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THE EFFECT OF ATTITUDES ON REFERENCE-DEPENDENT PREFERENCES: ESTIMATION AND VALIDATION FOR THE CASE OF ALTERNATIVE-FUEL VEHICLES

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ABSTRACT

Several recent studies in transportation have analysed how choices made by individuals are influenced by attitudes. Other studies have contributed to our understanding of apparently non-rational behaviour by examining how choices may reflect reference-dependent preferences. This paper examines how reference-dependent preferences and attitudes together may explain individual choices. In a modelling framework based on a hybrid choice model allowing for both concepts, we investigate how attitudes and reference-dependent preferences interact and how they affect willingness-to-pay measures and demand elasticities. Using a data set with stated choices among alternative-fuel vehicles, we see that allowing for reference-dependent preferences improves our ability to explain the stated choices in the data and that the attitude (appreciation of car features) explains part of the preference heterogeneity across individuals. The results indicate that individuals have reference-dependent preferences that could be explained by loss aversion and that these are indeed related to an individual's attitude toward car features. The models are validated using a large hold-out sample. This shows that the inclusion of attitudes improves the models' ability to explain behaviour in the hold-out sample. While neither reference-dependent preferences nor the attitude affect the average willingness-to-pay measures in our sample, their effect on choice behaviour has implications for policy recommendations as segments with varying attitudes and reference values will act differently when affected by policy instruments related to the demand for alternative-fuel vehicles, e.g. subsidies.

Keywords:
Loss aversion, attitudes, hybrid choice model, alternative-fuel vehicles, reference-dependent preferences

1 INTRODUCTION

Over the past 30 years, research in behavioural decision making has demonstrated that individuals making choices are often affected by a variety of factors that have not traditionally been included in standard discrete choice models. McFadden (1999) divides these factors into four groups: context effects, reference point effects, availability effects, and superstition effects.

A theory that has been commonly used to include both context effects and reference-point effects is the theory of reference-dependent preferences as introduced by Tversky and Kahneman (1991). It which has been applied to test whether loss aversion affects choices in various contexts of riskless choice, see e.g. Bateman et al. (1997), De Borger and Fosgerau (2008). The framework is based on an assumption that preferences are formed relative to some reference point. This assumption is in contrast with conventional utility theory where a change is valued independently of any reference point. In a conventional model, the marginal utility of an attribute may depend on the attribute level or socio-economic variables but the marginal utility is independent of any choice made in the past prior to the stated choice survey, e.g. a previous vehicle purchase. In a model allowing for reference dependence, the marginal utility may depend on the difference between an attribute and the reference level of the attribute. The framework allows to test whether changes in the attribute relative to a reference value are valued asymmetrically, i.e. that a change in attributes perceived as a loss is weighted differently from an equivalent gain. When the weights differ the common finding has been that losses have a higher weight than gains, and this has been interpreted as a manifestation of loss aversion. This includes the recent literature in transport related to reference-dependent preferences and loss aversion on individual choices, e.g. in freight transport (Masiero and Hensher, 2010), in air transport (Suzuki et al., 2001), in valuation of travel time (Fosgerau et al., 2007), in location choice (e.g.; Habib and Miller, 2009), as well as in more methodological studies (Börjesson et al. 2013; Stathopoulos and Hess, 2012).

We follow this line of research but it has to be noted that the interpretation of the weights as loss aversion is not obvious. Recent psychological literature has debated the causes for the behavioural phenomenon explained as loss aversion, i.e. whether the different weights attached to losses and gains in some choice situations are actually loss aversion or something else; see e.g. Yechiam and Hochman (2013) for a review. In this paper we refer to loss aversion as the notion that we observe different weights on losses when compared to equivalent gains. We do not assume anything about the reasons for these weights as we do not have data that can distinguish between the competing explanations but we refer to it as loss aversion in line with the literature on the subject within transportation. While we will not dwell on possible sources for this effect, we note that besides loss aversion, i.e. different subjective weights on losses and equivalent gains, other sources could be the attention-based model proposed by Yechiam and Hochman (2013), negativity bias (Baumeister et al., 2001), status-quo bias not captured as loss aversion (Samuelson and Zeckhauser, 1988), or income effects (see, e.g. Randall and Stoll, 1980).

Another important effect that has recently been the focus of many studies in various fields is the effect of attitudes on choice behaviour (for a recent review, see e.g. Cherchi, 2012). Studies have shown that, in contrast to conventional utility theory, attitudes and personality are major factors in determining motivation and the structuring of cognitive tasks. Following the hybrid choice model framework described in Swait (1994) and Walker (2001), the majority of the work in transport captures the effect of attitudes and perceptions via latent constructs that affect the utility of the alternatives. One area where attitudes have been included to explain choices is the demand for alternative-fuel vehicles (AFVs) where several papers have used a hybrid choice model to study the effect of attitudes. Generally these studies found that a positive attitude towards the environment and new car features increases the probability to choose AFVs when compared to conventional vehicles (Bolduc et al., 2008; Alvarez-Daziano and Bolduc, 2013; Jensen et al., 2013; Glerum et al., 2014).

In this paper, we focus on the demand for AFVs to test for the effect of attitudes on possible loss aversion using a hybrid choice modelling framework allowing for reference-dependent preferences. This focus raises two important questions: 1) whether vehicle purchase is in fact affected by reference-dependent preferences and whether these reflect loss aversion, and 2) to what extent attitudes affect possible loss aversion.

