Transportation Research Part A 83 (2016) 30–41

Contents lists available at ScienceDirect

Transportation Research Part A

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

The potential of electromobility in Austria: Evidence from hybrid choice models under the presence of unreported information

Francisco J. Bahamonde-Birke [a,b,*], Tibor Hanappi [c,d]

[a] Energy, Transportation and Environment Department, Deutsches Institut für Wirtschaftsforschung, Berlin, Germany
[b] Technische Universität Berlin, Germany
[c] Center for Tax Policy and Administration, OECD, Paris, France
[d] Institut für Höhere Studien, Wien, Austria

ARTICLE INFO

Article history:
Received 20 February 2015
Received in revised form 31 August 2015
Accepted 18 November 2015
Available online 14 December 2015

Keywords:
Electromobility
Electric vehicles
Hybrid discrete choice model
Latent variables
Unreported income

ABSTRACT

This paper analyses the impact of the introduction of electromobility in Austria, focusing specifically on the potential demand for electric vehicles in the automotive market. We estimate discrete choice behavioral mixture models considering latent variables; these allows us to deal with this potential demand as well as to analyze the effect of different attributes of the alternatives over the potential market penetration. We find out that some usual assumptions regarding electromobility also hold for the Austrian market (e.g. proclivity of green-minded people and reluctance of older individuals), while others are only partially valid (e.g. the power of the engine is not relevant for purely electric vehicles). Along the same line, it is established that some policy incentives would have a positive effect for the demand for electrical cars, while others – such as an annual Park and Ride subscription or a one-year-ticket for public transportation – would not increase the willingness-to-pay for electromobility. Our work suggests the existence of reliability thresholds concerning the availability of charging stations.

Finally this paper enunciates and successfully tests an alternative approach to address unreported information regarding income in presence of endogeneity and multiple information sources. We find that, for our sample, the presence of endogeneity and correlation makes both classical imputation techniques unsuitable.

1. Introduction

Both the coming scarcity and the negative environmental impact of fossil fuel resources as well as governmental guidelines are driving the automobile industry to focus on alternative, more efficient and cleaner, propulsion technologies. In addition, an increasing number of restrictive CO_2 emission regulations (Fontaras and Dilara, 2012) accompanied with rising fuel prices (Macharis et al., 2010) have led to a significant change in the way that some characteristics of the automobiles are

* Corresponding author at: Energy, Transportation and Environment Department, Deutsches Institut für Wirtschaftsforschung, Berlin, Germany.
E-mail addresses: bahamondebirke@gmail.com (F.J. Bahamonde-Birke), hanappi@ihs.ac.at, tibor.hanappi@oecd.org (T. Hanappi).

http://dx.doi.org/10.1016/j.tra.2015.11.002
0965-8564/

perceived. Consumers – and the public in general – are pushing for lower emission, more fuel efficient, and smaller engines (Fontaras and Samaras, 2010; Thiel et al., 2014).

This attitudinal change has not only led to significant changes in market shares, favoring more efficient technologies (e.g. rise of diesel engines at the expense of less-efficient Otto-cycle engines; Fontaras and Samaras, 2007), but also to an increased interest in alternative fuel vehicles. The new millennium has seen the composition of the car fleet change, with hybrid electric vehicles (HEV) playing an increasingly important role (Jenn et al., 2013). The expansion of other alternative engines, such as plug-in hybrid electric vehicles (PHEV) or battery electric vehicles (BEV) has been slower; mainly due to technical issues (Lu et al., 2013), user concerns (Egbue and Long, 2012), and economic hurdles (Dimitropoulos et al., 2013). However, the market expects significant sales increases when these issues are overcome (Eppstein et al., 2011; Lebeau et al., 2012; Shafiei et al., 2012; Hackbarth and Madlener, 2013; among many others).

Along this line, numerous governments, including Japan (Åhman, 2006), the USA (Diamond, 2009) and members of the European Union (Kley et al., 2012) have introduced policies that promote electromobility, ranging from the development of the charging infrastructure to free or reduced price access to express lanes and parking.

However, the adoption of electric vehicles is not only driven by economic benefits but also by the environmental concern of individuals. While the effectiveness of electromobility in reducing CO_2 emissions is disputed by some (Sandy Thomas, 2012; Kasten and Hacker, 2014), several studies show that a positive attitude toward the environment tends to increase the willingness-to-pay for electromobility (Bolduc et al., 2008; Daziano and Bolduc, 2013; Jensen et al., 2013, 2014; Sexton and Sexton, 2014).

Although the perspectives of electric vehicles are extensively studied, to our knowledge only one attempt based on disaggregated data for Austria exists (Link et al., 2012). Pfaffenbichler et al. (2009) summarize other attempts to establish the acceptance of electromobility in Austria, but these studies rely either on plain attitudes toward alternative transportation modes (tns infratest, 2008; Auto Bild, 2006; Landmann et al., 2009) or on current aggregated data and hypothetical scenarios (Haas, 2009; Enerdata, 2009; Roland Berger Strategy Consultants, 2009). These approaches do not seem to be suitable for reliable prognoses, as the former make it impossible to derive functional models and the latter attempt to derive the demand for a certain transportation mode (whose attributes are unknown to the wider public, as the current market share of electric vehicles is very small; Link et al., 2012) based on the characteristics of other alternatives.

Deriving reliable estimates for the future demand for electric vehicles is crucial, not only for the automobile and battery industries, but also for the electricity market, as the energy consumption of electric vehicles impacts electricity networks (Pieltain Fernández et al., 2011; Schill and Gerbaulet, 2014).

This paper aims to analyze the acceptance of electric vehicles by the Austrian population as well as the perspectives of electromobility in the country, which, as previously mentioned, have only been cursorily studied in the past. This way, we provide functional models to analyze how different features of alternative powered vehicles may impact their adoption in Austria. Along this line, we analyze the impact that different incentive policies may have on the acceptance of electric vehicles, considering not only classical subsidies (as reported in the literature by Jenn et al., 2013; Zhang et al., 2014; among many others) but also policies encouraging the joint use of electrical vehicles and public transportation. Additionally, as we are forced to deal with unreported income under the presence of endogeneity and correlation with socio-economical characteristics of the individuals (making unsuitable the classic imputation techniques reported in the literature; Kim et al., 2007; Fosgerau and Bierlaire, 2009), we develop an alternative approach to address this problem, extending the method proposed by Sanko et al. (2014). The rest of the paper is organized as follows; Section 2 presents a brief description of our dataset as well as of the variables we are considering, while Section 3 offers a theoretical overview of the modeling background and enunciates our approach the deal with unreported income. Our results are discussed in Sections 4 and 5 summarizes our conclusions.

2. Description of the dataset

Data was collected through a web-based survey conducted by a German commercial subcontractor (GfK) in February 2013. The sample of 1449 respondents was drawn from an online panel and divided into two subgroups on the basis of screening questions and randomized selection. The first subgroup was assigned to a discrete choice experiment (DCE) on vehicle purchase. Participation in this experiment was restricted to individuals with a driver's license and an explicit intention to buy a new vehicle in the near future. In total 787 respondents were selected into this subgroup.[1] Individuals in the second subgroup did not receive the same DCE.

