 1989; Greene & Hensher, 2003), where class membership is modelled as a stochastic function of drivers' socio-demographic characteristics and environmental concerns.

[1] The term plug-in electric vehicle (PEV) is used here to denote both full electric vehicles (FEVs), i.e. vehicles powered exclusively by electric motors, and plug-in hybrid and extended-range electric cars, i.e. vehicles propelled by both electric motors and internal combustion engines, whose batteries can be recharged by plugging them into an electricity outlet. Vehicles with electric motors which cannot be plugged into an electricity outlet, such as hybrid electric vehicles (HEVs), are not considered PEVs.

[2] A full list of the acronyms used in the study is presented in Appendix A.

[3] Technological differences between plug-in hybrid EVs and extended-range EVs are not of primary interest in this study and we denote both with the encompassing term plug-in hybrids (PHEVs).

We consider two ways of treating concerns. First, we follow traditional practice in the use of Likert-type items in latent class membership models (e.g. Boxall and Adamowicz, 2002) and assume that the Likert scale accurately measures environmental concerns. As this approach has been criticised for resulting in biased estimates, we later relax this assumption and consider the possibility that individual responses to the relevant Likert-type questions are only approximate manifestations of consumers' underlying latent environmental concerns. Structural equation modelling techniques are then used to estimate concerns' impact on class membership.

This paper aims to complement relevant stated preference literature by developing an intuitively appealing modelling framework to elicit drivers' preferences for state-of-the-art electric vehicle technologies and identify how the latter are influenced by drivers' environmental concerns and sociodemographic background. The methodological contribution of the study lies in the development of flexible latent class models, whereby the implications of alternative assumptions for the accuracy of the measurement of underlying psychological constructs (such as environmental concerns) are tested.

The remainder of the paper is organised as follows. Section 2 provides the background of our study. Section 3 describes the design and implementation of the survey, with emphasis on the choice experiment. Section 4 presents our modelling framework. Section 5 discusses the results of the empirical analysis. Section 6 concludes.

2. Background

Stated preferences have played a central role in the study of consumer choice among alternative fuel vehicles (see e.g. Beggs et al., 1981; Brownstone and Train, 1999; Dimitropoulos et al., 2013). At the same time, there is a growing literature investigating the influence of environmental concerns, attitudes and related psychological constructs on consumer choices. The discussion that follows focusses on studies examining the influence of these psychological constructs on vehicle choice. In stated preference literature, these constructs are usually assumed to be reflected in individual responses to rating questions, often used to form a Likert scale, or binary response ones. Somewhat confusingly, relevant constructs are not uniformly defined in this literature. A list of the psychological constructs used in relevant SP studies, following authors' terminology, is presented in Table 1. This overview also reveals that there is wide heterogeneity in the methods used by researchers to have these psychological constructs manifested. So far, researchers have employed Likert scales, cluster analysis and direct use of rating scores for this purpose.

Two approaches have mainly been used to identify the impact of these constructs on consumer preferences for alternative vehicle types. The traditional approach deployed for this purpose is to include environmental concerns or attitudes as covariates in the random utility function of more environmentally benign alternatives (e.g. Ziegler, 2012) and/or let them interact with vehicle attributes related to the environmental performance of these vehicles (e.g. CO_2 emissions – see Achtnicht et al., 2012; Hackbarth and Madlener, 2013a). This way the analyst can capture, for instance, the influence of the construct on individuals' preferences for low emission vehicles or for relevant vehicle attributes. This approach is depicted in panel (a) of Figure 1. Following the establishment of latent class modelling in transportation and environmental economics (Boxall and Adamowicz, 2002; Greene and Hensher, 2003), researchers explored the contribution of such constructs in explaining individual membership to different latent classes. This approach allows the analyst to link one's environmental concerns or attitudes with one's probabilistic allocation to classes with specific preferences for vehicles with more environmentally benign characteristics (e.g. Beck et al., 2013; Hidrue et al., 2011). Panel (b) of Figure 1 illustrates this approach.

Table 1: Overview of studies on the influence of environmental concerns and related constructs on vehicle choice.

Study	Psychological construct	Modelling	Treatment	Manifestation
Achtnicht et al. (2012)	Environmental Awareness	Random Utility Model	Measured	4-item Likert scale
Beck et al. (2012)	Environmental Attitudes	Latent Class Membership Model	Measured	5 Likert items
Daziano & Bolduc (2013)	Environmental Concerns	Random Utility Model	Latent	14-item Likert scale
Ewing and Sarigöllü (1998, 2000)	Environmental Concerns	Random Utility Model	Measured	Likert scales & Cluster analysis
Hackbarth and Madlener (2013a)	Environmental Awareness	Random Utility Model	Measured	9-item Likert scale
Hackbarth and Madlener (2013b)	Environmental Awareness	Latent Class Membership Model	Measured	9-item Likert scale
Hidrue et al. (2011)	Environmentally Responsible Behaviour	Latent Class Membership Model	Measured	Rating question
Jensen et al. (2013)	Environmental Concerns	Random Utility Model	Latent	7-item Likert scale
Ziegler (2012)	Environmentally Responsible Behaviour	Random Utility Model	Measured	Rating question

Studies further differ in the modelling of the underlying psychological constructs as deterministic functions of the indicators used (e.g. scores to Likert scales) or as latent variables. In the former case, variables taking values equal to the (transformed) scores obtained by individuals (e.g. the scores obtained on a Likert scale or a Likert item) directly enter the random utility or the class membership model. In the latter case, the Likert items are assumed to be reflections of the underlying *latent* constructs. The influence of constructs on individual preferences is then estimated by the use of hybrid choice models (i.e. integrated choice – latent variable models, see also Ben-Akiva et al., 1999, 2002). The latter provide a framework whereby the explanatory potential of discrete choice models is enhanced by the use of latent variables. In this framework, latent variables are modelled as stochastic functions of individuals' observed characteristics (structural model), while their effect on observed indicators (e.g. Likert items) is explained through a set of measurement equations (measurement model).

The motivation behind the treatment of psychological constructs as latent variables is usually justified on attempts to confront two econometric concerns, which, if valid, imply inconsistent parameter estimates. First, the scores to Likert items may well suffer from measurement error, and second, they are likely to be endogenous, i.e. there might be unobserved factors influencing both vehicle choice and the choice of a specific level of agreement to a Likert-type question (see also Ashok et al., 2002; Daly et al., 2012).[4] In the context of identifying environmental concerns' influence on vehicle choice, applications of hybrid choice models can be found, for example, in Daziano and Bolduc (2013), who employ Bayesian estimation techniques, and Jensen et al. (2013). The approach developed in these studies is shown in panel (c) of Figure 1.

The studies cited in Table 1 generally find that environmental concerns and attitudes play an influential role in vehicle choice. Achtnicht et al. (2012) and Hackbarth and Madlener (2013a) show that higher consumer environmental awareness is associated with a more positive view of alternative fuel vehicle technologies and a higher valuation of reductions in CO_2 emissions. The first finding is also confirmed by Ziegler (2012), while Ewing and Sarigöllü (1998, 2000) illustrate along similar lines that environmentally concerned individuals are more likely to opt for more fuel efficient and electric vehicles. In agreement to these studies, applications of hybrid choice models reveal that environmental concerns have a positive effect on drivers' likelihood to opt for PEVs (Jensen et al., 2013), or other types of alternative fuel vehicles (Daziano and Bolduc, 2013). The structural models used in these two studies indicate that one's level of environmental concerns and attitudes is positively correlated with one's age and education level. Daziano and Bolduc (2013) further suggest that females have higher environmental concerns than males.

Applications of panel latent class models show that individuals scoring higher in relevant Likert-type questions are more likely to belong to classes with stronger preferences for vehicles with lower tailpipe emissions. Hackbarth and Madlener (2013b) and Hidrue et al. (2011) show that

[4] In the current context, for instance, households with children are likely to have both higher environmental concerns (as they are concerned about the environmental conditions experienced by their children) and higher driving range needs (since they have to make more trips to satisfy the needs of their dependants).

more environmentally aware consumers and individuals reporting to have recently made behavioural changes to help the environment are more likely to belong to classes with a more positive stand towards PEVs and other alternative fuel vehicles and with a higher valuation of emission reductions. Beck et al. (2013) find that environmental attitudes and concerns play a critical role in the assignment of individuals to classes with different sensitivities to vehicle emission charges and preferences for diesel cars and hybrids.

Figure 1: Different approaches for identifying the influence of environmental concerns on vehicle choice.

Note: We hereby use the general notation suggested by Walker and Ben-Akiva (2002). Rectangles denote observed elements, whereas ellipses latent ones. Solid arrows indicate structural relationships, dashed arrows measurement relationships, and dotted ones disturbances.

In what follows, we identify the influence of environmental concerns on consumer vehicle choice in the context of panel latent class models. We focus on this family of models as they provide an informative framework for the study of consumer segments with different preferences for PEVs and their key attributes. Environmental concerns enter the class membership component, partially explaining individual's likelihood to belong to each class. We start by assuming that the scale used for environmental concerns provides accurate measurements of them (see panel (b) of Figure 1). We later relax this assumption and model concerns as a latent variable to take into account the possibility that the scale suffers from measurement error. To the best of our knowledge, the resulting *hybrid panel latent class model* has not been used before in the context of vehicle choice. A sketch of our approach is presented in panel (d) of Figure 1. In contrast to previous applications of hybrid panel latent class models (e.g. Hess et al., 2013; Hoyos et al., 2013), individual characteristics are not restricted to have a direct effect *only* on the latent variable; instead, they also directly influence random utility and class membership. Before proceeding with the presentation of the methodology used in our study, we present the survey tool employed to collect the data.

3. Data

We use a new dataset stemming from a survey carried out between November 2012 and January 2013. Survey respondents were drawn from a panel of motorists of a Dutch market research company (TNS-NIPO). The sampling strategy employed for the survey is described in detail in Dimitropoulos et al. (2014).