As summarised in Novemsky and Kahnemann (2005), there is a discussion to what extent loss aversion affects various types of choice. The key issue is whether the change in an attribute is perceived as a loss. This discussion needs further evidence to be settled as the evidence found, e.g. in Novemsky and Kahnemann (2005) is in conflict with the evidence found in Bateman et al. (1997). An attempt to settle the discussion is reported in Bateman et al. (2005) who conclude that most evidence is in favour of the interpretation by Bateman et al. (1997) that any spending of money is perceived as a loss. We do not have the ambition to solve this important issue in the present paper. We define loss aversion in line with most transportation research on loss aversion and Bateman et al. (2005), i.e. preferences are formed with respect to preference points and losses with respect to the reference point have higher weights than equivalent gains.

An additional cause for reference dependence related specifically to the studies of demand for AFVs is that most of these studies use stated preference/choice data to elicit preferences because, and with the exception of a very few cases, AFVs are not yet an important player in the private vehicle sector. These stated choice experiments are often pivoted around an actual recent purchase, giving credibility to the choice experiment as respondents have recently faced a similar choice situation. This framing could in itself cause preferences elicited by the experiment to be reference dependent since respondents are reminded of their recent purchase and instructed to see the alternatives as equivalent to the reference vehicle in all aspect but those varied as attributes. Mabit and Fosgerau (2011) investigated the potential market for AFVs and found that allowing for reference-dependent preferences in the model was important as individuals on average valued a loss (paying more) compared to their reference price 52% higher than an equivalent gain (paying less). While the hypothetical choices such as stated choices may confirm reference-dependent preferences it raises the issue whether this reference dependence is real, created by the design, or a mixture of these. It may be possible that the reference vehicle acts as a strong reference point in a hypothetical setting a few months after the reference purchase but that in real life where consumers keep their cars for several years the old car acts as a much weaker reference point. This question is left for future research as an investigation would demand new data. Irrespectively of this uncertainty, it is still interesting to see if reference points affect vehicle choices since this would have implications for subsidies if consumers see the unsubsidised price as the reference price.

In general attitudes have been included in choice models to improve the modelling of heterogeneity in preferences. If the premise that loss aversion may affect vehicle purchase is accepted, the second question is then whether attitudes may explain heterogeneity in loss aversion. As attitudes are affected by experience (Walker, 2001) and reference points represent another manifestation of past experiences, it seems plausible that there is a relation between the valuation of losses and gains within a reference-dependent framework and an individual’s attitudes. A few previous studies have related attitudes to loss aversion; see e.g. Klapper et al. (2005), Nicolau (2011). These studies establish that there is a relation between the two psychological concepts. The current paper analyses the same relation within vehicle choice related to AFVs. In contrast to these former studies we integrate both concepts within the hybrid choice modelling framework allowing for a simultaneous estimation of the effects.

A few papers that have looked at heterogeneity in loss aversion, e.g. Hjorth and Fosgerau (2011), show that loss aversion may depend on socio-economic characteristics (such as age, education, income, and gender) and on experimental design, while Plott and Zeiler (2005;2007) suggest that the experience of individuals in making similar transactions and the incentives induced by experimental designs may have an influence on people’s apparent valuations of gains and losses. Furthermore research in marketing has shown the necessity to exploit heterogeneous preferences in relation to loss aversion as some studies have found that loss aversion disappears once heterogeneity is taken into account, see e.g. Bell and Lattin (2000).

In this paper, we test to what extent preferences specifically regarding the car price are affected by a latent variable capturing appreciation of car features and/or reference dependence. We estimate hybrid discrete choice models where we allow the effect of the latent appreciation of car features to affect the preference for the various AFVs, the preference for specific attributes characterising the AFVs, and also the preferences for the price that are allowed to be reference dependent. In particular we test to which extent both attitudes and reference points relate to individual preferences. We explicitly recognise that the latent appreciation of car features can affect individuals’ valuation of losses compared to gains. To investigate the implication of our models, we compute willingness-to-pay measures and elasticities to compare the various models.

We also validate our models using a hold-out sample. Klapper et al. (2005) also validate their models but only the models without the latent variables. The lack of validation in many published models has been criticized, because unfortunately a good model for a specific sample does not guarantee that the model is good at explaining the behaviour in a sample not used for the estimation (see a recent discussion in Cherchi and Cirillo, 2010). Besides testing the validity of our models we use our hold-out sample to illustrate how the size of the hold-out sample may affect the outcome of the validation.

The paper is organised as follows. In Section 2, we describe how our dataset was gathered and its main features. In Section 3, we describe the specification of a hybrid choice model that allows for reference dependence in the price coefficient. In Section 4, we discuss the results from the model estimation and validation, and in Section 5, the main conclusions of the work are presented.

2 DATA

The data used in this research were collected in a stated choice survey conducted in 2007-2008 to assess Danish consumers' preferences concerning AFVs. The stated choice experiments included four technology types: conventional, hybrid non-plugin, bio-diesel, and electric vehicles. The conventional fuel was either petrol or diesel depending on the reference vehicle of the respondent. The experiments comprised binary choices between any two of the four fuel types. Given the four alternatives there were six such comparisons. Each respondent made a total of four or eight choices: four comparing conventional fuel to one alternative fuel, and/or four comparing either hybrid to bio-diesel, hybrid to electric, or bio-diesel to electric. To add realism, the experiment was designed around a reference vehicle that the respondent had recently purchased. This recent purchase was used to provide reference values for the attributes included in the experiments.

The attributes in the experiments were generated using a random design with the reference values as pivot points. In a random design, each attribute in an experiment is found as a draw from a random distribution with zero mean, which is then added to the individual-specific reference value of that attribute. This design is less efficient than a correctly specified efficient design (Rose et al., 2008). On the other hand it is useful when efficiency is not a concern because of a large sample size as the design does not assume any a priori restrictions on interactions among attributes. See (Mabit and Fosgerau, 2011) for more discussion on the data.