Each respondent received nine independent choice scenarios, which took about 20–30 min to complete; including the standard demographic questions. Although comparable studies sometimes restrict the number of choice scenarios to avoid a potential drop in attention, pre-testing of the questionnaire showed that respondents were generally comfortable with the load of information and the total duration. An important issue that emerged from this test was the relevance of the descriptions of (a) the propulsion technologies and (b) the availability of charging stations. While the choice scenarios were

[1] To strengthen the link between the hypothetical choice scenarios and the real purchase decision, additional information on observed driving behavior and purchase preferences was used to individualize the choice sets.

described within a simple table to facilitate comparison, additional pop-up boxes were used to convey more detailed information. This approach proved to be especially important to communicate e.g. the differences between hybrid-electric and conventional vehicles or improvements in the charging station network.

Apart from the DCE, the survey also included an extensive questionnaire on socio-economic background, mobility behavior and attitudes. Several detailed questions on household composition, educational attainment and occupational status were included in order to confirm self-reported measures of personal and household income. As regional structures are highly relevant for mobility behavior, additional emphasis was put on the federal structure and the degree of urbanization. In addition, the survey also included sections on car ownership and purchase, frequency and purpose of car use, as well as detailed information on recent and recurring trips.

To further address heterogeneity in preferences among the respondents environmental attitudes were elicited in a separate section that included a set of eight preference statements. Each statement was aimed at a specific environmental issue and the respondents had to indicate the degree to which they agreed on a six point Likert scale. The following eight statements were included in the analysis:

(i) I am an ecologically aware person;
(ii) Climate protection is an important topic nowadays;
(iii) I believe many environmentalists often exaggerate climate problems;
(iv) I pay attention to regional origins when shopping foods and groceries;
(v) I buy ecologically friendly products;
(vi) Environmental protection measures should be enacted even if they result in job losses;
(vii) There are limits to growth that have been or will soon be reached by countries in the industrialized world; and
(viii) I pay attention to the CO2 footprint of the products I buy.

Although this type of preference-statement data cannot be directly used as explanatory variables in a discrete choice model, it provides further information on the underlying preferences of the individuals. Therefore it is argued, for instance, by Breffle et al. (2011) that this type of data is crucial for improving the modeling of heterogeneous preferences within standard discrete choice models. Our approach to this issue is outlined in Section 3. In the context of this work, we only consider the information associated with the DCE on vehicle purchase. Nevertheless for estimating the models associated with attitudes toward life and income (see next section), we consider the information provided by all individuals.

Although the overall sample reflects the Austrian population in terms of employment status, lower-educated individuals and individuals from low-income households are somewhat under-represented. Due to the focus on vehicle purchase, individuals from households without car are also under-represented while those from households with more than one car are slightly over-represented. However, the overall sample is representative not only with regard to the age and gender structure, but also regarding to Austria's nine federal states and the degree of urbanization (rural, sub-urban and urban).

The vehicle purchase DCE was based on a labeled experimental design including four choice alternatives referring to one propulsion technology each: conventional vehicles (CV), plug-in hybrid-electric vehicles (PHEV), hybrid-electric vehicles (HEV) and battery electric vehicles (BEV). Each alternative is described in terms of the purchase price (PP), power (PS), fuel costs (FC), and maintenance costs (MC). In addition to these attributes, the BEV is further characterised by the full driving range (RA), availability of charging stations (LS), and policy incentives (IM). Charging station availability varied across three categories (low, intermediate and high) and was described qualitatively within a separate pop-up box. Policy incentives included a Park and Ride subscription for one year (IM2), investment subsidies to support private charging stations (IM3), or a one-year-ticket for public transportation (IM4).

3. Methodological approach

In order to derive a functional model to establish the preferences for electromobility, we rely on a disaggregated approach, specifically on discrete choice modeling (Ortúzar and Willumsen, 2011). This approach is based on the Random Utility Theory (Thurstone, 1927; McFadden, 1974), which assumes that the utility a given individual (i) ascribes to a given alternative (q) can be represented in terms of a systematic utility (V_{iq}), depending on the characteristics of the individual and the attributes of the alternative, as well as an error component accounting for omitted and incomplete information (ε_{iq}). This way, the utility ascribed to a certain alternative can be depicted as the sum of the error term and the representative utility. Then the individual will opt for the alternative promising the higher utility.

If it is assumed that the error terms follow an extreme value distribution type 1 (EV1) with equal mean and scale parameter λ, this difference distributes Logistic with zero mean and λ scale. This leads to the well-known Multinomial Logit Model (MNL, Domencich and McFadden, 1975) and the probability of choosing alternative i is given by:

$$P_{iq} = \frac{e^{\lambda \cdot V_{iq}}}{\sum_{j \in A(q)} e^{\lambda \cdot V_{jq}}} \tag{3.1}$$

In this case, the scale parameter λ cannot be identified and it is customary to normalize it to one, without loss of generality (Walker et al., 2007). Regarding the specification of the systematic utility, it is common to assume an additive specification of the observed attributes as well as of the possible interactions (it is noteworthy that it can be interpreted as a first-order Taylor expansion of a more complex specification).

A limitation of this approach is that it only allows testing the impact of variables that were actually measured, such as prices or gender. Notwithstanding (as mentioned above) it is well established that immaterial non-measurable attitudes also play an important role in the willingness-to-pay (WTP) for given products or services. It is important to note that some variables may not have been accurately or completely reported (e.g. income), meaning that assumptions about the missing information are necessary.

To address this problem, we rely on a hybrid discrete choice modeling structure (Ben-Akiva et al., 2002). Here, the modeler assumes the existence of immaterial constructs called latent variables (η_{liq}), which are explained by a set of characteristics of the individuals and the alternatives (s_{iqr}), through structural equations. These variables are assumed to represent the unknown attitudes and perceptions or, similarly, the missing information. As this information cannon be directly observed, it is necessary to include error terms (v_{liq}), accounting for the uncertainty of the estimation. This way, the structural equations assume the following structure:

$$\eta_{liq} = \sum_{r} \alpha_{lri} \cdot s_{riq} + \upsilon_{liq} \tag{3.2}$$

where α_{lri} are parameters to be estimated and the index l refers to a certain latent variable. The error term v_{liq} can follow any distribution, but it is customary to consider a normal distribution with mean zero and a given covariance matrix. As observed, the system cannot be estimated without additional information; this additional information is provided by measurement equations that consider the latent variables as explanatory variables and yield a positively measured outcome as output, thus allowing for the estimation.