3.1. Survey design

The survey was carried out with an online questionnaire developed in Sawtooth SSIWeb. The questionnaire comprised seven sections. The first section collected information about households' vehicle holdings and respondents' use of the car they drive mostly in. Respondents who were driving less often than once a week in household's cars and had a minor role in their household's vehicle choice making were asked whether they intended to purchase a car in the next 5 years. If they did not have that intention, they were excluded from the sample. At the end of the first section, they were requested to state whether their next car choice would be made in the context of purchasing or leasing a vehicle. This paper draws only on the responses of individuals reporting that they would *purchase* a vehicle.[5] The second section gathered details about the car that the respondent would buy next, such as whether it would be a new or second-hand car, its body and fuel type, its purchase price and the annual distance expected to be travelled in it.

Respondents were then introduced to the choice experiment. The context provided was that of their next car purchase, either being a replacement of the current vehicle or the adoption of an extra car. Following an elaborate presentation of the alternative types of propulsion systems and the

[5] Choices made in the context of vehicle leasing are analysed in Dimitropoulos et al. (2014).

vehicle attributes used in the study, respondents were given the opportunity to familiarise themselves with the choice experiment by means of an example choice scenario. Thereafter, they were invited to address 8 hypothetical choice scenarios. The design of the choice experiment is described in the next subsection. After engaging in the choice scenarios, respondents were asked to report how they made their choices, i.e. whether they considered all attributes or just a subset of them or whether they chose an option at random.

The questionnaire also invited respondents to express their level of concern about various possible effects of car use on the environment. Last, respondents were asked to select the gross household income category which is applicable to them and provide comments on the questionnaire layout and length. The time that respondents spent to handle different parts of the questionnaire was closely monitored, in order to provide us with a measure of how seriously they addressed the questionnaire. Demographic characteristics of respondents were provided by TNS-NIPO.

Details about the testing of the questionnaire are provided in Dimitropoulos et al. (2014). The response rate to the survey (after excluding respondents reporting that they made random choices in the choice scenarios) was about 75%. Slightly more than 15% of complete responses were excluded from the rest of our analysis, due to respondents' extremely fast handling of choice scenarios. All questionnaires with a median duration of response to the choice scenarios of less than 10 seconds were not further processed, as it would be hard to argue that these respondents actually made trade-offs between the vehicle attributes. Eventually, 1514 valid responses were collected. A few unreliable responses were not considered further, and thus 1501 responses are used in the rest of the analysis. An overview of respondents' background characteristics is provided in Appendix B.

3.2. Choice experiment

Before being introduced to the experiment, respondents were instructed to think about their next car purchase and treat each choice scenario presented to them as a real choice task. Each respondent addressed 8 choice scenarios. In each scenario, respondents were invited to choose their preferred option, assuming that the car model they were intending to purchase next was available in 4 versions: a plug-in hybrid (PHEV), an electric with fixed battery (FBEV), an electric with swappable battery (SBEV) and a version driving on respondents' preferred propulsion system and fuel (e.g. petrol, diesel, LPG, HEV, biofuels, etc.). When respondents reported that they would opt for a FEV or a PHEV at their next car purchase, the fourth alternative was automatically set to a petrol-fuelled car. Respondents were instructed to assume that the four options were different only in the 9 attributes presented to them. Table 2 presents an overview of the attributes and attribute levels employed in the choice experiment. Details about the descriptions of the PHEV and FEV technologies provided to the respondents are offered in Appendix C. We only mention here that

PEVs were described as more environmentally benign alternatives than ICE-propelled cars, i.e. as vehicles with substantially lower emissions of CO_2 and air pollutants.

Table 2: Attributes and attribute levels used in the choice experiment.

Attributes	**Attribute levels**			
Propulsion system and fuel type	**ICE or Hybrid**	**Plug-in hybrid**	**Electric with fixed battery**	**Electric with swappable battery**
Purchase Price (€)	Customised on respondent's reported price range for next car purchase	0.8 * ICE 1.4 * ICE 2.0 * ICE	0.8 * ICE 1.4 * ICE 2.0 * ICE	0.8 * ICE 1.1 * ICE 1.4 * ICE
Fuel costs (€/100km)	Base value - 2.5 Base value Base value + 2.5	3.5 5.5 7.5	3 4.5 6	9 11 13
Residual value after 5 years (% of purchase price)	40% 50% 60%	30% 45% 60%	30% 45% 60%	30% 45% 60%
Range (kilometres)	600 750 900	500 700 900	100 300 500	100 300 500
Refuel time at the station (minutes)	5	5	15 30 45	5
Charging time at home or work (hours)	N.A.	1.5 3 5	4 8 10	4 8 10
Extra detour time (minutes)	N.A.	N.A.	0 10 20	0 15 30
Exemption from annual road tax (years)	No exemption	No exemption Exemption for 2 years Exemption for 4 years	No exemption Exemption for 2 years Exemption for 4 years	No exemption Exemption for 2 years Exemption for 4 years

Note: ICE encompasses vehicles propelled solely by an internal combustion engine.

Apart from the propulsion system, the options differed with respect to 8 attributes, i.e. purchase price, fuel costs, residual value after 5 years, driving range, refuelling time at the station, charging time at home and work, extra detour time to reach the nearest refuelling station, and duration of exemption from the payment of the annual road tax. The *purchase price* of the ICE car was customised on respondent's selected price range.[6] The purchase price of the three other options varied around the price of the ICE car in accordance with the coefficients shown in Table 2. The purchase price of PEVs included the costs of a charging cable and a standard home-charging unit.

[6] Before engaging in the choice scenarios, respondents were asked to select the anticipated price range of their next car from a list of possible ranges. The price ranges presented to respondents whose next purchase would be a second-hand car were narrower and lower than the ones of respondents opting for new cars. For each choice scenario, a random number was drawn from a uniform distribution defined in the interval between 1/100th of the minimum value of that price range and 80% of 1/100th of the maximum one. The resulting integer was then multiplied by 100 to present the respondent with a price rounded to hundreds of Euros. For example, if the respondent reported that their next car would fall in the price range €15,000-€20,000, a random number was drawn in the interval [150,190]. The integer was then multiplied by 100 to provide a price between €15,000 and €19,000.

As the table shows, we also considered cases where PEVs were priced lower than ICE-propelled cars, in order to have the flexibility to examine a wider range of attribute trade-offs.

In regard to *fuel costs*, respondents were presented with three figures for each alternative; one indicating fuel costs per 100km, and two annual fuel costs figures based on the yearly distance expected to be travelled by their next car. Annual fuel costs were presented for the minimum and maximum distance in the range selected by respondents in a question preceding the experiment. The computation of the base value of the fuel costs/100km of the ICE car depended on the average fuel efficiency of the fuel type and propulsion system selected by the respondent and on retail fuel prices at the time of the survey.[7] Fuel costs of PEVs vary according to the values presented in Table 2. The SBEV fuel costs are higher than the FBEV and PHEV ones as the former also include the rental price of the battery-pack and the costs of using the battery-swapping stations.

In the Netherlands, cars remain on average under the ownership of the same individual for about five years. Under the precondition that the car would be in good condition at that time, we assumed that the individual would then have the opportunity to sell their car at a satisfactory price, captured by the *residual value* of the car *after 5 years*. Since there is much uncertainty about the trajectories that the technology and the prices of battery packs and other EV components will follow in the next years, we considered a wider range of depreciation rates for PHEVs and FEVs than for ICE-propelled cars.

Driving range varied for all alternatives. For PHEVs, we considered values spanning from the current situation for extended-range electric cars to the current situation for plug-in hybrids. For FEVs, we employed driving range levels from as low as 100 km, slightly lower than the level advertised for most commercially available FEVs, to 500 km, somewhat higher than the one estimated for the 85-kWh battery-pack of Tesla Model S.[8] *Refuel time at the station* denoted the time required to refuel the tank of the ICE car or the PHEV, to fast-charge the battery of the FBEV, or to swap the batteries of the SBEV at specialised stations. It varied only for the FBEV, from 15 to 45 minutes for a full charge. Standard *charging time at home or work* was substantially shorter for PHEVs than FEVs, due to their usually smaller battery-packs. It varied from 1½ to 5 hours for the PHEVs and from 4 to 10 hours for the FEVs. *Extra detour time* to reach the nearest fast-charging or battery-swapping station was essentially a measure of the availability of refuelling infrastructure, as it informed respondents about the extra time they would have to spend in searching for a quick alternative to standard home-charging if they adopted an FEV (cf. Hoen and Koetse, 2014; Train,

[7] We assumed that oil-derived fuel and biofuel prices would be more volatile than electricity prices and thus larger deviations were considered for the fuel costs of ICE-propelled cars than for the ones of PEVs. The smallest deviations were considered for FBEVs, as fuel costs are least affected by changes in oil prices or the terms of battery-rental contracts. With the exception of petrol-fuelled ICE cars, where we considered different base values for compact and large cars, we employed a single base value per fuel type.

[8] See: http://www.teslamotors.com/models/options.

2008).[9] As the investment required for the building of a battery-swapping station was at the time of the survey about 20 times higher than the one required for the installation of an AC fast-charging unit, we considered slightly higher levels of this attribute for SBEVs than for FBEVs.

The annual road tax constitutes a substantial share of the operating costs of a private car in the Netherlands. Its value primarily depends on the fuel type and weight of the car. It ranges from around €160/year for a very light, petrol-fuelled, car to more than €2000/year for a diesel-fuelled car weighing more than 2 tonnes.[10] *Road tax exemptions* are currently provided for cars with very low CO_2 emissions (i.e. up to 50 g CO_2/km) but they are expected to be suspended at the end of 2015. The tax values presented to the respondents were customised on the size of the car they were most likely to purchase next and their preferred fuel type. No tax exemptions were considered for ICE cars. For PEVs we considered 3 cases: no tax exemption, and tax exemptions for 2 and 4 years.

Regarding the design of the study, we used SSIWeb's *Complete Enumeration* method to generate a close to orthogonal design with 300 choice experiment versions (Sawtooth Software, 2008). To accommodate the attribute differences among the four propulsion systems presented to the respondents, we used an alternative-specific design. The sequence of the four alternatives was randomised, whereas the attribute sequence was fixed to reduce the complexity of the task. Perl and HTML scripting was extensively used to accommodate the alternative-specific nature of the attribute levels and to customise monetary attribute values (purchase price, fuel costs, residual value and road tax) on respondents' statements for their next transaction. Figure 2 presents an example of a choice scenario.