The design included two monetary attributes and four non-monetary attributes. The monetary attributes were purchase price and annual cost, where the latter was computed as the sum of maintenance costs, fuel expenses (based on intended driving), and annual taxes. Both purchase price and annual cost attributes were customised for each respondent based on the reference vehicle.

The non-monetary attributes were operation range, acceleration time, a service dummy, and the level of pollution. The operation range was defined based on how far the reference vehicle could operate on a full tank. Acceleration time was presented as the number of seconds the vehicle would use to accelerate from 0 to 100 km/h. The service dummy was used to describe whether extra service and repairs other than maintenance were included in the annual cost.[1] The pollution levels of the

[1] In this survey the service dummy was an information attribute. So while it was related to repairs that could cost money it had no separate price in the design. While respondent may have attached a subjective value to the attribute we do not know this monetary value. So we classify it as a non-monetary attribute.

alternatives were specified relative to the conventional vehicle (the reference vehicle) that the respondent had recently purchased. So the pollution levels were fixed for each respondent across choice sets, but it varied among respondents depending on the reference vehicle as seen in Table 1.

TABLE 1 Fuel types and their pollution

Fuel type	Description
Conventional	Pollution as reference vehicle
Hybrid	Pollution at 50% of reference vehicle
Bio-diesel	Pollution as reference except CO_2 at 50%
Electric	No Pollution

Attributes were selected based on a literature review available at the time of the survey, qualitative interviews, and a pilot. In all remaining aspects, each respondent was instructed that both alternatives were similar to the reference vehicle. Table 2 reports some descriptive statistics for the attributes.

TABLE 2 Descriptive statistics for the attributes

Fuel		Price (*Euro*)	AnnCost (*Euro*)	Range (*km*)	Acc (*seconds*)	Service (*dummy*)
Conventional	Mean	32,492	3,700	684	13.0	0.5
	Min	11,907	2,187	575	5.9	0
	Max	152,813	12,693	950	21.5	1
Hybrid	Mean	32,322	3,682	680	13.0	0.5
	Min	6,520	1,800	300	5.8	0
	Max	152,813	12,693	1400	26.2	1
Bio-diesel	Mean	32,625	3,720	683	13.0	0.5
	Min	7,027	1,733	300	4.7	0
	Max	186,787	15,267	1425	25.2	1
Electric	Mean	32,947	3,703	688	13.0	0.5
	Min	6,013	1,667	300	4.9	0
	Max	171,067	12,867	1425	25.7	1

Data were collected during one year from August 2007 until July 2008. Each month during the survey period, 1500 individuals were chosen randomly from the population of individuals who had registered a new car within the preceding month in Denmark. In an Internet survey, they were asked to complete a background questionnaire first, then a stated choice experiment, and finally questions related to attitudes and perceptions toward the environment, car driving, and AFVs. In this paper, we used the data collected in 2007 to estimate the model, while we kept the data collected in 2008 as a hold-out sample to validate the estimated models. After removing some special registrations that had car use restrictions, a few individuals without driver's licences, and some with unknown reference vehicle, we were left with 2,093 individuals who completed the stated choice survey during 2007 giving a total of 14,694 observations of choices. The remaining observations from 2008 were used as a validation sample with a total of 18,739 observations. Some characteristics of the individuals in the sample as well as the validation sample are presented in Table 3.

TABLE 3 Descriptive statistics for the sample and the validation sample

Variable	Values	Sample	Validation sample
Sample size	Number of individuals	2093	2671
Gender	Female	0.29	0.31
	Male	0.71	0.69
Net monthly household income	< 4,000 Euro	0.42	0.40
	4,000 Euro to 5,333 Euro	0.32	0.31
	> 5,333 Euro	0.22	0.24
	unknown	0.04	0.05
Household type	Single	0.12	0.11
	Single w. child	0.03	0.04
	Couple	0.46	0.45
	Couple w. child	0.38	0.38
	Other	0.01	0.02
Age	18-29	0.09	0.09
	30-44	0.29	0.27
	45-60	0.36	0.38
	61-85	0.26	0.25
Cars	1 car	0.57	0.59
	2 cars	0.38	0.37
	3+ cars	0.05	0.04
Employment	Worker	0.78	0.78
	Outside work force	0.22	0.22
Commute distance	<4 km	0.24	0.25
	4-25 km	0.66	0.65
	>25 km	0.10	0.10
Reference fuel	Petrol	0.52	0.55
	Diesel	0.48	0.45
Expected driving	Weekly	0.91	0.92
	Less than weekly	0.09	0.08
Main user	Response person	0.74	0.74
	Other household member	0.26	0.26
Financing	Loan	0.55	0.53
	Cash or other	0.45	0.47

Finally, the survey included several questions on attitudes and perceptions regarding vehicles as well as the environment. The questions on attitudes were grouped into three categories:

1. Attitudes towards the importance of vehicle characteristics, e.g. *comfort, safety, reliability, resale price*.
2. Attitudes related to the environment and car driving, e.g. "*I prefer a car that pollutes less*".
3. Attitudes towards car driving in general, e.g. "*I don't care which car I drive*".

These attitudinal statements can be seen as indicators that allow us to identify several latent factors. A factor analysis revealed that one factor, denoted "*appreciation of car features*" (ACF), was clearly the most influential, explaining a variance of 3.70 (a proportion of 0.35) in the factor analysis of the three groups of attitudinal statements. Whereas the second factor, denoted "*environmental concern*" only explained a variance of 0.94 (a proportion of 0.13). For this reason, we decided to include the ACF factor in the modelling.[2] We captured the effect of this latent variable using the six most important indicators. These indicators captured on a scale from 1-6 (very important to not important) the importance placed by the respondent on *road position of the car, joy of driving the car, car comfort, and car design,* as well as the answer of the respondent on a scale from 1-6 (totally agree to totally disagree) to the two questions "*It is important for me to drive a car that I like"* and *"I notice the type of car others drive"*. These factors loaded with the highest coefficients, all of which were above 0.5. A reason why ACF is the most influential factor could be that our sample consists of new-car buyers whereas the sample in many other studies consists of car users in general. While this of course may limit the direct transferability of our results to other studies, we think that this sample is much more relevant for the study of AFVs as these for the next 5 years mainly will be purchased by new-car buyers as there is no used-car market for these vehicle types. So we would argue that any difference between our study and other studies related to the demand for AFVs stemming from this sample difference should rather be seen as a problem for these other studies. Putting the sample differences aside we still think that the methodology that we propose to study the relation between attitudes and loss aversion is of interest irrespectively of the specific sample.