Normally the output of the measurement equations are perceptual and attitudinal indicators (y_{ziq}), which are gathered exogenously making use of a subjective scale. This approach leads to a Multiple Indicators MultIple Causes (MIMIC) model (Zellner, 1970) that has two major advantages: first, it allows for identification and, more importantly, it enriches the model incorporating exogenous information, which is in fact closely related to the attitudes and perceptions (the stated indicators may be considered to be an expression of underlying attitudes and perceptions; Bollen, 1989; Ortúzar and Willumsen, 2011), providing further theoretical support for the model. Assuming a continuous distribution of the perceptual and attitudinal indicators, the measurement equations take the following form:

$$y_{ziq} = \sum_{l} \gamma_{lzi} \cdot \eta_{liq} + \varsigma_{ziq} \tag{3.3}$$

where the index z is referred to a given indicator and the parameters γ_{lzi}, must be estimated (simultaneously with the aforementioned structural equations). ζ_{ziq} represents the error term, which, again, can follow any possible distribution, but is typically considered to be normally distributed with mean zero and a certain covariance matrix.

The latent variables are then used in the representative utility function as explanatory variables in the same way as the observed attributes, with the difference that these variables exhibit an intrinsic variability. Therefore the model should be considered as a behavioral mixture model (Walker and Ben-Akiva, 2011).

The estimation of the hybrid discrete choice model (including latent variables) should be performed simultaneously, as the sequential estimation (considering first the MIMIC model as an isolated system) does not produce unbiased estimators (Bahamonde-Birke and Ortúzar, 2014a), unless the variability induced through the latent variables is negligible when compared to the model's own variability (Bahamonde-Birke and Ortúzar, 2014b). When estimating the model simultaneously the modeler usually maximizes the following likelihood function (Ben-Akiva et al., 2002):

$$L = \int_{\eta} P_{ij}(X,\eta) \cdot P(y|\eta;\gamma,\varsigma) \cdot f(\eta|s,\alpha,\upsilon) \cdot d\eta \tag{3.4}$$

where the first term refers to the probability of the chosen alternative, as depicted in Eq. (3.1) (which, in turn, depends on observable characteristics of the individuals and of the alternatives of the alternatives X_{iq} and on the latent variables η_{liq}). The second term stands for the probability of observing a given indicator for a given individual and the last component represents the probability distribution of the latent variables.

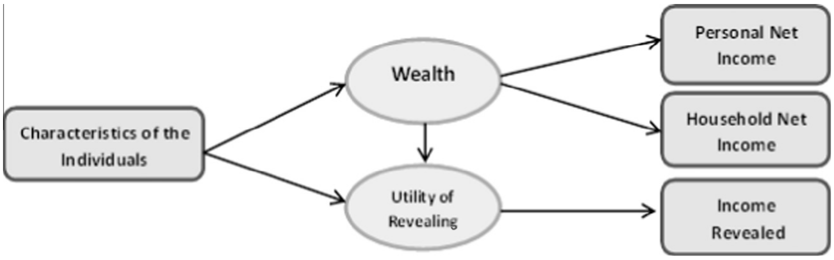

Fig. 1. Modelling framework for treating income information.

3.1. Treatment of unreported information and other income related issues

The survey included questions regarding personal and household net income. Given the reluctance of individuals to reveal this information, respondents were not required to answer this question and 30.02% of the sample skipped these questions. A potential alternative addressing this problem is to construct a variable for all individuals skipping this question (Hall et al., 2006; Fosgerau and Bierlaire, 2009; among many others), but it is highly debatable if it can be assumed that individuals skipping the income questions behave in a similar way, since the underlying factors affecting the decision to skip the question vary widely. Another approach would be to impute these variables (Kim et al., 2007), based on other characteristics of the individuals; but this could lead to endogeneity issues if the likelihood of omitting this question is also driven by income.

Finally, it is not clear what kind of income variable (personal or household net income) should be included in the model, as, depending on the individual, the WTP may be affected to greater extent by the one or the other. As both variables are highly correlated, it is not advisable to simultaneously include both in the utility function and the decision as to which variable is ultimately included should rely on theoretical arguments.

To address this problem we construct a latent variable measuring wealth in a broader sense, defined by a structural equation considering the socio-economic characteristics of the individuals. The personal and household net incomes are considered to be measured indicators of the individual's wealth, therefore explained by the latent variable through measurement equations. We use a discrete choice framework to model the decision whether to reveal information on personal and/or household income within the survey, as proposed by Sanko et al. (2014). To do this, we introduce a utility function associated with the likelihood of revealing income, which depends on the characteristics of the individuals as well as on the latent variable wealth, yielding as outcome the probability with which a certain individual would reveal their income. Fig. 1 summarizes the way in which income is included in the model.

The latent variable wealth is constructed for all individuals in the sample through the structural equations, but the measurement equations related to personal and household net income are only considered for the individuals reporting this information. As the model is considered jointly, the parameters of the structural equations adapt in order to reflect the information associated with the decision of reporting or not reporting the income (which may be driven by the individuals' wealth), thus considering the information provided implicitly by individuals skipping the question and overcoming endogeneity issues.

Both personal and household net incomes are considered to be continuous outputs (as they were reported) and measurement errors are assumed to be independent, normally distributed, with mean zero. The error term associated with the utility of revealing income is considered to follow a Logistic distribution with mean zero and scale parameter 1, leading to a binomial logit framework.

Finally, as a linear effect of the wealth on the decision making process is unrealistic, it is convenient to segment individuals into different categories. Therefore, the latent variable is categorized as proposed by Bahamonde-Birke et al. (2014a). That being the case, Eq. (3.4) takes the following shape (when considering a categorization in two levels; straightforward for more levels):

$$L = \int_\eta P_{ij}(X,\eta,\eta_{WC}=0)\cdot P(y|\eta;\gamma,\varsigma)\cdot f(\eta|s,\alpha,\upsilon)\cdot d\eta\cdot P(d\eta_W<\psi|s,\alpha,\upsilon) + \int_\eta P_{ij}(X,\eta,\eta_{WC}=1)\cdot P(y|\eta;\gamma,\varsigma)\cdot f(\eta|s,\alpha,\upsilon)\cdot d\eta\cdot P(d\eta_W\geqslant\psi|s,\alpha,\upsilon) \tag{3.5}$$

where η_W stands for the latent variable wealth and η_{WC} for its categorized counterpart; ψ is threshold to be calibrated. It is assumed that the error term associated with the structural equation of the LV follows a logistic distribution with mean 0 and standard deviation 1, allowing it to represent the probability of this being greater than the threshold through a closed-form expression (Logit).

3.2. Treatment of the environmental concern

As previously noted, empirical evidence suggests that environmental attitudes affect the willingness-to-pay for electromobility. To analyze this effect, we rely on a latent variable accounting for ecological concern. This variable is explained by characteristics of the individuals (making them more or less likely to exhibit a high environmental concern), while simultaneously describing the environmental indicators.

The analysis reveals that not all of the indicators collected can be linked beyond doubt with greener attitudes. In fact, a factor analysis reveals that it is only possible to identify a high correlation for five of the statements (i, iv, v, vi and viii; see Appendix A). Notwithstanding, an evaluation of the remaining indicators reveals that those are not actually related to their own attitudes but rather to an evaluation of either society (b and c) or the economy (g). Under these circumstances, the latent variable was constructed omitting these latter indicators.