4. Methodology

We investigate consumer preference heterogeneity in the framework of panel latent class models (PLCMs). We believe that this class of models provides a more appropriate framework for our study than logit models based on continuous mixing distributions for two reasons. First, PLCMs do not require that specific distributional assumptions are imposed on taste parameters. Second, they provide a more structured and intuitively appealing framework to work with when the identification of potential adopters of new technologies and other groups of interest is of primary importance for the study, as it is here.

[9] An alternative approach employed in most previous studies (e.g. Achtnicht et al., 2012; Brownstone and Train, 1999) is to use an attribute presenting the availability of refuelling infrastructure as a percentage of the current availability of petrol stations. However, this approach does not inform respondents about the proximity of these refuelling stations to the routes they usually follow.

[10] The road tax for diesel and LPG cars is about twice as high as the one for petrol-fuelled ones, while the tax for compressed natural gas (CNG) cars is about 50% higher than the one for the latter.

In this framework, we use PLCMs where class-membership is modelled as a stochastic function of driver's socio-demographic background, car use patterns and environmental concerns. Our baseline is a PLCM where environmental concerns are assumed to be accurately measured by the relevant Likert scale (see also panel (b) of Figure 1). The outcome of this model is then contrasted to the outcome of a hybrid panel latent class model (HPLCM), whereby we treat individuals' environmental concerns as unobserved (panel (d) of Figure 1). The HPLCM is developed in the spirit of Hess et al. (2013) and Hoyos et al. (2013), who apply analogous models in the context of rail travel and land-use policy valuation.

Choice Question 1

The four options presented below are different versions of the same model. They differ only in the presented attributes.

	Option 1	Option 2	Option 3	Option 4
Fuel type	Plug-in hybrid	Petrol	Electric with fixed battery	Electric with swappable battery
Purchase price	€ 46,400	€ 23,200	€ 18,600	€ 25,500
Fuel costs	€ 3.50 per 100 km	€ 16.50 per 100 km	€ 6.00 per 100 km	€ 11.00 per 100 km
Annual fuel costs for a travelled distance of 10,000 km	*(€ 350 per year)*	*(€ 1,650 per year)*	*(€ 600 per year)*	*(€ 1,100 per year)*
Annual fuel costs for a travelled distance of 15,000 km	*(€ 525 per year)*	*(€ 2,475 per year)*	*(€ 900 per year)*	*(€ 1,650 per year)*
Residual value after 5 years	€ 20,900	€ 9,300	€ 11,100	€ 7,700
Range	900 kilometers	750 kilometers	300 kilometers	100 kilometers
Refuel time at the station	5 minutes	5 minutes	30 minutes	5 minutes
Refuel time at home or work	3 hours	Not applicable	10 hours	4 hours
Extra detour time	No extra time	No extra time	20 minutes	No extra time
Annual road tax	No exemption from road tax, €650 per year from the first year	No exemption from road tax, €650 per year from the first year	Exemption from road tax for 4 years, thereafter € 650 per year	Exemption from road tax for 2 years, thereafter € 650 per year

Please indicate below which option you would choose:

	Option 1	Option 2	Option 3	Option 4
Your choice →	○	○	○	○

Figure 2: Example of a vehicle choice scenario.

Note: In the example above, the respondent stated that his next purchase would be a new, medium-sized, petrol-fuelled car, costing €20,000–€25,000. He would drive 10,000–15,000 km per year in it.

4.1. General formulation of the model

We now proceed with the general mathematical formulation of the models. The PLCM is presented first, followed by the HPLCM. We assume that, conditional on membership in class g, car driver n behaves according to a random utility model when choosing alternative i in choice scenario s. Utility is modelled in preference space and is of the form:

$$U_{\text{nis}}^{g} = \boldsymbol{\beta}^{g\prime}\mathbf{X}_{\text{nis}} + \varepsilon_{\text{nis}}^{g}, \tag{1}$$

where U denotes random utility, **X** is a vector of variables related to individual n and alternative i at choice situation s, **β** represents a class-specific vector of parameters to be estimated, and ε is an idiosyncratic, unobserved by the researcher, component of utility, assumed to be i.i.d. Gumbel across individuals. Conditional on her membership in class g, the logit probability that individual n chooses alternative i among J alternatives in scenario s, can then be expressed as:

$$P_{\text{nis}}^{g} = \frac{e^{\boldsymbol{\beta}^{g\prime}\mathbf{X}_{\text{nis}}}}{\sum_{j=1}^{J} e^{\boldsymbol{\beta}^{g\prime}\mathbf{X}_{\text{njs}}}}, \tag{2}$$

while the probability that she makes the sequence of choices that she is observed to make can be calculated as (Greene and Hensher, 2003):

$$P_{\text{n}}^{g} = \prod_{s=1}^{S} P_{\text{nis}}^{g}. \tag{3}$$

Individuals are probabilistically assigned to different classes according to a class membership model (CMM). Assuming that the random component of the membership likelihood function is also i.i.d. Gumbel, the logit probability that individual n is a member of class g among G classes is (Boxall and Adamowicz, 2002):

$$p_{\text{n}}^{*g} = \frac{e^{\alpha^{*g} + \boldsymbol{\zeta}^{*g\prime}\mathbf{Z}_{\text{n}} + \theta^{*g} Q_{\text{n}}^{*}}}{\sum_{g=1}^{G} e^{\alpha^{*g} + \boldsymbol{\zeta}^{*g\prime}\mathbf{Z}_{\text{n}} + \theta^{*g} Q_{\text{n}}^{*}}}, \tag{4}$$

where parameters and vectors of parameters of the Gth class (α^{*G}, $\boldsymbol{\zeta}^{*G}$, and θ^{*G}) are normalised to zero to ensure identification (Greene and Hensher, 2003). In Equation (4), $\mathbf{Z}_{\text{n}}$ is a vector of observed socio-demographic characteristics and car use patterns of individual n, Q_{n}^{*} denotes environmental concerns, assumed to be accurately measured by the psychometric scale used, while class-specific constants α^{*}, parameters θ^{*} and vectors of parameters $\boldsymbol{\zeta}^{*}$ are to be estimated. The unconditional probability that the individual makes the choices she is observed to have made is given by Equation (5):

$$L_{\text{n}_{\text{PLCM}}} = \sum_{g=1}^{G} p_{\text{n}}^{*g} P_{\text{n}}^{\text{g}}, \tag{5}$$

The assumption that the psychometric scale provides an accurate measurement of the psychological construct of interest might, however, be invalid. If the scale used for the construct suffers from measurement error, the parameter estimates of the PLCM will be biased. This econometric concern, as well as concerns about the validity of the assumption that the construct is exogenous, have led a number of researchers to consider psychological constructs in the framework of structural equation modelling. In this framework, the psychological constructs of interest are modelled as latent variables (Walker, 2001). The latent variable Q is expressed as a stochastic linear function of individuals' observed characteristics according to the following structural equation:

$$Q_{\mathrm{n}} = \boldsymbol{\gamma}'\mathbf{R}_{\mathrm{n}} + \omega_{\mathrm{n}} \ , \tag{6}$$

where $\mathbf{R}_{\mathrm{n}}$ is a vector of observed socio-demographic characteristics of individual n (whose elements can be partially or fully shared with $\mathbf{Z}_{\mathrm{n}}$) and ω_n is a random component distributed normally with mean zero and standard deviation σ, which has to be estimated alongside with the vector of parameters $\boldsymbol{\gamma}$. The estimation of the model requires additional information about the latent construct. This information is obtained from individuals' responses to the Likert-type questions.

In line with recent work by Daly et al. (2012) and Hess et al. (2013), we acknowledge the ordered structure of the Likert-type data and employ ordered logit specifications in the measurement model used to analyse the responses to the indicators of interest. The probability that individual n provides response m to indicator t of the latent variable will then be provided by Equation (7):

$$\pi_{\mathrm{ntm}} \equiv P_{\mathrm{n}}(I_{\mathrm{t}} = m) = \frac{e^{\tau_{\mathrm{tm}} - \lambda_{\mathrm{t}} Q_{\mathrm{n}}}}{1 + e^{\tau_{\mathrm{tm}} - \lambda_{\mathrm{t}} Q_{\mathrm{n}}}} - \frac{e^{\tau_{\mathrm{t(m\text{-}1)}} - \lambda_{\mathrm{t}} Q_{\mathrm{n}}}}{1 + e^{\tau_{\mathrm{t(m\text{-}1)}} - \lambda_{\mathrm{t}} Q_{\mathrm{n}}}} \ , \tag{7}$$

where λ_t denotes the effect of Q on indicator I_t, and τ_{tm}, with m=0,…,M, are cut-off values to be estimated. For normalisation, τ_{t0} is set to $-\infty$, τ_{tM} to $+\infty$, and λ_1 to 1.

The logit probability that individual n is a member of class g among G classes will now be:

$$p_{\mathrm{n}}^{g} = \frac{e^{\alpha^{g} + \boldsymbol{\zeta}^{g\prime}\mathbf{Z}_{\mathrm{n}} + \theta^{g} Q_{\mathrm{n}}}}{\sum_{g=1}^{G} e^{\alpha^{g} + \boldsymbol{\zeta}^{g\prime}\mathbf{Z}_{\mathrm{n}} + \theta^{g} Q_{\mathrm{n}}}} \ . \tag{8}$$

Assuming independence between the sequence of choices made in the experiment and the chosen levels of agreement to the attitudinal questions, the likelihood that individual n makes the sequence of choices she is observed to have made and that she provides the response to the indicators that she actually provided over classes will then be given by Equation (9):

$$L_{\mathrm{n}_{\mathrm{HPLCM}}} = \int_{\omega_{\mathrm{n}}} \sum_{g=1}^{G} p_{\mathrm{n}}^{\mathrm{g}} P_{\mathrm{n}}^{\mathrm{g}} \prod_{t=1}^{T} \pi_{\mathrm{ntm}} \phi(\omega_{\mathrm{n}})\, \mathrm{d}\omega_{\mathrm{n}} \ , \tag{9}$$

where $\phi(\omega_n)$ is the density of ω_n. The log-likelihood for the sample will be:

$$LL_{(\bullet)} = \sum_{n=1}^{N} \ln(L_{\mathrm{n}_{(\bullet)}}) \ , \tag{10}$$

where $(\bullet)$ denotes PLCM or HPLCM.