3 A REFERENCE-DEPENDENT HYBRID CHOICE MODEL

The models used in this paper are discrete choice models that allow for reference dependence in the price coefficient and account for the effect of the attitude *appreciation of car features* through latent constructs.

The standard choice model based on random utility maximisation assumes that individual n when facing a choice among J alternatives in choice set C_n

[2] We have not included the results of the factor analysis as this is not important for the purpose of the paper. The only result needed from the analysis was the finding of the most influential factor.

associates a utility function U_{in} with each alternative, $i \in J$, and chooses the alternative with the maximum utility.

We assume, as it is standard, that the utility has additive noise independent of the explanatory variables so that we can split the utility into a measurable part and a random part, as shown in Equation (1):

$$U_{in} = V(x_{in}; \beta) + \varepsilon_{in} \quad (1)$$

where x_{in} is a vector of attributes of alternative i, characteristics specific to individual n, and interactions of these,
β is a vector of coefficients associated to each of these variables, and
ε_{in} is a random term, that in our model is distributed iid extreme value type 1.

The utility of alternative i for individual n used in our models has the following specification:

$$V_{in} = \alpha_{in} + \beta_n{}' x_{in} + \beta_n^p (p_{in} - p_{0n}) * \exp(\eta_n * sign(p_{in} - p_{0n})) \quad (2)$$

where p_{in} is the price of alternative i,
p_{0n} is the reference price,
x_{in} is a vector of non-price attributes,
$sign(p)$ is the sign of the difference between the price attribute and the reference price, and
$\alpha_{in}, \beta_n = (\beta_{n1}, \dots, \beta_{nL}), \beta_n^p, \eta_n$ are coefficients parameterised by individual characteristics and the latent variable, i.e.

$$\alpha_{in} = \alpha_i^0 + \sum_k \beta_k S_{nk} + \delta_i^\alpha * ACF_n, \quad (2a)$$
$$\beta_{nl} = \beta_l{}^0 + \sum_k \beta_{lk} S_{nk} + \delta_l * ACF_n, \quad (2b)$$
$$\beta_n^p = \beta^p + \sum_k \beta_k^p S_{nk} + \delta^p * ACF_n, \text{ and} \quad (2c)$$
$$\eta_n = \eta^0 + \sum_k \eta_k S_{nk} + \delta^\eta * ACF_n. \quad (2d)$$

In the context of vehicle choice it seems reasonable to hypothesize that individuals' preferences depend on their own vehicle purchase history. Here we restrict previous experience to be represented by the most recent vehicle purchase. So attributes from this most recent purchase were used as reference values in our modelling. While this is the most obvious reference, there may of course be other reference values that could frame a future purchase, see e.g. Koop and Johnson (2012), Stathopoulos and Hess (2012). Another reason why we use this reference is that the data were designed by pivoting around values from the previous purchase as the reference values.

We allow the marginal utility of price to depend on whether the price of an alternative is above or below the price of the reference vehicle. Preliminary tests showed that price was the only variable to show reference dependence. Following Mabit and Fosgerau (2011), we use a value function without curvature effects for the price attribute (i.e. $\exp(\eta * \mathrm{sign}(p))$). This specification of reference-dependent preference to test for loss aversion is adapted from De Borger and Fosgerau (2008).

Individuals are loss averse if $\eta > 0$, i.e. they care more about a price change above their reference price (a loss) than about an equivalent price change below (a gain).

Our model allows for systematic heterogeneity in the preference for the alternatives and for the attributes. Following Hjorth and Fosgerau (2011) it also allows the loss aversion to be a function of the individual characteristics. But we extended this formulation to account for the fact that the utility function depends also on latent variables, which the modeller can measure only through indicators that are manifestations of the latent variables. In particular we assume that an individual's attitude can affect directly the preference of the type of car, the preference for specific attributes, but it can also affect the degree of loss aversion.

Following the standard approach of the hybrid choice models (see e.g. Walker, 2001) we specify the latent effect ACF as a linear function of background characteristics:

$$ACF_n = \lambda' S_n + \sigma_\omega * \omega_n \tag{3}$$

where S_n is a vector of individual characteristics, including: age, commute distance, fuel type, driving frequency, and financing of the reference vehicle,
λ is a vector of coefficients associated with these background characteristics,
ω_n is a normally distributed error term with zero mean and variance one, and
σ_ω is a scale coefficient.

The individual characteristics can be different from the vector included in the discrete choice model, but we chose to allow the same vector in order to avoid that the latent variable acts as a proxy for the direct effect from the characteristics. Furthermore we estimated the latent variable model without the choice model. This confirmed that the effects found in the latent variable model were direct effects on the latent variable and not non-linear effects as a result of the combined estimation together with the choice model. While all characteristics in x_{in} and $S_n$were tested as part of both vectors, we only included the significant effects in the final models.