For identification purposes (without loss of generality), it is assumed that the variability of the error term of the structural equation is independent, normally distributed and with a standard variability equal to one. Similarly, the error terms of the measurement equations are considered to be normal distributed and uncorrelated. Along the same line, intercepts are only considered in the measurement equations (and not in the structural equations), due to identifiability issues.

4. Estimation and results

The models are estimated simultaneously, making use of PythonBiogeme (Bierlaire, 2003). To compute the maximum simulated likelihood, we utilize 500 MLHS (Modified Latin Hypercube Sampling; Hess et al., 2006) draws.

Variables relevant for the model are presented in Table 1. As can be seen from the table, the wealth latent variable is categorized in order to reflect potentially divergent behavior by wealthier individuals. The categorization threshold was calibrated in accordance with Eq. (3.5). Appendix B presents the levels for the attributes considered in the DCE.

Three different models are estimated. First, a classical multinomial logit model (MNL-P) considering the correlation among the answers provided by the same individuals (via random panel effects; Bhat and Gossen, 2004) was calibrated. Additionally,

Table 1
Definition of the variables considered in the model.

Variable	Definition
FullTime	Dummy variable indicating that the individual works on a full-time basis
Married	Dummy variable indicating that the individual is married
MidSkill	Dummy variable indicating a career and technical education
HighSkill	Dummy variable indicating a college education or higher
Suburban, Urban	Dummy variables indicating a suburban residence or a urban residence
NCars	Count variable indicating car ownership
NewCar	Dummy variable indicating if the automobile mainly used by the individual was new at the moment of the purchase
Vienna	Dummy variable indicating a residence in Vienna
Male	Dummy variable indicating masculine gender
Old	Dummy variable indicating individuals older than 60 years
MidAge	Dummy variable indicating individuals older than 35 years, but no older than 60 year
Carsharing	Dummy variable indicating that the individual relies on Car Sharing on a regular basis
CarUser	Dummy variable indicating that the individual drives to their main occupational activity on a regular basis
PP	Purchase price in €·10^5
FC	Fuel cost in €/100 km
MC	Maintenance cost in €/100 km
PS	Power of the engine in hp
RA	Driving range in km
IM2, IM3, IM4	Dummy variables indicating the execution of the respective policy incentive
Wealthy	LV Wealth > *threshold*
LSMid, LSHigh	Dummy variables indicating medium or high availability of charging stations for BEV
EcAwareness	Attitudinal Indicator for “I am an ecologically aware person”
LocalFood	Attitudinal Indicator for “I pay attention to regional origins when shopping foods and groceries”
EcoFriendly	Attitudinal Indicator for “I buy ecologically friendly products”
Protection	Attitudinal Indicator for “Environmental protection measures should be enacted even if they result in job losses”
CO2Footprint	Attitudinal Indicator for “I pay attention to the CO2 footprint of the products I buy”

Table 2
Parameter estimates for the different models.

Variable	Equation	MNL-P		MBM1		MBM2	
Married	*S.E. LV Wealth*	–		–		0.939	(9.59)***
HighSkill	*S.E. LV Wealth*	–		–		0.647	(4.63)***
MidSkill	*S.E. LV Wealth*	–		–		0.391	(3.59)***
FullTime	*S.E. LV Wealth*	–		–		0.699	(8.22)***
Suburban	*S.E. LV Wealth*	–		–		0.159	(1.67)*
Urban	*S.E. LV Wealth*	–		–		0.382	(3.94)***
NCars	*S.E. LV Wealth*	–		–		0.659	(11.88)***
NewCar	*S.E. LV Wealth*	–		–		0.491	(5.99)***
Constant	*Utility Reveal Income*	–		–		0.616	(3.22)***
LV Wealth	*Utility Reveal Income*	–		–		−0.152	(−2.36)**
Male	*Utility Reveal Income*	–		–		0.567	(4.58)***
Old	*Utility Reveal Income*	–		–		0.656	(3.99)***
MidAge	*Utility Reveal Income*	–		–		0.531	(3.83)***
Vienna	*S.E. LV Green*	–		−0.258	(−3.27)***	−0.294	(−3.76)***
Male	*S.E. LV Green*	–		−0.281	(−4.61)***	−0.307	(−5.04)***
HighSkill	*S.E. LV Green*	–		0.461	(4.5)***	0.376	(3.61)***
MidSkill	*S.E. LV Green*	–		0.253	(3.02)***	0.226	(2.72)***
Old	*S.E. LV Green*	–		0.68	(8.05)***	0.611	(7.06)***
MidAge	*S.E. LV Green*	–		0.398	(5.45)***	0.314	(4.3)***
Carsharing	*S.E. LV Green*	–		0.666	(3.48)***	0.657	(3.69)***
CarUser	*S.E. LV Green*	–		−0.229	(−3.55)***	−0.243	(−3.84)***
Threshold		–		–		1.91	(4.52)***
ASC_CV	*Utility CV*	0	(fixed)	0	(fixed)	0	(fixed)
ASC_HEV	*Utility HEV*	0.423	(0.64)	0.191	(0.28)	0.859	(1.16)
ASC_PHEV	*Utility PHEV*	−0.0551	(−0.08)	−0.378	(−0.57)	0.16	(0.22)
ASC_BEV	*Utility BEV*	−1.73	(−2.14)**	−2.26	(−2.85)***	−1.09	(−1.16)
PP	*Utility CV*	−1.89	(−5)***	−1.69	(−4.43)***	−4.93	(−4.79)***
PP	*Utility HEV*	−2.36	(−24.27)***	−2.4	(−23.95)***	−5.64	(−5.64)***
PP	*Utility PHEV*	−2.38	(−20.37)***	−2.3	(−19.93)***	−5.68	(−5.96)***
PP	*Utility BEV*	−1.62	(−10.44)***	−1.52	(−10.19)***	−7.21	(−3.73)***
PP ∗ Wealthy	*Utility CV*	–	(–)	–	(–)	3.15	(3.38)***
PP ∗ Wealthy	*Utility HEV*	–	(–)	–	(–)	3.65	(3.85)***
PP ∗ Wealthy	*Utility PHEV*	–	(–)	–	(–)	3.73	(4.08)***
PP ∗ Wealthy	*Utility BEV*	–	(–)	–	(–)	5.59	(3.22)***
MC	*Utility CV, HEV; PHEV, BEV*	−31.2	(−12.09)***	−30.5	(−11.94)***	−31.8	(−11.42)***
FC	*Utility CV, HEV; PHEV, BEV*	−31.5	(−20.68)***	−31.1	(−20.64)***	−31.7	(−18.63)***
PS	*Utility CV*	0.0557	(3.98)***	0.0527	(3.73)***	0.0655	(4.76)***
PS	*Utility HEV*	0.0503	(9.02)***	0.0511	(9.09)***	0.0503	(8.55)***
PS	*Utility PHEV*	0.0528	(8.92)***	0.0522	(8.93)***	0.0531	(8.45)***
PS	*Utility BEV*	0.00666	(1.28)	0.00653	(1.27)	0.0133	(2.23)**
PS ∗ Male	*Utility CV*	−0.0191	(−3.51)***	−0.0232	(−4.29)***	−0.0246	(−4.16)***
PS ∗ Male	*Utility HEV*	−0.0161	(−2.88)***	−0.0178	(−3.2)***	−0.0198	(−3.26)***
PS ∗ Male	*Utility PHEV*	−0.015	(−2.66)***	−0.0162	(−2.91)***	−0.0185	(−3.03)***
PS ∗ Male	*Utility BEV*	−0.00575	(−0.98)	−0.00491	(−0.84)	−0.0059	(−0.91)
MidAge	*Utility HEV*	−0.171	(−0.6)	−0.377	(−1.3)	−0.248	(−0.73)
MidAge	*Utility PHEV*	−0.276	(−0.97)	−0.469	(−1.7)	−0.31	(−0.96)
MidAge	*Utility BEV*	−0.768	(−2.1)**	−1.13	(−3.1)***	−1.27	(−3.03)***
Old	*Utility HEV*	−1.23	(−3.73)***	−1.44	(−4.36)***	−1.79	(−4.54)***
Old	*Utility PHEV*	−1.59	(−4.77)***	−1.95	(−5.94)***	−2.2	(−5.65)***
Old	*Utility BEV*	−2.35	(−5.6)***	−3.13	(−6.72)***	−3.51	(−6.88)***
LV Green	*Utility HEV*	–	(–)	0.794	(5.27)***	0.619	(4.85)***
LV Green	*Utility PHEV*	–	(–)	1.03	(7.49)***	0.818	(6.84)***
LV Green	*Utility BEV*	–	(–)	1.21	(6.97)***	1.1	(6.39)***
RA	*Utility BEV*	0.00529	(10.11)***	0.00531	(10.12)***	0.00606	(8.66)***
LSMid	*Utility BEV*	0.312	(1.76)*	0.296	(1.68)*	0.307	(1.55)
LSHigh	*Utility BEV*	1.02	(6.34)***	1.01	(6.36)***	1.13	(6.14)***
IM3	*Utility BEV*	0.499	(3.62)***	0.486	(3.56)***	0.511	(3.2)***
Sigma CV	*Utility CV*	−2.82	(−21.56)***	2.6	(21.47)***	−2.79	(−19.62)***
Sigma HEV	*Utility HEV*	−1.05	(−7.18)***	−1.27	(−9.85)***	−1.06	(−7.57)***
Sigma PHEV	*Utility PHEV*	0.965	(6.81)***	−0.567	(−2.4)***	0.981	(6.67)***
Sigma BEV	*Utility BEV*	−2.45	(−15.81)***	2.27	(14.9)***	2.73	(12.74)***
Log-likelihood		−5130.4		−15,108.9		−18,671.1	