The parameters of interest are estimated by maximising this log-likelihood function. All models were coded and estimated in PythonBiogeme 2.3 (Bierlaire, 2003, 2009). Regarding the desirable number of latent classes, it is determined by estimating models with different numbers of classes and comparing them on the basis of the meaningfulness of the yielded estimates and their performance with respect to the Schwarz Information Criterion (SIC, see also Gupta and Chintagunta, 1994).[11] It is worth noting here that this criterion is only of use for comparisons of models with the same treatment of the psychological construct. It is meaningless to compare the fit of a PLCM model with the fit of its HPLCM counterpart, as the latter not only explains the sequence of vehicle choices made by individuals, but also their responses to the indicators of environmental concerns.

4.2. PLCM specification

We hereby specify the formulation used for the PLCM. The only difference between the PLCM and the HPLCM developed in this study concerns the treatment of *environmental concerns*. The formulation of the random utility and class membership models is otherwise identical.

Random Utility Model

The formulation of random utility function does not vary among classes. All vehicle attributes used in the experiment enter the deterministic component of utility function linearly, with the exception of driving range, where the logarithmic transformation is employed instead. This conforms to the suggestions made in Dimitropoulos et al. (2013) and to the empirical finding that the logarithmic specification performed significantly better than the linear one.

We also take into account possible income effects by considering interaction effects between price and the income category of the consumer. After experimenting with a number of different income categories, we distinguish here only between drivers with low or average income, ones with higher income, and ones who preferred to keep their income category unrevealed. Descriptive statistics for annual gross household income are provided in Table 3 and Appendix B.

Class Membership Model

Class membership is modelled as a function of individual's sociodemographic background, car ownership and use characteristics and environmental concerns. Definitions and descriptive statistics of the variables employed in the class membership model are presented in Table 3. The selection of

[11] SIC = -2ln(LL_c)+$r$ln(N), where LL_c is the value of the log-likelihood function at convergence, r is the number of parameters used in the model, and N is the size of the sample.

the variables used in the model and their functional form followed extensive search of possible specifications.[12]

Table 3: Description and descriptive statistics of the variables used in the models.

Variable	Description	Model component	Mean	Std. dev.
Female	Female respondent	CMM , LVSM	0.37	n.a.
Age	Respondent's age in years	CMM , LVSM	52.58	13.74
High education	Respondent has at least college / university education	CMM , LVSM	0.39	n.a.
High income	Household's gross annual income ≥ € 77,500	RUM, LVSM	0.19	n.a.
Unreported income	Respondent did not report household's income category	RUM	0.07	n.a.
Low driving needs	Annual distance expected to be travelled with next car < 15,000 km	CMM	0.57	n.a.
Often abroad	Respondent travels more than twice a year abroad by the car in context	CMM	0.24	n.a.
First car replacement	Next car will replace household's first car	CMM	0.83	n.a.
Long-term decision	Household's next car purchase will occur in more than 3 years	CMM	0.43	n.a.

Note: All variables follow a dummy specification, with the exception of age. RUM: Random Utility Model; CMM: Class Membership Model; LVSM: Latent Variable Structural Model.

4.3. Latent environmental concerns

Latent environmental concerns are specified as a stochastic function of individual's gender, age, education and income. Age is modelled as a continuous variable, whereas dummy variables are used to capture the influence of education and income. We distinguish highly educated individuals (i.e. individuals with at least college or university education) and high income households (i.e. households with annual gross income of at least €77,500). As the variables used in the structural model are also employed in the class membership or random utility model, descriptive statistics for them are provided in Table 3. The table also provides information about the model components whereby the variables are used.

Regarding the measurement model formulated for the latent variable, we deploy information from individuals' responses to 4 items assessing how serious different possible environmental impacts of car use are perceived. The text used for these items and their descriptive statistics are illustrated in Table 4. All items are measured in a scale from 1 to 6, where 1 indicates the lowest level of concern and 6 the highest. Internal consistency checks for the set of indicators presented in

[12] Among other variables, we tested the performance of various consumer characteristics, such as whether the consumer owns or rents the house she lives in, whether she commutes to work by the car in context, whether that car is the primary (or only) car of the household, as well as various characteristics of the municipality where the individual's dwelling is located, such as population, address density, and pollution levels (as measured by SO_x, NO_x and PM emissions). None of these variables, however, influence the results presented here.

Table 4 suggest that they can reliably manifest the underlying psychological construct. The four items used for the measurement of environmental concerns have a *Cronbach's α* of 0.859.

Table 4: Indicators used in the measurement model of latent environmental concerns.

	Car use can have various effects. In your opinion, how serious are the following possible impacts of car use?	Mean	Std. dev.
$Ienv_1$	Noise caused by vehicle traffic.	3.54	1.15
$Ienv_2$	Local air pollution caused by vehicle traffic.	4.38	1.13
$Ienv_3$	Climate change caused by vehicle traffic.	4.14	1.26
$Ienv_4$	Environmental degradation caused by the extraction of oil and gas.	4.35	1.22

5. Empirical results

5.1. PLCM estimates

Table 5 presents the estimation results of the panel latent class model (PLCM). We tested PLCMs with 2-7 latent classes. Information about the statistical performance of the models is provided in Table 6. A comparison of the statistical fit of the models on the basis of SIC revealed that the 6-class model had the best statistical performance. However, our preferred specification is the model with 5 latent classes, as models with 6 or more classes resulted in inflated standard errors in small segments.[13]

As already noted, we examine variation in consumers' sensitivity to purchase price changes according to their gross household income. Although we estimate a price parameter per class, the coefficients of interactions between price and income category are constrained to be the same among classes. This specification is more informative than a more flexible specification allowing income effects to vary among classes. Individuals not reporting their household income are found to have a lower sensitivity to changes in vehicle price, which makes us suspect that they belong to higher income households (cf. e.g. van Ommeren et al., 2012).

The labels assigned to the classes are inspired by the estimates of the random utility parameters and the importance of consumer characteristics entering the class membership model. *Status quo captives* comprise the largest class, containing about 27% of the sample. While being open to new technologies, this class is very reluctant to relinquish the convenience of long driving

[13] The smallest segment identified in the 6-class model encompassed about 10.6% of the sample. However, heteroskedasticity-robust standard errors were peculiarly high for this class, resulting in only the estimates of price, fuel costs, resale value and driving range being statistically significant.

range and short refuelling time offered by ICE-propelled cars. *Status quo captives* constitute the only class valuing fast-charging time and charging time at home or work. They are particularly sensitive to changes in fast-charging time, valuing a 1-minute reduction in the duration of each fast-charging action more than a 27-minute reduction in the duration of each home-charging one. Young and highly educated drivers and males are more likely to belong to this class. Their behaviour is well-grounded on their intensive car use, both within the national borders and abroad.

Table 5: PLCM estimation results.

	Status quo captives		Combustion engine diehards		Price conscious buyers		Full electric optimists		Plug-in hybrid enthusiasts	
Random Utility Model	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Plug-in hybrid [PHEV]	-0.193	(0.149)	-4.261***	(0.460)	0.248	(0.257)	0.864**	(0.380)	1.370***	(0.328)
Electric: fixed battery [FBEV]	-1.154***	(0.389)	-5.961***	(1.160)	0.513	(0.364)	1.186**	(0.465)	-0.916	(0.649)
Electric: swappable battery [SBEV]	-0.920***	(0.253)	-4.937***	(0.871)	0.083	(0.271)	0.860**	(0.409)	-0.071	(0.494)
Purchase price (1000 €)	-0.133***	(0.014)	-0.094***	(0.021)	-0.323***	(0.042)	-0.077***	(0.011)	-0.064***	(0.012)
Purchase price (1000 €) * Income > € 77,500 [a]	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)
Purchase price (1000 €) * Income unreported [a]	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)
Fuel costs (€/100km)	-0.150***	(0.014)	-0.089**	(0.040)	-0.097***	(0.030)	-0.190***	(0.042)	-0.246***	(0.043)
Road tax savings (1000 €)	0.070**	(0.029)	0.011	(0.078)	0.115*	(0.060)	0.173***	(0.037)	0.101**	(0.042)
Residual value of the car after 5 years (%)	0.028***	(0.003)	0.002	(0.008)	0.007	(0.005)	0.014***	(0.003)	0.021***	(0.007)
ln(Driving range) (km)	1.119***	(0.133)	0.355	(0.328)	0.845***	(0.124)	0.473***	(0.069)	0.638***	(0.175)
Detour time (10 min/refuelling action)	-0.402***	(0.103)	-0.010	(0.233)	-0.068	(0.071)	-0.070	(0.050)	-0.355***	(0.120)
Charging time at station (10 min/refuelling action)	-0.280**	(0.109)	0.270	(0.176)	-0.099	(0.082)	-0.048	(0.053)	-0.093	(0.127)
Charging time at home/work (100 min/charging action)	-0.102**	(0.041)	0.067	(0.101)	-0.044	(0.036)	-0.020	(0.026)	-0.070	(0.069)
Class Membership Model			estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Environmental concerns			-0.190**	(0.090)	0.317**	(0.129)	0.388***	(0.113)	0.228*	(0.128)
Female			0.405**	(0.207)	0.679**	(0.266)	0.628**	(0.246)	0.141	(0.250)
Age			0.065***	(0.008)	0.008	(0.010)	0.012	(0.009)	0.016	(0.011)
High education			-0.561***	(0.183)	-0.306	(0.252)	-0.548**	(0.212)	-0.284	(0.219)
Low driving needs	*Reference Class*		0.479**	(0.192)	1.156***	(0.295)	0.052	(0.241)	0.297	(0.257)
Often abroad			-0.308	(0.205)	-0.789**	(0.315)	-0.450*	(0.236)	-0.240	(0.293)
First car replacement			-0.127	(0.287)	-0.887**	(0.328)	-0.442	(0.295)	-0.396	(0.338)
Long-term decision			-0.192	(0.178)	0.289	(0.247)	0.401*	(0.222)	0.032	(0.226)
Constant			-2.690***	(0.554)	-2.357***	(0.819)	-2.444***	(0.653)	-2.002***	(0.703)
Class size	*0.269*		*0.266*		*0.155*		*0.161*		*0.148*	
Parameters	93									
Observations (Individuals)	12008 (1501)									
Log-likelihood at convergence	-9281.0									

Note: Standard errors are heteroskedasticity-robust. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

[a] Parameter estimates are constrained to be equal among classes.