As discussed in section 2, six indicators were used as manifestations for the ACF. These are linked to the latent variable with the following measurement equations:

$$I_{kn} = \gamma_k + \alpha_k ACF_n + \upsilon_n, \qquad \text{k=1,2,…,6} \tag{4}$$

where I_{kn} is the *k-th* indicator for the latent variable, γ_k is the intersect, α_k is the coefficient associated to the latent variable (γ_1 and α_1 are normalised to zero and one for identification purposes), and υ_{kn} are independently normally distributed error terms with zero mean and standard deviation $\sigma_{\upsilon k}$. We treat the indicators as continuous while in the data they are discrete variables with six levels. This approximation has been found to be reasonable when the indicator has more than five levels.

The models are estimated by maximum likelihood estimation. The choice model specified in Equations (1-4) gives rise to choice probabilities:

$$P(i|x_{in}) = \int P(i|x_{in}, ACF_n) f(ACF_n - \lambda' S_n) f(I_{1n}) \dots f(I_{6n}) d\,\omega_n. \quad (5)$$

In the model, the latent variable is treated as individual-specific and therefore constant across the various choice tasks made by the same individual. As this integral is one dimensional we approximate it using numerical integration. The parameters of the model, $\theta = (\alpha, \beta, \eta)$, are then estimated by maximising the log-likelihood (LL) with the approximated probability in place of $P(i|x_{in}, \theta)$, i.e.

$$\hat{\theta} = argmax\ \sum_n y_{in} P(i|x_{in}, \theta). \quad (6)$$

The LL values of the models that include the latent variable are computed for the choice model alone integrating over the latent variable using the estimated parameters, i.e.

$$P(i|x_{in}) = \int P(i|x_{in}, ACF_n) f(ACF_n - \lambda' S_n) d\,\omega_n. \quad (7)$$

4 APPLICATION

4.1 Model specifications and estimation results

In order to test the relative effect of attitudes and reference dependence, we estimated four models: (a) a standard multinomial logit (MNL) model without reference dependence and latent effects, (b) a MNL model that allows for reference dependence in the price coefficient, (c) a hybrid choice model that includes only the effect of the attitude but assumes linear marginal utility of price, and (d) a reference-dependent hybrid choice model that is the full model as specified in Equations (1)-(4). All parameters in each model were estimated simultaneously with Python Biogeme, see Bierlaire and Fetiarison (2009). The results are shown in Tables 4 and 5.

Model I is a standard MNL model with linear marginal utility of the price that accounts for systematic heterogeneity, i.e. all η_n and δ parameters are restricted to zero in Equation (2). It is important to mention that many socio-economic characteristics (all coded as dummy variables) were tested, and the results reported in Table 4 only include the interactions that were significant at the 5% level in one of the models. We see that all the coefficients have the expected signs and that they are significant with the exception of acceleration time that is significant at the 5% level only for males and individuals below the age of 30.

TABLE 4 Estimation results for the discrete choice part of the model

Model	**Model I**		**Model II**		**Model III**		**Model IV**	
Variable	*Estimate*	*t-stat*	*Estimate*	*t-stat*	*Estimate*	*t-stat*	*Estimate*	*t-stat*
Conventional	0.00	-----	0.00	-----	0.00	-----	0.00	-----
Hybrid ASC	0.51	8.0	0.57	8.6	0.14	1.1	0.24	1.9
Bio-diesel ASC	0.20	3.1	0.32	4.8	-0.10	-0.8	0.11	0.9
Electric ASC	0.75	9.5	0.92	11.1	-0.17	-1.2	0.15	0.9
Electric ASC * male	-0.34	-5.6	-0.33	-5.3	-0.35	-5.7	-0.33	-5.4
Hyb,Bio,Elec ASC * worker	0.20	2.8	0.21	2.9	0.16	2.2	0.17	2.3
Acceleration	-0.15	-0.6	-0.18	-0.7	-1.02	-2.1	-1.10	-2.3
Acceleration * male	-0.94	-3.3	-0.94	-3.3	-0.92	-3.2	-0.93	-3.2
Acceleration * age (30-44)	-0.98	-2.1	-0.98	-2.1	-0.95	-2.0	-0.96	-2.0
Annual cost	-0.52	-9.1	-0.51	-8.9	-0.16	-1.0	-0.14	-0.9
Annual cost * dist>25	-0.35	-2.9	-0.35	-2.9	-0.32	-2.7	-0.33	-2.7
Range	0.96	12.7	0.95	12.6	0.67	3.2	0.67	3.1
Range * age (30-44)	0.91	4.1	0.92	4.2	0.91	4.1	0.93	4.2
Range * dist>25	0.50	3.4	0.50	3.4	0.48	3.2	0.48	3.2
Price	-1.72	-22.7	-1.70	-23.1	-0.60	-3.8	-0.60	-4.0
Price * age>60	0.23	2.2	0.27	2.7	0.26	2.5	0.29	3.1
Price * children	-0.22	-2.5	-0.16	-1.9	-0.18	-2.2	-0.13	-1.6
Price * dist<4	0.27	2.8	0.23	2.5	0.15	1.7	0.13	1.5
Price * high income	0.36	4.4	0.34	4.4	0.33	4.2	0.32	4.2
Price * single	-0.66	-4.6	-0.57	-4.2	-0.61	-4.4	-0.55	-4.0
Service	0.17	4.1	0.15	3.7	0.18	4.4	0.16	3.9
Service * diesel	0.14	2.6	0.19	3.3	0.14	2.6	0.19	3.4
Reference effect in the purchase price								
η^0	-----	-----	0.27	5.1	-----	-----	0.52	5.3
η * diesel			0.14	2.6	-----	-----	0.13	2.6
η * loan			-0.13	-2.5	-----	-----	-0.17	-3.4
Latent variable effect in the preference for fuel type								
Hybrid ASC * ACF					0.25	3.6	0.22	3.2
Bio-diesel ASC * ACF					0.21	3.1	0.14	2.1
Electric ASC * ACF					0.59	7.5	0.49	5.8
Latent variable effect in the preference for vehicle characteristics								
Acceleration * ACF					0.51	2.0	0.55	2.2
Annual cost * ACF					-0.24	-2.2	-0.24	-2.3
Range * ACF					0.20	1.6	0.19	1.5
Price * ACF					-0.73	-7.6	-0.73	-7.8
Latent variable effect in the purchase price reference effect								
η * ACF	-----	-----	-----	-----	-----	-----	-0.15	-3.5
Number of observations	14694		14694		14694		14694	
DoF	21		24		52		56	
Final global function					-127135		-127085	
Final loglikelihood	-7910		-7855		-7869		-7823	
Choice model $\bar{\rho}^2$	0.221		0.227		0.224		0.228	