* Indicate that the variable is statistically significant at the 10% levels, respectively.
** Indicate that the variable is statistically significant at the 5% levels, respectively.
*** Indicate that the variable is statistically significant at the 1% levels, respectively.

we estimate a behavioral mixture model (MBM1) considering the environmental concerns and a third model (MBM2) considering both environmental awareness and differences in income following the approach presented in Section 3.[2]

The results for the estimated models are presented in Table 2. Linear measurement equations results are presented in Appendix C. The results of the *t*-test for statistical significance are presented in parenthesis. The final value for the log-likelihood is also reported, although it does not provide a significant insight into the goodness-of-fit of the different models as the number of measurement equations considered varies between them.

As shown in Table 2, wealth negatively affects the likelihood of revealing income, which is in accordance with results previously reported in the literature (Turrell, 2000). This way, imputing the income directly would have led to spurious results due to endogeneity issues. In a similar way, male and older individuals are more prone to reveal their income. Regarding the wealth variable itself, it is possible to confirm that highly skilled individuals as well as individuals working full time are more likely to earn higher incomes. Similarly, urban or suburban residency and the number of automobiles are positively correlated with wealth. Finally, married individuals tend to have higher incomes. It is not possible to establish a relationship between wealth and either gender or age.

With respect to environmental concern, our results support the idea that male and younger individuals care less about the environment than their female and older counterparts, respectively. These findings are in line with previous empirical evidence (Vredin-Johansson et al., 2006; Bolduc et al., 2008; Daziano and Bolduc, 2013; Jensen et al., 2013; Bahamonde-Birke et al., 2014b). Highly skilled individuals tend to exhibit more ecological attitudes, while individuals living in Vienna are less concerned about the environment than individuals living in smaller cities or in the countryside. As expected, the attitude toward the environment is reflected in the use of automobiles: green-minded individuals tend to rely more on carsharing and drive less often to their main occupational activity.

Thus, the results show that environmental attitudes impact the preferences for electromobility. Despite the fact that it is not clear whether electric vehicles are actually greener than conventional vehicles, green-minded individuals ascribe greater utility to automobiles with electric engines. However, this preference does not impact all technologies equally, as pure electric vehicles are preferred. As expected, older individuals are more reluctant to adopt new technologies (Hackbarth and Madlener, 2013; Hidrue et al., 2011).

As expected, higher fuel and maintenance costs negatively impact the utility ascribed to a certain alternative and it is not possible to identify a statistically different valuation of these two features, meaning than fuel and maintenance costs are perceived equally by our population. At the same time, the purchase price also negatively affects the utility associated with a given alternative. It is noteworthy that the disutility of the purchase price associated with the conventional vehicles is smaller than the disutility ascribed to the electric vehicles. A possible explanation for this phenomenon relies on the fact that conventional vehicles may be considered as a safer investment, as the market information for electric vehicles, such as resale price and depreciation, is likely unknown for large segments of the population. Finally, the disutility of the purchase price is smaller for wealthier individuals, which is in line with our expectations.

Regarding engine power, it is possible to establish that this is an important feature that positively affects utility when the alternatives considered include at least one conventional motor. When the propulsion choices are purely electric, this effect either vanishes (in models MNL-P and MBM1) or is very weak (model MBM2). Interestingly, women show a statistically significantly higher willingness-to-pay for bigger engines than men do; an effect that, to our knowledge, is not found in earlier literature.

In line with previous findings, a greater driving range has a significant positive impact on the adoption of BEV (Hidrue et al., 2011; Daziano, 2013). The individuals exhibit a willingness-to-pay (WTP) for an added kilometer of driving range of 32.7 €/km, 34.9 €/km and 8.4 €/km (poorer) and 37.4 €/km (wealthier), according to the models MNL-P, MBM1 and MBM2, respectively. These WTP are consistent with the values presented in the Dimitropoulos et al. (2013) meta-study. However, and opposite to the findings of Dimitropoulos et al. (2013), we establish that our population perceives gains in the driving range linearly, as it was not possible to reject the hypothesis of linearity (which was tested with help of a Box–Cox transformation). It must be pointed out that our population should be considered as unexperienced regarding the use of electric vehicles, as Jensen et al. (2013) have shown that experiencing electric vehicles increase the WTP for an extended driving range.