The class of *combustion engine diehards* is of similar size to *status quo captives*. This class is, however, unwilling to consider PEV technologies, regardless of their characteristics. It encompasses older drivers who are not highly educated and have low environmental concerns. *Combustion engine diehards'* aversion towards PEVs is not based on higher driving needs. This class is very unlikely to get behind the steering wheel of a PEV, unless they become the prevalent vehicle technology.

Price-conscious buyers take their name from their noteworthy sensitivity to changes in the purchase price of the car. Fuel technology is not a determinant of their choice and the operating costs of the vehicle have a secondary role in their decision-making process. Driving range is an important attribute for them, even though they value it less than other classes do. In short, this class of drivers would be willing to consider PEVs, provided that they were priced equivalently to their ICE-propelled counterparts. *Price-conscious buyers* are primarily females and their behaviour is in line with a higher probability that the car in context is not the primary car of the household. This is also in agreement with the low driving needs associated with one's membership in this class.

Full electric optimists are the most likely potential adopters of full electric cars. Amounting to slightly more than 16% of the sample, this is the only class preferring FEVs from the rest of the alternatives. These drivers consider fixed-battery electric cars more attractive alternatives than swappable battery ones. *Full electric optimists* are also the class placing the strongest emphasis on PEVs' exemptions from road taxes, implying that incentives provided for the adoption of FEVs can be influential in the vehicle choices made by this class. Increases in driving range are also highly appreciated by these drivers. *Full electric optimists* have high environmental concerns, are more likely to be females, and have a longer-term view to the purchase of the next car, i.e. more than 3 years ahead. A further implication of the last finding might be that *full electric optimists* have considered optimistic scenarios of FEV performance more realistic than members of other classes.

Plug-in hybrid enthusiasts are likely early adopters of plug-in hybrids. This class corresponds to about 15% of the sample, who have high appreciation for reductions of vehicle operating costs. They are very sensitive to changes in fuel costs and vehicle's resale value and suffer the highest losses from shorter vehicle range and longer detour time among classes. This renders FEVs a less attractive option for them. On the contrary, plug-in hybrids' lower operating costs and similar levels of comfort in terms of range and refuelling needs with ICE-propelled cars make them an appealing alternative for this class. High environmental concerns are also a determinant of one's membership to *Plug-in hybrid enthusiasts*.

Table 6: Statistical performance of PLCMs with varying number of classes.

Latent Classes	Parameters	Log-likelihood at convergence	AIC	SIC
2	33	-10295.1	20656.2	20831.6
3	53	-9782.2	19670.5	19952.1
4	73	-9462.9	19071.8	19459.7
5	93	-9281.0	18748.0	19242.2
6	113	-9182.1	18590.1	19190.6
7	133	-9115.5	18496.9	19203.7

Note: AIC: Akaike Information Criterion; SIC: Schwarz Information Criterion.

Further insights into the sociodemographic composition of latent classes can be provided by the calculation of expected values for environmental concerns and the variables in vector $\mathbf{Z}_n$ of the class membership model for each class. These values are presented in Table 7. The expected value of each variable in class g is based on estimated prior class membership probabilities (see Equation (4)) which can be simply computed by the following formula (see also Hoyos et al., 2013):

$$\mathrm{E}[Y_{\mathrm{n}} \mid g] = \frac{\sum_{n=1}^{N} \hat{p}_{\mathrm{n}}^{*g} Y_{\mathrm{n}}}{\sum_{n=1}^{N} \hat{p}_{\mathrm{n}}^{*g}}\ , \tag{11}$$

where $\hat{p}_{\mathrm{n}}^{*g}$ is the estimate of the probability of membership to class g obtained by the PLCM and Y_n is the variable of interest.

Table 7: Expected values of the variables used in the class membership model of PLCM.

Variable	Status quo captives	Combustion engine diehards	Price-conscious buyers	FEV optimists	PHEV enthusiasts
Age (years)	48.9	59.5	50.0	50.5	51.8
Female (%)	29.9	31.2	52.2	46.8	33.6
High education (%)	47.6	32.5	37.1	34.9	40.3
Low driving needs (%)	42.4	63.9	77.9	53.4	55.5
Often abroad (%)	31.4	24.9	13.6	20.7	25.5
First car replacement (%)	86.9	88.3	69.7	82.0	82.8
Long-term decision (%)	38.0	38.0	51.5	51.2	41.7
Environmental concerns (scale 1-6)	4.0	3.9	4.3	4.4	4.2

5.2. Hybrid PLCM estimates

To the best of our knowledge, this is the first study where class membership is modelled as a function of both observed consumer characteristics and latent variables. Earlier studies of hybrid latent class models (e.g. Hess et al., 2013; Hoyos et al., 2013) do not consider observed consumer characteristics in the class membership model.[14] The underlying assumption behind their approach is that individuals' sociodemographic background and other characteristics influence their class membership probabilities only indirectly, i.e. via the latent variables. This assumption also plays a pivotal role in supporting the argument that the use of latent variables can mitigate analyst's concerns about the endogenous nature of the observed measure. In fact, if this assumption is relaxed, and observed consumer characteristics are found to affect class membership both directly

[14] Hoyos et al. (2013) consider consumer sociodemographic characteristics in the general formulation of the class membership function. However, they report that these characteristics do not have a significant effect on class membership and, thus, they exclude them from their model specification.

and indirectly, the use of latent variables does not address endogeneity. In other words, these observed characteristics cannot serve as *instruments* for the measurement of the latent variables.

In this study, we relax this assumption and allow the same individual characteristics to enter both the class membership and the latent variable structural model. Our estimates show that these characteristics might well impact class membership not only indirectly, but also directly, thereby failing to manifest themselves as appropriate *instruments* for environmental concerns. Even though all modules of HPLCM were estimated simultaneously, we first present the estimates of the parameters of random utility and class membership modules (Table 8) and then the estimates of the structural and measurement model parameters (Table 9). A comparison of Table 8 with Table 5 immediately reveals that the parameter estimates of the HPLCM are very similar to the ones of PLCM, with the expected exception of the estimate for environmental concerns and, therefore, the one of the class-specific constant.[15]

The upper panel of Table 9 shows the estimates of the structural model parameters. We find that females and highly educated individuals are more highly concerned about the environmental impacts of car use than males and individuals who have achieved lower levels of education. Similarly, environmental concerns increase with one's age, a finding probably reflecting one's increasing concerns about the environmental conditions faced by one's descendants, as well as about one's vulnerability to health risks stemming from the deterioration of the state of the environment. Even though environmental concerns are far from uniformly defined in relevant SP literature, these findings are in agreement with studies of environmental concerns or related constructs in the context of vehicle choice (Daziano and Bolduc, 2013; Jensen et al., 2013), or in other relevant contexts (Hess et al., 2013; Vredin Johansson et al., 2006).

Previous studies have not identified a significant impact of income on environmental concerns, but we find that representatives of households with relatively higher income have lower environmental concerns than representatives of households with lower income.[16] This finding has important implications for policies and marketing strategies targeted at stimulating the demand for PEVs, as households who are likely to have the financial means to purchase them are not attracted

[15] The log-likelihood of the vehicle choice component at convergence is slightly lower than the one of the PLCM. This is an expected finding, as the HPLCM seeks for a set of parameter values which can explain both vehicle choice and Likert item responses.

[16] We also experimented with other cut-off values defining high income households (e.g. €103,500/year). The results are very similar to the ones presented here. We also looked into differences in environmental concerns between low income households (gross household income < 32,500/year) and other household income categories, but we did not find any significant effects of low income on environmental concerns.

by their labelling as more environmentally benign products. These people might, however, be attracted to other special characteristics of PEVs, such as their innovativeness.[17]

Table 8: HPLCM estimation results.