TABLE 5 Estimation results for the latent variable part of the model

Model	**III**		**IV**	
Variable	*Estimate*	*t-stat*	*Estimate*	*t-stat*
Constant	2.04	77.7	2.04	77.7
Age above 44 years	-0.10	-7.4	-0.10	-7.4
Commute distance < 4 km	-0.16	-11.1	-0.16	-11.1
Commute distance > 25 km	0.06	4.5	0.06	4.5
Dummy for diesel reference vehicle	-0.13	-10.8	-0.13	-10.7
Dummy for frequent car user	-0.20	-9.0	-0.20	-9.0
Dummy for car financed by loan	-0.09	-7.5	-0.09	-7.5
Sigma_lv	0.62	71.1	0.62	71.1
Indicators1: Road position	1	-----	1	-----
ASC Ind1	0	-----	0	-----
Sigma1	0.52	73.2	0.52	73.2
Indicators2: Joy of driving	1.24	77.8	1.24	77.7
ASC Ind2	-0.35	-14.2	-0.35	-14.2
Sigma2	0.48	42.2	0.48	42.2
Indicators3: Car likeability	0.80	38.6	0.80	38.6
ASC Ind3	0.47	14.2	0.47	14.2
Sigma3	0.87	95.4	0.87	95.4
Indicators4: Car noticeable	0.56	19.3	0.56	19.3
ASC Ind4	2.33	46.2	2.33	46.2
Sigma4	1.70	238.0	1.70	238.0
Indicators5: Comfort	0.99	59.6	0.99	59.6
ASC Ind5	0.17	6.7	0.17	6.7
Sigma5	0.67	83.4	0.67	83.4
Indicators6: Design	0.98	43.9	0.98	43.9
ASC Ind6	0.91	24.9	0.91	24.9
Sigma6	1.08	117.1	1.08	117.2

Model II generalises Model I as it allows for η_n to be non-zero, i.e. for reference-dependent preferences. All the common coefficients have similar values and the same significance in both models, but Model II rejects Model I in a likelihood ratio (LR)-test (with 3 degrees of freedom). In Model II, individuals value price relative to their reference prices so that price sensitivity depends on whether the price is a loss or a gain compared to the reference value. The model indicates that individuals behave as loss averse in the SP experiments since losses have a more negative weight than gains relative to the reference values (η>0 and significant at the 1% level). Differently from Hjorth and Fosgerau (2011) we did not find that loss aversion depends on age, education, income, and gender, but we found that individuals with a diesel reference vehicle were more loss averse while those that financed their reference vehicle by a loan were less loss averse. The effect of financing makes sense as the loan will spread out any price effects over a period of time. In general, diesel buyers have higher kilometrage than non-diesel buyers making them purchase larger and more expensive cars (this was true in the sample as it is dated before the large increase in the market share of smaller and cheaper diesel vehicles following 2008). As these buyers are generally more experienced with respect to cars, this could result in more attention on the search process for the best car so that their reference vehicle is much stronger and deviations from the attributes of the reference vehicle are weighted more.

Model III allows for the δ parameters in Equations (2a)-(2c) to be non-zero. It generalises Model I by allowing the latent variable ACF to affect the fuel type coefficients as well as the coefficients of the attributes included in the stated choice experiments except for the service dummy (Table 4 only reports the effect of the latent variable in the discrete choice model. The coefficients of the latent variable model are reported in Table 5). We see that the coefficients related to the latent variable are all significant at the 5% level except for the coefficient for range*ACF that has a t statistic of 1.6. This indicates that individual preferences for the specific characteristics of the car are dependent on the individual attitudes toward car features. In particular, as expected, the less individuals care about car features (indicated by a higher ACF), the less they also care about acceleration time, because higher ACF reduces the absolute value of the marginal utility of acceleration. In Model III the main effect of acceleration becomes significant and the main effect of annual cost becomes insignificant. This reflects that ACF does not have zero mean. Likewise, we note that the main effects, e.g. Hybrid ASC, of the attributes interacted with the ACF change compared to Model I but this is only natural as ACF does not have zero mean. Model III rejects Model I in a LR test with 15 degrees of freedom if we look at the LL value for the discrete choice model alone, see Equation (7).

Model IV combines the specifications used in Models II and III. It rejects both Models II and III in LR tests with 16 (for the choice model) and 4 degrees of freedom, respectively. Firstly we note that all the coefficients common with either Model II or Model III have similar values and the same significance in both models. This indicates that both effects are important when explaining heterogeneity in choice behaviour as they are not confounded in our application. This is in contrast to Bell and Lattin (2000) where loss aversion disappears once heterogeneity is accounted for. The negative significant interaction between the loss aversion parameter and the latent variable shows that an individual who cares more about car features (indicated by a lower ACF) is more loss averse. This is in line with the result that diesel owners are more loss averse as these individuals that care about car features were probably more conscious about what mattered in their own recent car purchase. This may enforce their reference points to be stronger and make them penalise deviations from the reference points more than other individuals. Finally, it is worth noting that disentangling the effect of ACF on the loss aversion does not affect the significance of the other coefficients (neither in the loss aversion nor in any other coefficients in the utility), but it significantly improves the model fit (we compared Model IV with a model where only δ^{η} was restricted to zero and Model IV is significant at the 1% level in a LR-test with 1 degree of freedom).