The wide-spread availability of charging stations positively impacts the utility ascribed to pure electrical vehicles. This contrasts with the fact that an intermediate level of charging station availability is not significantly better than a low availability level (at least, in the more complex model – or at a significance level of 5% in the other models). This phenomenon can be understood in light of the fact that at intermediate levels of service, the availability of charging stations is still unreliable and individuals would still most frequently charge their batteries at home, which suggests the existence of reliability thresholds.

With regard to policy incentives, it is only possible to identify an increase in the willingness-to-pay for electrical cars associated with investment subsidies to support private charging stations (IM3). No change of attitude could be identified in association with the incentives polices related to interactions with transit systems, such as a Park and Ride subscription

[2] For the continuous latent variable (ecological concern), we integrate over the domain on individual level. For the categorized latent variable, the correlation among the answers provided by the same individuals is not taken into account due to computational issues associated with the estimation technique (simulated maximum likelihood; Ben-Akiva et al., 2002), which causes minor discontinuity issues to arise.

(IM2) or a one-year-ticket for public transportation (IM4). This is an important topic, as Holtsmark and Skonhoft (2014) identify policy incentives as the main reason for the success of electric vehicles in Norway and according to our results subsidies aiming for the joint use of electric vehicles ant public transportation would not have the desired effects. Along this line, other alternatives such as direct subsidies (Potoglou and Kanaroglou, 2007; Holtsmark and Skonhoft, 2014) may have a higher impact.

Finally, it is important to note that the analyzed features are quite orthogonal across the different models, meaning that including additional information does not significantly affect the relationship between the attributes of the alternatives (except in the case of socioeconomic characteristics – also considered in the MIMIC model) i.e. the omitted information is mostly captured by the alternative specific constants.

5. Conclusions

The expansion of electromobility is a major challenge facing the automobile industry. Its adoption and potential is debated in the economic, engineering, electric, and transportation literature, as its impact will depend on the characteristics of the alternatives provided to the market. Our research focusses on the effects of these attributes, providing a model that quantifies their impact on the potential of the electromobility.

In this paper we estimate several behavioral mixture models considering characteristics of the individuals and of the alternatives, environmental awareness as well as income information. To do this, we also present an alternative approach to deal with unreported income. Our results support the validity of this approach and the fact that the decision of revealing the income is related to the income itself. Along the same line, this decision is also correlated with other social-economical characteristics of the individuals. These findings are of crucial importance as the presence of endogeneity and correlation makes both classical imputation techniques (imputing missing data based on other attributes available; Kim et al., 2007), as well as constructing a variable for all individuals not reporting the income, the dominant approaches in the literature, unsuitable.

It is possible to establish that many of the typical assumptions regarding electromobility also apply to the Austrian market, with the reluctance of older people and the proclivities of environmentally-minded individuals proving true. In a similar fashion, it is established that engine power does not have a major effect when dealing with purely electrical vehicles. It may be of significant importance, as bigger engines require bigger batteries, which, in turn, represent one of the main costs of BEVs. Additionally we also determine that Austrian females appreciate bigger engines more than males do.

The adoption of battery electric automobiles depends on an increased driving range and charging station availability as well as effective policy incentives. The WTP of the Austrian population for an added kilometer of driving range averages approximately 34 €/km. Regarding the latter, our research supports the theory that proposed policy incentives must be properly evaluated, as some policies, such as a Park and Ride subscription or a one-year-ticket for public transportation, may have a significant cost to the government but no actual impact on the adoption of alternative fuel vehicles. The fact that incentive policies advocated to the joint use of electric vehicles and transit systems have no significant impact on the adoption of electromobility suggest that individuals buying electric vehicles have no major prior interest in public transportation. Nevertheless, despite of their insignificant effect on the adoption of electromobility, these policies may still have positive social outcome, as they may induce individuals acquiring electric vehicles to use the transit system. Further research is required in this regard.

Finally, an intermediate level of availability of charging stations should not have a significant effect (in contrast with a high availability). This finding suggests the existence of reliability thresholds concerning the charging infrastructure. Therefore effort should focus on offering reliable coverage of charging stations.

Acknowledgments

This paper is based on the scientific work done in the DEFINE project (Development of an Evaluation Framework for the Introduction of Electromobility). We gratefully acknowledge the funding for DEFINE as part of the ERA-NET Plus Electromobility+ call by the EU-Commission and national funding institutions: the Ministry for Transport, Innovation and Technology (Austria), the Federal Ministry of Transport and Digital Infrastructure, formerly Federal Ministry for Transport, Building and Urban Development (Germany), and the National Centre for Research and Development (Poland). For further information on DEFINE, please see https://www.ihs.ac.at/projects/define/. The authors also thank Prof. Juan de Dios Ortúzar for his useful comments and insights. Several referees also provided valuable suggestions. All errors are the authors' sole responsibility

A. Indicators' Principal Component Matrix

Indicator	Meaning	
(i)	*I am an ecologically aware person*	*0.714*
(ii)	*Climate protection is an important topic nowadays*	*0.2*
(iii)	*I believe many environmentalists often exaggerate climate problems*	*−0.32*
(iv)	*I pay attention to regional origins when shopping foods and groceries*	*0.738*
(v)	*I buy ecologically friendly products*	*0.745*
(vi)	*Environmental protection measures should be enacted even if they result in job losses*	*0.603*
(vii)	*There are limits to growth that have been or will soon be reached by countries in the industrialized world*	*0.467*
(viii)	*I pay attention to the CO2 footprint of the products I buy*	*0.746*

B. Levels for the attributes considered in the DCE

Attribute	CV	HEV	PHEV	BEV
PP	–	140	140	140
(% of reference)	–	130	130	130
	–	120	120	120
	–	110	110	110
	100	100	100	100
	–	90	90	90
	–	80	80	80
PS	100	100	100	100
(% of reference)	–	95	95	–
	–	90	90	90
	–	85	85	–
	–	85	80	80
	–	–	–	70
	–	–	–	60
FC	0.10	0.10	0.10	–
(€/km)	0.09	0.09	0.09	–
	0.08	0.08	0.08	–
	0.07	0.07	0.07	–
	0.06	0.06	0.06	0.06
	0.05	0.05	0.05	0.05
	0.04	0.04	0.04	0.04
MC	0.060	0.060	0.060	0.060
(€/km)	0.055	0.055	0.055	0.055
	0.050	0.050	0.050	0.050
	0.045	0.045	0.045	0.045
	0.040	0.040	0.040	0.040
RA	500	500	500	–
(km)	–	–	–	350
	–	–	–	280
	–	–	–	210
	–	–	-	140
	–	–	–	70