	Status quo captives		Combustion engine diehards		Price conscious buyers		Full electric optimists		Plug-in hybrid enthusiasts	
Random Utility Model	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Plug-in hybrid [PHEV]	-0.193	(0.149)	-4.270***	(0.462)	0.252	(0.255)	0.868**	(0.377)	1.370***	(0.327)
Electric: fixed battery [FBEV]	-1.165***	(0.391)	-5.967***	(1.150)	0.516	(0.363)	1.193**	(0.460)	-0.911	(0.645)
Electric: swappable battery [SBEV]	-0.926***	(0.254)	-4.944***	(0.868)	0.084	(0.271)	0.867**	(0.405)	-0.074	(0.497)
Purchase price (1000 €)	-0.133***	(0.014)	-0.094***	(0.021)	-0.323***	(0.042)	-0.077***	(0.011)	-0.063***	(0.012)
Purchase price (1000 €) * Income > € 77,500 [a]	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)
Purchase price (1000 €) * Income unreported [a]	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)
Fuel costs (€/100km)	-0.150***	(0.014)	-0.090**	(0.040)	-0.097***	(0.029)	-0.190***	(0.041)	-0.246***	(0.043)
Road tax savings (1000 €)	0.071**	(0.029)	0.010	(0.078)	0.115*	(0.059)	0.173***	(0.037)	0.101**	(0.042)
Residual value of the car after 5 years (%)	0.028***	(0.003)	0.002	(0.008)	0.007	(0.005)	0.014***	(0.003)	0.021***	(0.006)
ln(Driving range) (km)	1.116***	(0.133)	0.346	(0.319)	0.848***	(0.123)	0.474***	(0.069)	0.633***	(0.178)
Detour time (10 min/refuelling action)	-0.400***	(0.103)	-0.004	(0.228)	-0.070	(0.071)	-0.070	(0.050)	-0.356***	(0.121)
Charging time at station (10 min/refuelling action)	-0.275**	(0.109)	0.267	(0.174)	-0.100	(0.082)	-0.048	(0.053)	-0.094	(0.127)
Charging time at home/work (100 min/charging action)	-0.103**	(0.041)	0.066	(0.101)	-0.044	(0.036)	-0.020	(0.026)	-0.070	(0.069)
Class Membership Model			estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Environmental concerns (latent)			-0.151**	(0.067)	0.210**	(0.087)	0.259***	(0.076)	0.141	(0.090)
Female			0.419**	(0.207)	0.670**	(0.265)	0.617**	(0.245)	0.139	(0.250)
Age			0.065***	(0.008)	0.008	(0.010)	0.012	(0.009)	0.016	(0.011)
High education			-0.553***	(0.183)	-0.316	(0.252)	-0.560**	(0.212)	-0.286	(0.220)
Low driving needs	*Reference Class*		0.487**	(0.192)	1.158***	(0.295)	0.055	(0.241)	0.305	(0.257)
Often abroad			-0.310	(0.205)	-0.782**	(0.314)	-0.446*	(0.237)	-0.237	(0.292)
First car replacement			-0.124	(0.288)	-0.893**	(0.328)	-0.447	(0.296)	-0.395	(0.338)
Long-term decision			-0.190	(0.178)	0.284	(0.246)	0.401*	(0.221)	0.031	(0.226)
Constant			-3.391***	(0.504)	-1.197	(0.826)	-1.045*	(0.621)	-1.182*	(0.700)
Class size	*0.277*		*0.271*		*0.152*		*0.153*		*0.148*	
Parameters	121									
Observations (Individuals)	12008 (1501)									
Log-likelihood at convergence	-17042.4									
Log-likelihood vehicle choice component	-9308.3									
AIC	34326.7									
SIC	34969.7									

Note: Standard errors are heteroskedasticity-robust. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. AIC: Akaike Information Criterion; SIC: Schwarz Information Criterion.

[a] Parameter estimates are constrained to be equal among classes.

The estimates of measurement model parameters (lower panel of Table 9) are consistent with our expectations, i.e. that individuals with higher environmental concerns would express a higher level of agreement with the four statements of Table 4. Drivers' environmental concerns are primarily reflected in concerns about climate change and local air pollution and secondarily in concerns about environmental degradation and noise. This implies that environmentally concerned individuals are more likely to be influenced by policies and campaigns emphasising the contribution of PEVs to the combat of climate change and local air pollution, rather than to other environmental problems exacerbated by the use of ICE-propelled cars.

[17] Even though we tested for it, we did not find any statistically significant direct effect of high household income on class membership. The results produced by that model were almost unnoticeably different from the ones presented here.

Table 9: Latent variable model estimation results.

Structural Model

	estimate	std. error
γ_{Female}	0.446***	(0.087)
γ_{Age}	0.009**	(0.003)
$\gamma_{High\ education}$	0.293***	(0.093)
$\gamma_{Income > € 77,500}$	-0.307**	(0.111)
σ	1.509***	(0.097)

Measurement Model

Noise	estimate	std. error	*Climate change*	estimate	std. error
λ_1	1.000	-	λ_3	2.577***	(0.309)
τ_{11}	-3.695***	(0.241)	τ_{31}	-6.102***	(0.688)
τ_{12}	-1.349***	(0.197)	τ_{32}	-3.741***	(0.578)
τ_{13}	0.577***	(0.202)	τ_{33}	-0.607	(0.482)
τ_{14}	2.474***	(0.227)	τ_{34}	2.423***	(0.465)
τ_{15}	4.936***	(0.284)	τ_{35}	6.379***	(0.569)

Air pollution	estimate	std. error	*Environmental degradation*	estimate	std. error
λ_2	2.217***	(0.132)	λ_4	1.862***	(0.186)
τ_{21}	-7.075***	(0.567)	τ_{41}	-5.695***	(0.468)
τ_{22}	-4.412***	(0.446)	τ_{42}	-3.434***	(0.379)
τ_{23}	-1.368***	(0.403)	τ_{43}	-1.051***	(0.349)
τ_{24}	1.439***	(0.450)	τ_{44}	1.353***	(0.346)
τ_{25}	5.350***	(0.582)	τ_{45}	4.195***	(0.380)

Note: Standard errors are heteroskedasticity-robust. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

Individual class membership probabilities are conditional on the values taken by the latent variable which are in turn also dependent on the realizations of ω_n. We simulate prior class membership probabilities using 10,000 draws of ω_n, in order to calculate the expected values of the HPLCM class membership model variables per class. These expected values are shown in Appendix D, as they are largely similar to the ones presented in Table 7. The expected values of latent environmental concerns range between 0.32 for *combustion engine diehards* and 1.14 for *full electric optimist*s.

5.3. Willingness to pay

Table 10 presents mean willingness to pay (WTP) estimates for each attribute and class. We only show here WTP estimates for the PLCM, as differences in class-specific mean WTP values between PLCM and HPLCM are trivial. Mean WTP values are computed as averages of the WTPs of each sampled individual. While WTP estimates for PEV technologies are strongly dependent on the model specification employed, it is interesting to note that all classes except *full electric optimists* rank PEV alternatives in accordance to their proximity to ICE-propelled vehicles. Thus, PHEVs are preferred to FEVs, while swappable-battery EVs are slightly more attractive than fixed-battery ones.

WTP estimates for fuel costs range from around €306 per €1/100km saved for the class with the lowest driving needs, *price conscious buyers*, to €4421 per €1/100km saved for *PHEV enthusiasts*. This implies that consumers capitalise fuel savings of at least 3 years in the purchase price of the car (assuming an indicative annual distance travelled of around 10,000 km for *price conscious buyers*), while some classes even capitalise decades of fuel savings. An increase in the residual value of the car equal to 1% of its purchase price is valued between €201 and €369 by 3 of the classes, while *combustion engine diehards* and *price conscious buyers* do not consider it an important factor in their choice making process. A €1 saving of road taxes is appreciated differently by the classes, with values ranging from €0.4 (*price conscious buyers*) to €2.5 (*full electric optimists*). Variation in classes' valuation of this attribute essentially reflects variation in employed discount rates, as road tax exemptions reflect future savings.

As the logarithmic specification of driving range is used in drivers' utility function, we show the mean WTP values for three levels of range, 100, 300 and 500 kilometres.[18] The value of an additional kilometre of driving range varies from €27 to €115 at a range of 100 km, to values between €5 and €23 at a range of 500 km. Even though reductions in detour time are only appreciated by *status quo captives* and *PHEV enthusiasts*, a 1-minute reduction in the detour time spent per fast-refuelling action is valued between €318 and €638. This implies that expansions of the coverage of fast-charging or battery-swapping infrastructure which would lower detour times would be highly appreciated by more than 41% of drivers. Notably, *PHEV enthusiasts*' WTP for reductions in detour time is double the one of *status quo captives*. Reductions of fast-charging and home charging time are only valued by *status quo captives*. At a value of €221/minute, reductions of fast-charging time can bring noteworthy benefits to this class, while at a value of €486/hour, generous cuts in home charging time would be needed to make PEVs more attractive to these drivers.

So far, we looked at WTP at the class level. It is however, interesting to provide insights into class-membership weighted WTP estimates and the differences emerging in this context between PLCM and HPLCM. We focus on alternative specific constants and investigate how the distribution of class-membership weighted WTP for fixed-battery EVs, swappable-battery EVs and plug-in hybrids differs between PLCM and HPLCM. The expressions used to calculate person-specific WTP values for PEV technology *A* are:

[18] The average driving range level used in the study is 512.5 kilometres.

$$WTP_{n_{A_{PLCM}}} = \sum_{g=1}^{G} \hat{p}_{n}^{*g} WTP_{A_{PLCM}}^{g} \tag{12}$$

for PLCM, and:

$$WTP_{n_{A_{HPLCM}}} = \sum_{g=1}^{G} \hat{p}_{n}^{g} WTP_{A_{HPLCM}}^{g} \tag{13}$$

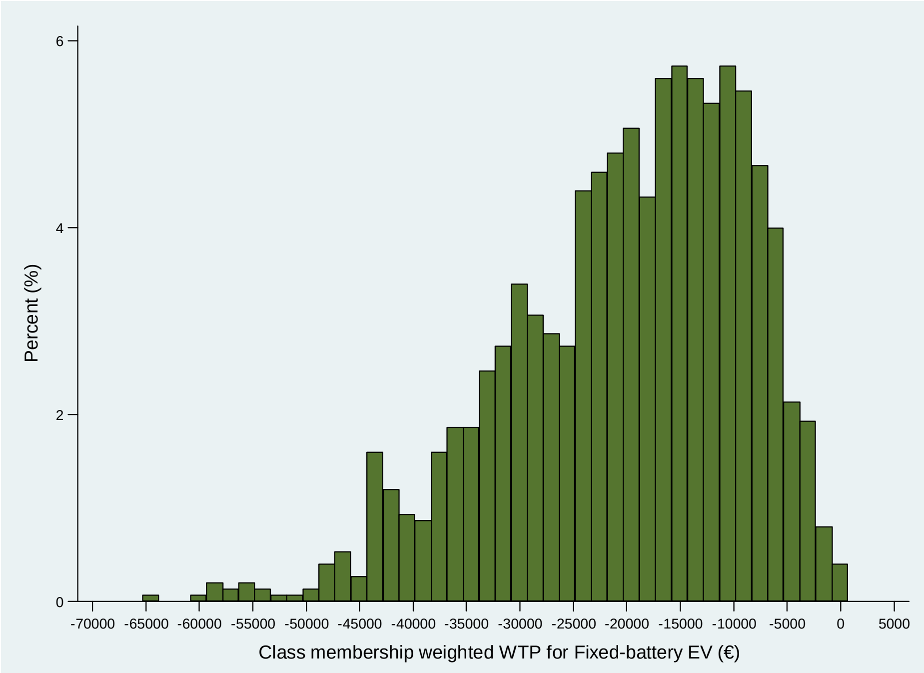
for HPLCM.