4.2 Model validation

As discussed in the introduction, the validation phase is crucial to assess the quality of our models. While this is generally accepted, it is rarely done in transportation research, especially when focus is on data-demanding models such as the hybrid choice model. In these models, all data available are used to improve the model estimation. Often no or little data are left for validation. Here we have a large data set so in addition to using the hold-out sample for validation we also test the effect of the size of the hold-out sample. To do so we validated our four models using four hold-out samples with 1,306, 2,510, 10,585 and 18,739 observations, respectively.

The four samples were observations from the first half of January only (early January), the entire month of January (January), all observations from January to April (January-April), and all observations from January to July (January-July). So the larger samples include the smaller ones. As in the sample used to estimate the model, each individual had 4 or 8 observations. We calculated the LL using each of the four models with each of the new samples, Equation (7), and the estimates from Tables 4 and 5. Again we only calculated the LL for the choice model as our main interest is how well our model can explain choice behaviour and not responses to indicator questions. The results from the hold-out samples are reported in Table 7.

TABLE 7 Validation results for the models based on the hold-out samples

Model	I	II	III	IV
Early January 2008				
Number of observations	1306	1306	1306	1306
DoF	21	24	36	40
Final loglikelihood	-689	-685	-683	-680
Choice model $\bar{\rho}^2$	0.216	0.217	0.206	0.204
AIC	1419	1417	1438	1443
January 2008				
Number of observations	2510	2510	2510	2510
DoF	21	24	36	40
Final loglikelihood	-1322	-1320	-1311	-1310
Choice model $\bar{\rho}^2$	0.228	0.227	0.225	0.224
AIC	2686	2688	2695	2701
January – April 2008				
Number of observations	10585	10585	10585	10585
DoF	21	24	36	40
Final loglikelihood	-5683	-5679	-5644	-5643
Choice model $\bar{\rho}^2$	0.223	0.223	0.226	0.225
AIC	11407	11406	11360	11365
January – July 2008				

Number of observations	18739	18739	18739	18739
DoF	21	24	36	39
Final loglikelihood	-10146	-10144	-10087	-10089
Choice model $\bar{\rho}^2$	0.217	0.217	0.221	0.220
AIC	20335	20336	20246	20258

The model fit is evaluated using $\bar{\rho}^2$ and the Akaike Information Criterion (AIC). As these have the same pattern we only comment on the former. We see that in the first two samples Models I and II have the highest $\bar{\rho}^2$ while for the two other samples the model with the highest $\bar{\rho}^2$ is Model III. This shows two things given that one is willing to accept the premise that if the results from a small validation sample and a larger validation sample that includes the smaller sample diverge then one should trust the conclusions from the larger validation sample. The first conclusion is that based on the two largest samples, the models including attitudes have the best out-of-sample model fit. While the differences in $\bar{\rho}^2$ are small they are still significant as they reflect differences in LL of 59 and 55 and the critical value in a LR test with 15 degrees of freedom at the 5%-level is 25. The second conclusion is that one has to be careful with small hold-out-samples as these may lead to false conclusions. In our case, the small sample shows that MNL has the best out-of-sample model fit which is not correct if we believe the premise that a larger hold-out sample gives a better model validation.

The same conclusion cannot be reached for reference dependence as this seems to vary between our sample and the validation samples. To test this further, we estimated a model using the largest validation sample itself. This estimation showed that there was significant loss aversion in the validation sample but the degree was much smaller than what we found in Model II.

4.3 Willingness-to-pay measures and elasticities

To assess the differences among the four models, we calculated the willingness-to-pay (WTP) measures for the attributes annual cost and operation range as well as price elasticity. We concentrated on these statistics because the two former valuations measures are the most important in our experiment related to the market potential for AFVs, while the elasticity is related to the attribute where we found loss aversion. The WTP is computed as the ratio between the marginal utilities of the annual cost (or operation range) and that of purchase price. Some of the models include interactions between the attributes and the latent variable, ACF. In this case, the marginal utility is a function of the latent variable. So the unconditional marginal utility is computed as the integral over the latent variable. This is similar to the calculation of marginal effects in mixed logit models when an attribute has an associate random parameter. Analogously, the elasticity is computed based on the derivative of the probability with respect to the attribute and then integrated across the distribution of the latent variable.

In Models II and IV, the choice probabilities are non-differentiable with respect to price at the reference price. For these two models, it is of interest to evaluate the statistics in domains where the choice probabilities are differentiable. This happens for choice situations that only include losses or only include gains. So we evaluated the statistics for the two subsamples that include either losses only or gains only. Analogously for the models that include the latent variable (Models III and IV), we calculated the WTP measures and the price elasticity separately for two specific subsamples: the first subsample included the individuals with expected ACF in the highest quartile (i.e. ACF above 1.74), while the second subsample included the individuals with expected ACF in the lowest quartile (i.e. ACF below 1.60). In this way we selected the subsample of individuals representing high and low attitude toward ACF, respectively.

Based on the above, we evaluated the three statistics for the full sample and the four subsamples. The differences among results for each of the subsamples may depend both on differences due to the models and differences due to subsamples. To control for the effect of subsamples we calculated the statistics for each of the subsamples for Model I. This captures the variation in the statistics due to subsamples as there are no modelling differences among the subsamples for Model I. This allows us to see whether differences for Models II-IV are due to the more advanced models or the subsamples.