C. Parameter estimates for the linear measurement equations

Variable	Equation	MNL-P[a]	MBM1		MBM2	
LV Wealth	*M.E. Household Net Income*	–	–		$0.778 * 10^3$	(*21.06*)***
Constant	*M.E. Household Net Income*	–	–		$0.79 * 10^3$	(*6.66*)***
St. Dev.	*M.E. Household Net Income*	–	–		$0.626 * 10^3$	(*15.98*)***
LV Wealth	*M.E. Personal Net Income*	–	–		$0.453 * 10^3$	(*17.27*)***
Constant	*M.E. Personal Net Income*	–	–		$0.723 * 10^3$	(*7.6*)***
St. Dev.	*M.E. Personal Net Income*	–	–		$0.847 * 10^3$	(*38.67*)***
LV Green	*M.E. EcAwareness*	–	−0.564	(*−24.33*)***	−0.556	(*−24.53*)***
Constant	*M.E. EcAwareness*	–	2.56	(*44.72*)***	2.49	(*44.74*)***
St. Dev.	*M.E. EcAwareness*	–	0.681	(*41.37*)***	0.68	(*41.12*)***
LV Green	*M.E. LocalFood*	–	−0.687	(*−26.06*)***	−0.675	(*−26.33*)***
Constant	*M.E. LocalFood*	–	2.36	(*34.47*)***	2.27	(*34.15*)***
St. Dev.	*M.E. LocalFood*	–	0.707	(*37.44*)***	0.708	(*37.69*)***
LV Green	*M.E. EcoFriendly*	–	−0.812	(*−24.82*)***	−0.796	(*−24.68*)***
Constant	*M.E. EcoFriendly*	–	2.95	(*36.48*)***	2.85	(*36.26*)***
St. Dev.	*M.E. EcoFriendly*	–	0.888	(*38.44*)***	0.892	(*38.54*)***
LV Green	*M.E. Protection*	–	−0.423	(*−13.55*)***	−0.418	(*−13.59*)***
Constant	*M.E. Protection*	–	3.35	(*67.37*)***	3.29	(*68.16*)***
St. Dev.	*M.E. Protection*	–	1.04	(*51.32*)***	1.04	(*51.26*)***
LV Green	*M.E. CO2Footprint*	–	−0.789	(*−25.31*)***	−0.78	(*−25.51*)***
Constant	*M.E. CO2Footprint*	–	3.49	(*43.86*)***	3.39	(*43.79*)***
St. Dev.	*M.E. CO2Footprint*	–	0.896	(*39.61*)***	0.893	(*39.67*)***

[a] No measurement equations were considered in this model.

References

Åhman, M., 2006. Government policy and the development of electric vehicles in Japan. Energy Policy 34 (4), 433–443.

Auto Bild, 2006. Alternative Antriebe – Öko 2.0?. Auto Bild Marktbarometer 2, Auto Bild Anzeigenabteilung.

Bahamonde-Birke, F.J., Ortúzar, J.de D., 2014a. On the variability of hybrid discrete choice models. Transportmetrica 10, 74–88.

Bahamonde-Birke, F.J., de Ortúzar, J.de D., 2014b. Is sequential estimation a suitable second best for estimation of hybrid choice models? Transport. Res. Rec.: J. Transport. Res Board 2429, 51–58.

Bahamonde-Birke, F.J., Kunert, U., Link, H., Ortúzar, J.de D., 2014a. About attitudes and perceptions – finding the proper way to consider latent variables in discrete choice models. Transportation. http://dx.doi.org/10.1007/s11116-015-9663-5, in press.

Bahamonde-Birke, F., Kunert, U., Link, H., Ortúzar, J.de D., 2014b. Bewertung der Angebotsmerkmale des Personenfernverkehrs vor dem Hintergrund der Liberalisierung des Fernbusmarktes. Zeitschrift für Verkehrswissenschaft 85 (2), 107–123.

Ben-Akiva, M.E., Walker, J.L., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 2002. Integration of choice and latent variable models. In: Mahmassani, H.S. (Ed.), In Perpetual Motion: Travel Behaviour Research Opportunities and Challenges. Pergamon, Amsterdam.

Bhat, C.R., Gossen, R., 2004. A mixed multinomial logit model analysis of weekend recreational episode type choice. Transport. Res. Part B: Methodol. 38 (9), 767–787.

Bierlaire, M., 2003. BIOGEME: a free package for the estimation of discrete choice models. In: Proceedings of the 3rd Swiss Transportation Research Conference, Ascona, Switzerland.

Bolduc, D., Boucher, N., Alvarez-Daziano, R., 2008. Hybrid choice modeling of new technologies for car choice in Canada. Transport. Res. Rec.: J. Transport. Res. Board 2082 (1), 63–71.

Bollen, K.A., 1989. Structural Equations with Latent Variables. John Wiley and Sons, Chichester.

Breffle, W.S., Morey, E.R., Thacher, J.A., 2011. A joint latent-class model: combining Likert-scale preference statements with choice data to harvest preference heterogeneity. Environ. Resource Econ. 50 (1), 83–110.

Daziano, R.A., Bolduc, D., 2013. Incorporating pro-environmental preferences towards green automobile technologies through a Bayesian hybrid choice model. Transportmetrica A: Trans. Sci. 9 (1), 74–106.

Daziano, R.A., 2013. Conditional-logit Bayes estimators for consumer valuation of electric vehicle driving range. Resource Energy Econ. 35 (3), 429–450.

Diamond, D., 2009. The impact of government incentives for hybrid-electric vehicles: evidence from US states. Energy Policy 37 (3), 972–983.

Dimitropoulos, A., Rietveld, P., van Ommeren, J.N., 2013. Consumer valuation of changes in driving range: a meta-analysis. Transport. Res. Part A: Policy Practice 55, 27–45.

Domencich, T., McFadden, D., 1975. Urban Travel Demand – A Behavioural Analysis. North Holland, Amsterdam.

Egbue, O., Long, S., 2012. Barriers to widespread adoption of electric vehicles: an analysis of consumer attitudes and perceptions. Energy Policy 48, 717–729.

Enerdata, 2009. The Impact of Lower Oil Consumption in Europe on World Oil Prices. Enerdata, Grenoble.

Eppstein, M.J., Grover, D.K., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy 39 (6), 3789–3802.

Fontaras, G., Samaras, Z., 2007. A quantitative analysis of the European Automakers' voluntary commitment to reduce CO_2 emissions from new passenger cars based on independent experimental data. Energy Policy 35 (4), 2239–2248.

Fontaras, G., Samaras, Z., 2010. On the way to 130 gCO_2/km – estimating the future characteristics of the average European passenger car. Energy Policy 38 (4), 1826–1833.

Fontaras, G., Dilara, P., 2012. The evolution of European passenger car characteristics 2000–2010 and its effects on real-world CO2 emissions and CO2 reduction policy. Energy Policy 49, 719–730.

Fosgerau, M., Bierlaire, M., 2009. Discrete choice models with multiplicative error terms. Transport. Res. Part B: Methodol. 43 (5), 494–505.