Table 10: Mean willingness to pay (€) estimates per class.

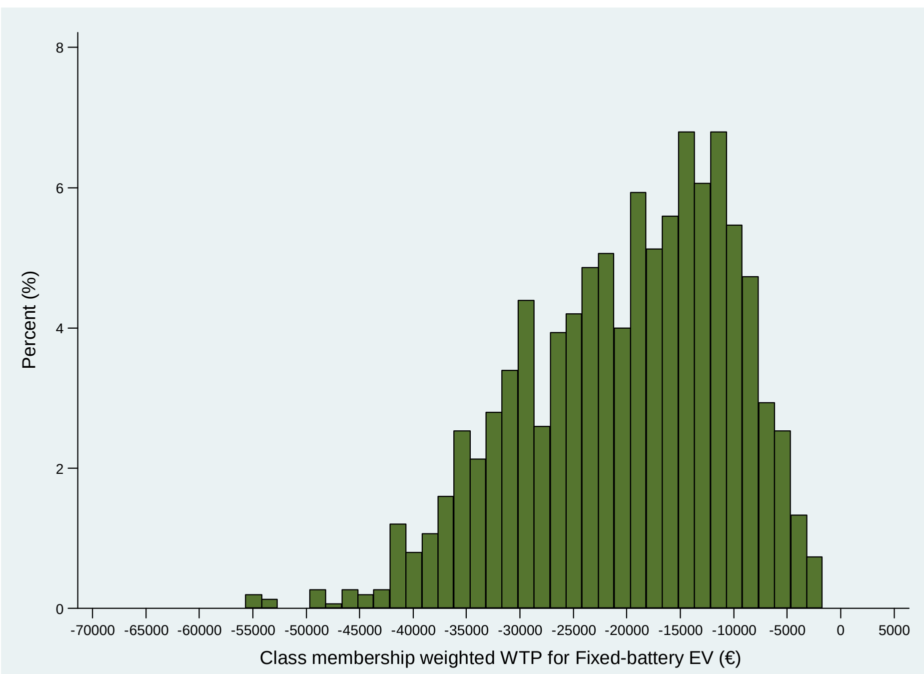
Willingness to pay	Status quo captives	Combustion engine diehards	Price-conscious buyers	FEV optimists	PHEV enthusiasts
PHEV	*ins.*	-48,854.8	*ins.*	12,411.9	24,618.8
FBEV	-9128.1	-68,334.4	*ins.*	17,032.5	*ins.*
SBEV	-7277.5	-56,599.4	*ins.*	12,348.2	*ins.*
Fuel costs (€/100km)	-1189.2	-1015.4	-305.9	-2732.8	-4420.7
Residual value (% of purchase price)	224.9	*ins.*	*ins.*	201.4	368.8
Road tax savings (€)	0.6	*ins.*	0.4	2.5	1.8
Range (km) at 100 km	88.5	*ins.*	26.7	68.0	114.6
Range (km) at 300 km	29.5	*ins.*	8.9	22.7	38.2
Range (km) at 500 km	17.7	*ins.*	5.3	13.6	22.9
Detour time (min)	-317.6	*ins.*	*ins.*	*ins.*	-637.7
Refuelling time at station (min)	-221.4	*ins.*	*ins.*	*ins.*	*ins.*
Charging time at home/workplace (min)	-8.1	*ins.*	*ins.*	*ins.*	*ins.*

Note: The term *ins.* denotes statistically insignificant estimates.

The histograms presented in Figures 3 to 5 present the distribution of WTP estimates for the three PEV technologies. In all cases, panel (a) depicts PLCM estimates, while panel (b) HPLCM ones. PLCM results in lower mean and median WTP estimates for all technologies. On the contrary, the distribution of PLCM estimates has substantially higher variance and is more negatively skewed than the distribution of the HPLCM ones. HPLCM estimates are generally more concentrated around mean values, implying that HPLCM constitutes a more attractive modelling approach when analyst's interest extends further from the estimation and use of average WTP values.

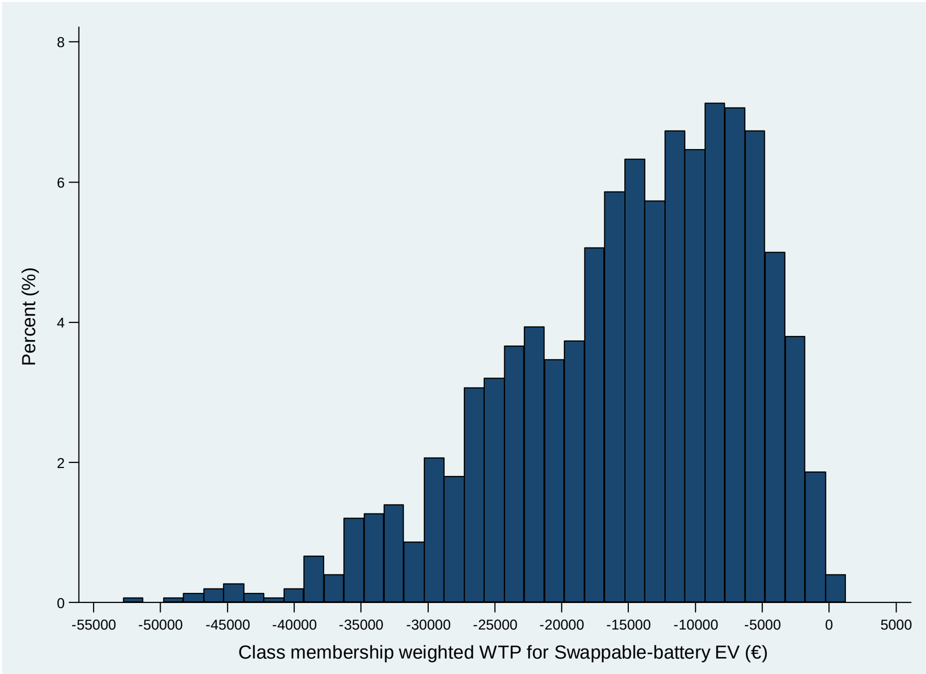


(a) PLCM

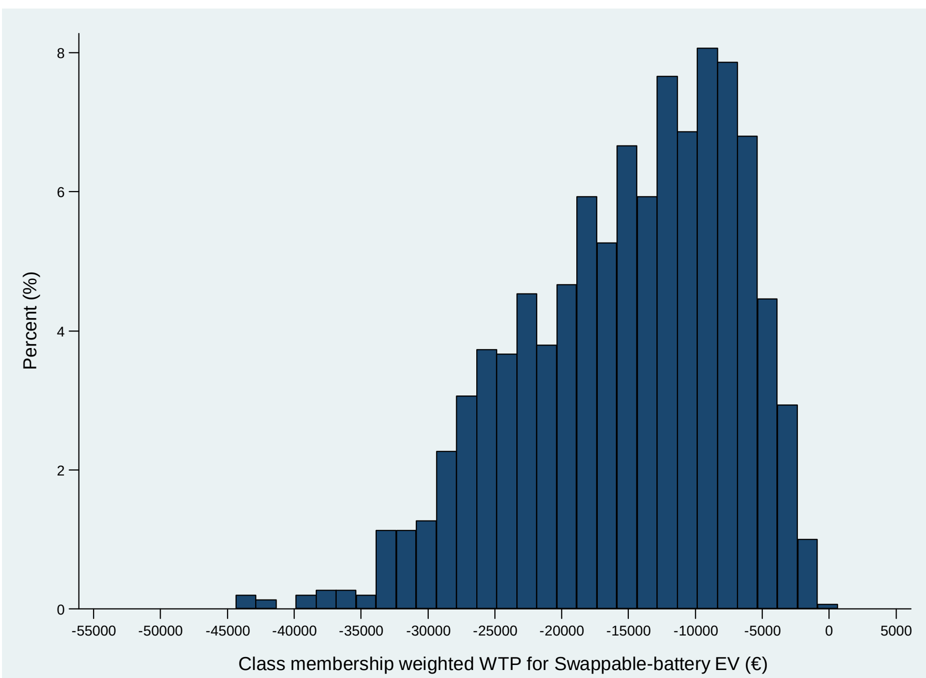


(b) HPLCM

Figure 3: Distribution of class membership weighted mean WTP for fixed-battery EVs.