The statistics were computed using sample enumeration, i.e. calculating the valuation for each individual in the sample and averaging. The elasticity was computed as the weighted average of the price elasticity for each of the alternatives using the number of choice experiments where the alternative was available as weight. The results are presented in Table 6.

TABLE 6 Valuation measures and price elasticities for the various models

Model	Sample	No. obs.	Valuation of annual cost	Valuation of operation range	Elasticity, price
Model I	All	14694	3.8	107.9	-2.2
	Loss	3911	3.7	104.3	-2.6
	Gain	5329	3.8	109.4	-1.8
	Low ACF	4108	3.7	122.8	-2.1
	High ACF	4118	3.9	107.1	-1.9
Model II	All	14694	4.0	117.5	-2.3
	Loss	3911	2.9	82.5	-3.4
	Gain	5329	5.0	145.2	-1.3
Model III	All	14694	3.7	104.6	-2.1
	Low ACF	4108	3.6	116.4	-2.2
	High ACF	4118	3.7	103.6	-1.8
Model IV	All	14694	3.9	112.6	-2.3
	Loss	3911	2.9	81.5	-3.3
	Gain	5329	4.8	137.1	-1.4
	Low ACF	4108	3.8	123.3	-2.3
	High ACF	4118	4.0	113.1	-1.9

We see that the statistics are similar for the four models when evaluated using the full sample. For Model I, we see that the different subsamples, i.e. the differences among the individuals in the subsamples, do not lead to differences in WTP but it has some effect on the elasticity. This is natural as the WTP measures are assumed constant in Model I for the two samples while the elasticity is affected by the higher level of prices in the sample with losses. On the other hand, in Models II and IV that explicitly account for loss aversion the different subsamples show differences in the WTP measures. So comparing the results from Model I with those from Models II and IV we can conclude that the differences between WTP measures in the loss and gain subsamples for Models II/IV can be interpreted as a result of the loss aversion captured by the model specifications as they are not cause by differences in the sample characteristics.

By the same reasoning, we can say that the difference in the elasticity between gain (-1.3) and loss (-3.4) in Model II is partly explained by the difference due to the subsample characteristics as found using Model I (i.e. -1.8 and -2.6), but the remaining difference is due to the model specification. Keeping this in mind we can conclude that both valuations and the price elasticity are different in the two subsamples in Models II and IV.

Looking at the samples with high and low ACF across models, we see that there is little effect on the elasticity and that the variations in valuations already exist for Model I. This means that the differences seen for the models that include the latent variable are due to the subsamples and not model differences. This shows that adding the latent variable has little effect on these average statistics calculated on our data. So while the inclusion of the latent variable, ACF, improves significantly the model fit and all the coefficients related to ACF are highly significant, it does affect neither the average WTPs nor the price elasticity. Similar differences between model fit and model predictions were found in a different context by Cherchi and Ortúzar (2010) testing for the effects of confounding effects in estimation and predictions. Our result indicates that for problems where the average valuation is the purpose of the study, it may be sufficient to use a simple model without attitudes (even though it will depend on the modelling context whether aggregation bias is important or not). However, in applications were it is not the average valuation but choice probabilities that matter, the added complexity of the hybrid choice model may be important as our results in sections 4.1-2 show that choice probabilities are different across segments with different attitudes. The hybrid choice model allows identifying the target for a policy instrument that could affect the demand for AFVs, as it indicates the characteristics of the individuals who care more or less about car features.

The standard relation between a conventional vehicle and an AFV is that the AFV is more expensive, have lower running cost, shorter operation range, and it is more environmentally friendly. If loss aversion exists with respect to the price, policy makers should adapt strategies that take this reference dependence into account. For most car users the reference values are the prices of conventional vehicles. If the government either removes this difference through subsidies or changes the reference vehicle through trials where households try out AFVs, then the additional penalty of the price difference due to loss aversion can be diminished. Finally we find less loss aversion for individuals caring less about car features. Since these individuals are also most prone to choose AFVs compared to individuals with higher ACF given their less negative alternative-specific constants in the model, this is indeed the most promising segment for campaigns to kick-start the demand for AFVs.

5 CONCLUSIONS

In this paper, we test how attitudes affect vehicle choice in a framework that allows for reference-dependent preferences. We discuss whether loss aversion may be present in the case of vehicle choice including AFVs and we discuss how individual attitudes may affect heterogeneity in this loss aversion. We present a modelling framework based on the hybrid choice model that jointly allows for the effect of attitudes and reference-dependent preferences on choice among vehicle fuel types.

Using stated choice data with choices among AFVs, the model is estimated and validated. The results show that apart from systematic effects, an individual's attitude toward car features significantly affects the degree of loss aversion in the choice of the fuel type. Our results also show that it may be important to account for both reference-dependent preferences and latent variables in modelling of choices as they complement each other as tools to explain the choice behaviour observed in the data in that the effect of either concept is not explained by the other.

On average, the additional heterogeneity that we explain through loss aversion and attitudes does not affect the valuation measures and the price elasticity. This highlights that the additional complexity introduced by including these effects is only necessary if the question that the model should address relies on heterogeneity and not just average measures. An example of the former would be policy instruments that leave the average individual unaffected, e.g. if AFVs are subsidised only sufficiently to make them attractive to the innovator segment in the population but not to the average individual. Furthermore the lower weight that individuals place on gains could mean that individuals not fully value the subsidies if the non-subsidised price is seen as a reference point. If this was the case it could be better to nudge the reference point instead of only focussing on the subsidy.

Finally, the paper shows that it is necessary to use sufficiently large hold-out samples for validation as our case study shows how false conclusions may be reached based on smaller hold-out samples. Our larger hold-out samples show that attitudes indeed help explain the choice behaviour also in the validation. This is an important result as we have not been able to find validation of models applying the hybrid choice modelling framework in the existing literature.

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