Haas, R., 2009. Präsentation – Entwicklung von Szenarien der Verbreitung von Pkw mit teil-und voll-elektrifiziertem Antriebsstrang unter verschiedenen politischen Rahmenbedingungen – ELEKTRA. Workshop Projekt ELEKTRA, 26.05.2009, Wien.

Hackbarth, A., Madlener, R., 2013. Consumer preferences for alternative fuel vehicles: a discrete choice analysis. Transport. Res. Part D: Trans. Environ. 25, 5–17.
Hall, J., Fiebig, D.G., King, M.T., Hossain, I., Louviere, J.J., 2006. What influences participation in genetic carrier testing?: Results from a discrete choice experiment. J. Health Econ. 25 (3), 520–537.
Hess, S., Train, K.E., Polak, J.W., 2006. On the use of a modified latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice. Transport. Res. Part B: Methodol. 40 (2), 147–163.
Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resource Energy Econ. 33 (3), 686–705.
Holtsmark, B., Skonhoft, A., 2014. The Norwegian support and subsidy policy of electric cars. should it be adopted by other countries? Environ. Sci. Policy 42, 160–168.
Jenn, A., Azevedo, I.L., Ferreira, P., 2013. The impact of federal incentives on the adoption of hybrid electric vehicles in the United States. Energy Econ. 40, 936–942.
Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before and after experiencing an electric vehicle. Transport. Res. Part D: Trans. Environ. 25, 24–32.
Jensen, A.F., Cherchi, E., Ortúzar, J.de D., 2014. A long panel survey to elicit variations in preferences and attitudes in the choice of electric vehicles. Transportation 41 (5), 973–993.
Kasten, P., Hacker, F., 2014. Two electromobility scenarios for Germany: market development and their impact on CO2 emissions of passenger cars in DEFINE. DEFINE: Development of an Evaluation Framework for the Introduction of Electromobility, 08.09.14, Berlin.
Kim, H.N., Shaw, W.D., Woodward, R.T., 2007. The distributional impacts of recreational fees: a discrete choice model with incomplete data. Land Econ. 83 (4), 561–574.
Kley, F., Wietschel, M., Dallinger, D., 2012. Evaluation of European electric vehicle support schemes. In: Paving the Road to Sustainable Transport. Routledge, New York, pp. 75–95.
Landmann, R., Hasenberg, J.-P., Steffen, N., Lutz, A., Wünsche, M., 2009. Winning the Automotive Powertrain Race – The Frontline Role of Marketing & Sales. Roland Berger Strategy Consultants, Munich.
Lebeau, K., van Mierlo, J., Lebeau, P., Mairesse, O., Macharis, C., 2012. The market potential for plug-in hybrid and battery electric vehicles in Flanders: a choice-based conjoint analysis. Transport. Res. Part D: Trans. Environ. 17 (8), 592–597.
Link, C., Raich, U., Sammer, G., Stark, J., 2012. Modeling demand for electric cars – a methodical approach. Procedia-Soc. Behav. Sci. 48, 1958–1970.
Lu, L., Han, X., Li, J., Hua, J., Ouyang, M., 2013. A review on the key issues for lithium-ion battery management in electric vehicles. J. Power Sources 226, 272–288.
Macharis, C., van Hoeck, E., Pekin, E., van Lier, T., 2010. A decision analysis framework for intermodal transport: comparing fuel price increases and the internalisation of external costs. Transport. Res. Part A: Policy Practice 44 (7), 550–561.
McFadden, D., 1974. Conditional logit analysis of qualitative choice behaviour. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Academic Press, New York, pp. 105–142.
Ortúzar, J.de D., Willumsen, L.G., 2011. Modelling Transport, fourth ed. John Wiley and Sons, Chichester.
Pfaffenbichler, P., Emmerling, B., Jellinek, R., Krutak, R., 2009. Pre-Feasibility-Studie zu "Markteinführung Elektromobilität in Österreich". Endbericht. Österreichische Energieagentur, Austrian Energy Agency (Hrsg), Wien.
Pieltain Fernández, L., Roman, T.G.S., Cossent, R., Domingo, C.M., Frías, P., 2011. Assessment of the impact of plug-in electric vehicles on distribution networks. Power Syst., IEEE Trans. 26 (1), 206–213.
Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transport. Res. Part D: Trans. Environ. 12 (4), 264–274.
Roland Berger Strategy Consultants, 2009. Powertrain 2020, China's ambition to become market leader in E-Vehicles. Roland Berger Strategy Consultants, Munich/Shanghai.
Sandy Thomas, C.E., 2012. How green are electric vehicles? Int. J. Hydrogen Energy 37 (7), 6053–6062.
Sanko, N., Hess, S., Dumont, J., Daly, A., 2014. Contrasting imputation with a latent variable approach to dealing with missing income in choice models. J. Choice Model. 12, 47–57.
Schill, W.P., Gerbaulet, C., 2014. Power System Impacts of Electric Vehicles in Germany: Charging with Coal or Renewables? Discussion Paper 1442, DIW-Berlin.
Sexton, S.E., Sexton, A.L., 2014. Conspicuous conservation: the Prius halo and willingness to pay for environmental bona fides. J. Environ. Econ. Manage. 67 (3), 303–317.
Shafiei, E., Thorkelsson, H., Ásgeirsson, E.I., Davidsdottir, B., Raberto, M., Stefansson, H., 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: a case study from Iceland. Technol. Forecast. Soc. Chang. 79 (9), 1638–1653.
Thiel, C., Schmidt, J., van Zyl, A., Schmid, E., 2014. Cost and well-to-wheel implications of the vehicle fleet CO_2 emission regulation in the European Union. Transport. Res. Part A: Policy Practice 63, 25–42.
Thurstone, L.L., 1927. A law of comparative judgment. Psychol. Rev. 34 (273), 286.
tns infratest, 2008. Umfrage Hybridfahrzeuge. im Auftrag von Continental.
Turrell, G., 2000. Income non-reporting: implications for health inequalities research. J. Epidemiol. Community Health 54 (3), 207–214.
Vredin-Johansson, M., Heldt, T., Johansson, P., 2006. The effects of attitudes and personality traits on mode choice. Transp. Res. 40A, 507–525.
Walker, J.L., Ben-Akiva, M., Bolduc, D., 2007. Identification of parameters in normal error component logit-mixture (NECLM) models. J. Appl. Econom. 22 (6), 1095–1125.
Walker, J.L., Ben-Akiva, M., 2011. Advances in discrete choice: mixture models. In: de Palma, A., Lindsey, R., Quinet, E., Vickerman, R. (Eds.), A Handbook of Transport Economics. Edward Elgar, pp. 160–187.
Zellner, A., 1970. Estimation of regression relationships containing unobservable variables. Int. Econ. Rev. 11, 441–454.
Zhang, X., Xie, J., Rao, R., Liang, Y., 2014. Policy incentives for the adoption of electric vehicles across countries. Sustainability 6 (11), 8056–8078.