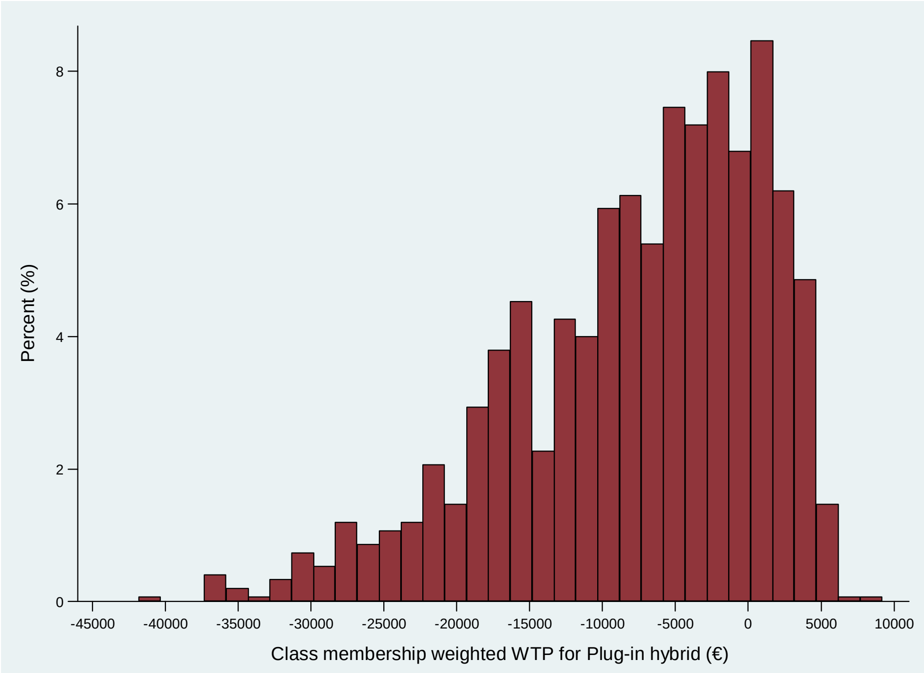


(a) PLCM

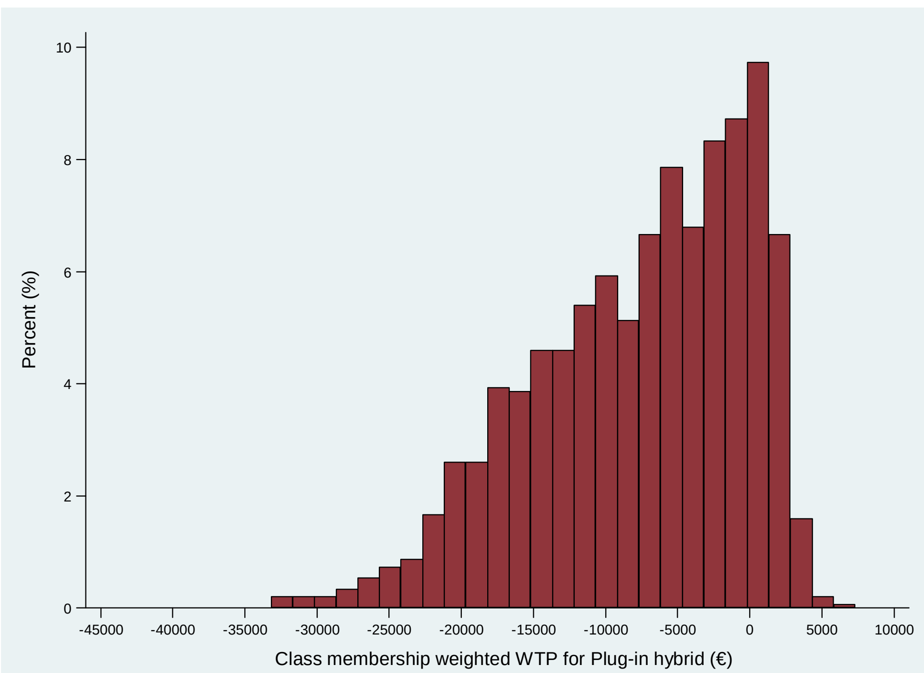


(b) HPLCM

Figure 4: Distribution of class membership weighted mean WTP for swappable-battery EVs.



(a) PLCM



(b) HPLCM

Figure 5: Distribution of class membership weighted mean WTP for plug-in hybrids.

6. Conclusions

Despite the fact that more than three decades have passed since the introduction of stated preference methods to the analysis of consumer preferences for full electric vehicles (FEVs) (Beggs and Cardell, 1980), the same barriers to FEV adoption identified in the 1980s studies still play an important role in consumer reluctance to adopt them. Their large-scale adoption is still conditioned on expectations for technological breakthroughs permitting substantial reductions in EV battery costs, increases in driving range, and decreases in the time needed to recharge vehicle's battery (Dimitropoulos et al., 2013). Recent developments to address these concerns by the car industry and mobility service providers include the construction of car alternatives combining the merits of conventional vehicles with the ones of plug-in electric ones (e.g. plug-in hybrids), and the building of facilities where drivers can swap the depleted battery of an FEV with a fully-charged one at the same time needed to refuel a conventional car with petrol.

Motivated by these developments, we conduct a choice experiment to provide insights into drivers' preferences for different types of plug-in electric vehicles (PEVs). In doing so, we are also especially interested in identifying the influence of drivers' *environmental concerns* on their preferences for PEVs. These concerns are manifested in drivers' responses to Likert-type questions. Our empirical analysis is based on the use of advanced panel latent class models, which enable the identification of consumer segments being more likely to become PEV adopters. Environmental concerns enter the class membership model, thereby influencing driver's likelihood to fall into each latent segment.

Drawing on the responses of about 1500 Dutch drivers, we find that full electric vehicles are still far from attractive for the majority of consumers, who seek for PEV alternatives whose attributes resemble the ones of ICE-propelled cars. To this end, the recently introduced plug-in hybrid and extended-range EVs have considerable potential to mitigate drivers' concerns over short driving ranges and long charging times. In contrast, swappable-battery EVs are not considered significant improvements to their fixed-battery counterparts by any of the segments identified in our study. An encouraging finding for FEVs is that we detect a non-negligible share of drivers (ca. 16% of the sample) who have a positive stand towards them. This segment is characterised by high environmental concerns, but also by a longer-term view to the adoption of the next car.

Our findings reveal that drivers' environmental concerns have strong and positive influence on their preferences for PEVs. Policies and communication strategies built around the environmental benefits of PEVs can attract highly concerned drivers' attention and stimulate them to consider PEVs as viable alternatives to ICE-propelled vehicles. Women, highly educated and older drivers are more likely to exhibit high environmental concerns, and are thus more likely to be attracted by the aforementioned means, while individuals belonging to households with relatively high income are less likely to do so. At the same time, raising drivers' awareness of the environmental impacts of car use by accurate and objective information campaigns is likely to improve their views about PEVs.

Our findings and suggestions are conditional on PEVs being more environmentally benign alternatives than ICE-propelled vehicles. Even though PEVs can provide important environmental improvements in urban environments, it is not equally clear whether they can currently contribute to the combat of climate change and environmental deterioration. This strongly depends on the carbon content of the energy sources used for electricity generation and the environmental performance of the manufacturing procedures used to produce battery packs and other PEV components. If drivers are desired to keep considering PEVs as greener transportation means than ICE-propelled vehicles, it is of utmost importance that they are convinced that the lifecycle environmental impact of PEVs is noticeably lower than the one of their ICE-propelled counterparts.

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Appendix A: Glossary of acronyms

Table A.1 presents a full list of the acronyms used in the study.

Table A.1: List of acronyms used in the study.

FBEV	Full Electric Vehicle with fixed battery
FEV	Full Electric Vehicle (operates only on electricity)
HEV	Hybrid Electric Vehicle (operates on conventional fuel)
HPLCM	Hybrid Panel Latent Class Model
ICE	Internal Combustion Engine
LPG	Liquefied Petroleum Gas
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle (operates on electricity or conventional fuel)
PLCM	Panel Latent Class Model
SBEV	Full Electric Vehicle with swappable battery
SIC	Schwarz Information Criterion
WTP	Willingness to pay

Appendix B: Sociodemographic background of respondents

Table B.1 presents the main sociodemographic characteristics of the sample.

Table B.1: Sociodemographic characteristics of the sample.

Characteristic	Frequency	Characteristic	Frequency
Sex		*2011 Gross household income (€)*	
Male	0.63	Less than 20,000	0.04
Female	0.37	20,000 - 32,500	0.14
Age		32,500 - 51,300	0.30
18-25	0.01	51,300 - 77,500	0.25
26-35	0.11	77,500 - 103,800	0.13
36-45	0.19	103,800 - 155,100	0.05
46-55	0.24	155,100 or above	0.01
56-65	0.25	Unreported	0.07
66 +	0.19	*Household size*	
Highest level of education followed		1	0.13
Primary and lower secondary	0.22	2	0.47
Higher secondary vocational	0.25	3	0.14
Higher secondary professional	0.13	4	0.19
College / University bachelor	0.27	5	0.05
Masters / PhD	0.12	6 or more	0.02
Unreported	0.005		

Appendix C: Description of the PEV technologies presented in the experiment

Before presenting respondents with the choice scenarios, we provided them with descriptions of the PHEV and FEV technologies. The fixed-battery EV (FBEV) was described as a car with a built-in battery pack. Due to the purchase of the battery-pack, the FBEV was usually more expensive than its ICE counterpart. However, its operational costs were much lower than the ones of the ICE car. The FBEV could be either charged at a standard charging point at home or work or at special fast-charging stations. Standard charging would take several hours, while fast-charging would bring the battery to full charge in substantially less than one hour.

The EV with swappable battery (SBEV) was different from FBEV in two aspects. First, the battery pack should be rented by the driver, as it was not built in the car. Second, while the SBEV adopter could use standard charging at home or work, fast-charging was not possible. Instead, the driver would have to exchange the depleted battery with a new one at specialised battery-swapping stations. This procedure would take the same time required to refuel an ICE car. Respondents were also offered the opportunity to watch a video of the battery-swapping procedure, in order to familiarise themselves with it.

The PHEV was described as a vehicle running on both oil-derived fuel and electricity, thereby incorporating both plug-in hybrid and extended-range technologies. Respondents were informed that the PHEV could run on electricity for a few tens of kilometres. Once the battery was almost depleted, the PHEV would run solely on oil-derived fuel. No fast-charging or battery-swapping option was offered for PHEVs.

Respondents were further informed that the FEV and PHEV technologies ran on automatic transmission and that driving electric was almost silent. FEVs and PHEVs were also described as more energy efficient and as having substantially lower (PHEV) or no (FEVs) *direct* emissions of air pollutants, CO_2 and particulate matters. Respondents were also instructed to assume that the battery packs would be recycled at the end of their lifespan.

Appendix D: Expected values of the variables of the HPLCM class membership model

Table D.1 presents the expected values of the variables entering the class membership model of HPLCM. They are calculated according to the HPLCM equivalent of Equation (11).

Table D.1: Expected values of the variables used in the Class Membership Model of HPLCM.

Variable	Status quo captives	Combustion engine diehards	Price-conscious buyers	FEV optimists	PHEV enthusiasts
Age (years)	48.9	59.4	50.0	50.5	51.9
Female (%)	29.8	31.3	52.3	46.8	33.5
High education (%)	47.7	32.5	37.1	34.7	40.4
Low driving needs (%)	42.6	64.8	77.4	52.5	55.1
Often abroad (%)	31.3	24.8	13.7	20.9	25.6
First car replacement (%)	87.1	88.8	69.1	81.6	82.6
Long-term decision (%)	38.2	39.0	50.7	50.5	41.3
Latent environmental concerns	0.52	0.32	1.03	1.14	0.87