Development of an Evaluation Framework for the Introduction of Electromobility

Electromobility+

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The potential of electromobility in Austria. An analysis based on hybrid choice models

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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 was possible to establish that some policy incentives would have a positive effect over 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.

Keywords: Electromobility, Electric Vehicles, Hybrid Discrete Choice Model, Latent Variables, Unreported Income

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 accompanied with rising fuel prices have led to a significant change of the way in which some characteristics of the automobiles are 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; Jenn *et al.*, 2013) playing an increasingly important role. The expansion of other alternative engines, such as plug-in hybrid electric vehicles (PHEV) or purely electric vehicles (EV) has been slower; mainly due to technical issues. 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 the individuals. While the effectiveness of electromobility in reducing CO_2 emissions has been disputed by some authors (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; 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). Pfaffenblichler *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; Ronald Berger Strategy Consultants, 2009). These approaches do not seem to be suitable for reliable prognoses, as the former makes it impossible to derive a functional model and the latter attempts to derive the demand for a certain transportation mode (whose attributes are unknown to the wider public) based on the characteristics of other alternatives.

Dering 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 may critically impact the electric networks (Pieltain Fernández *et al.*, 2011; Schill and Gerbaulet, 2014).

2. DESCRIPTION OF THE DATASET

Data was collected through a web-based survey conducted by an Austrian commercial subcontractor in February 2013. The sample of 1,449 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 the sample. 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, with each respondent asked to answer 9 independent choice scenarios. No restrictions were applied for the second subgroup, which responded to the DCE on transport mode choice. Of the 938 respondents in this subgroup, 73 individuals providing incomplete information were excluded.[1] This subgroup also received 9 independent choice scenarios.

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. A separate section addressed the environmental attitudes of the respondents through a set of eight questions. Each of these survey items consisted of a statement about a specific environmental issue. Respondents then had to indicate whether the degree to which they agree with these statements on a six point Likert-type scale:

The following eight statements were included: (a) I am an ecologically aware person; (b) Climate protection is an important topic nowadays; (c) I believe many environmentalists often exaggerate climate problems; (d) I pay attention to regional origins when shopping foods and groceries; (e) I buy ecologically friendly products; (f) Environmental protection measures should be enacted even if they result in job losses; (g) There are limits to growth that have been or will soon be

[1] Note that 276 individuals respond to both DCEs, resulting in a survey duration of about 30 minutes (as compared to 20 minutes for the remaining 1,173 individuals).

reached by countries in the industrialized world; and (h) I pay attention to the CO_2 footprint of the products I buy.

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 towards 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 labelled 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 electric vehicles (EV). Each of the alternatives is described by the following attributes: purchase price (PP), power (PS), fuel costs (FC) and maintenance costs (MC). In addition to these attributes, the EV is further characterised by the following attributes: 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).

To strengthen the link between the hypothetical choice scenarios and the real purchase decision, additional information on the segment of each respondent's prospective vehicle purchase was collected and used to individualize their choice sets. That is to say, in each segment a reference vehicle was defined such that purchase price and power of the alternative vehicles could be pivoted around the attribute levels of the reference. In addition, the choice sets were further individualised by multiplying fuel, maintenance and running costs-per-kilometre by the respondent's average kilometres per year.

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, and an error component accounting for omitted and incomplete information (ε_{iq}). This way, the utility (U_{iq}) can be represented in the following manner:

$$U_{iq} = V_{iq} + \varepsilon_{iq} \qquad [3.1]$$

Under this assumption, a given individual q will opt for the alternative i among a set of available alternatives $A(q)$ only if:

$$U_{iq} > U_{jq}$$

$$V_{iq} - V_{jq} > \varepsilon_{jq} - \varepsilon_{jq} \qquad \forall j \in A(q) \qquad [3.2]$$

As the modeler is only able to observe that an alternative is preferred over other possibilities and, therefore, the analysis relies on the differences between the expected utilities; hence we are not interested in the actual distribution of the error terms, but rather on the differences between them. If it is assumed that the error terms follow a extreme value distribution (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:

$$P_{iq} = \frac{e^{\lambda \cdot V_{iq}}}{\sum_{j \in A(q)} e^{\lambda \cdot V_{jq}}} \qquad [3.3]$$

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 usual 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 it was 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 so called *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:

$$\eta_{liq} = \sum_{r} \alpha_{lri} \cdot s_{riq} + \upsilon_{liq} \qquad [3.4]$$

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 it can be observed, the system cannot be estimated without additional information; this additional information is provided by so called *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) and it 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[2]. Assuming a continuous distribution of the perceptual and attitudinal indicators the measurement equations may take the following shape:

$$y_{ziq} = \sum_{l} \gamma_{lzi} \cdot \eta_{liq} + \varsigma_{ziq} \qquad [3.5]$$

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} represent the error term, which, again, can follow any possible distribution, but they are typically considered to be normally distributed with mean zero and a certain covariance matrix.

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[2] Although the discrete choice model can be actually considered as a measurement equation (when including latent variables into the representative utility function) it usually does not offer significant theoretical advantages (especially in relation with the theoretical identification of the latent variables). Moreover, given the structure of the covariance matrix, the identifiability of the structural equations tends to be very weak or even inexistent (depending on the specification).

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).

Treating the Income

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 (Kin *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 include both into the utility function at the same time, 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 structural 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. Figure 1 summarizes the way in which income is considered into the model:

Both personal and household net incomes are considered to be continuous outputs 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.

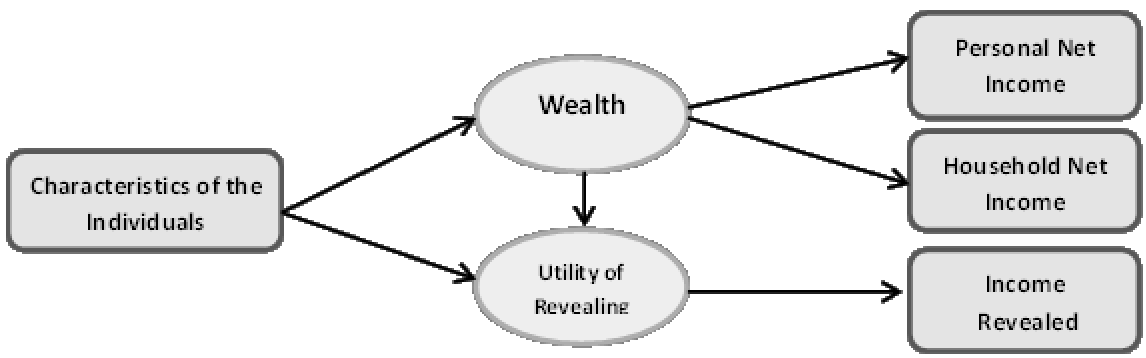

Figure 1 – Treatment of the income.

Finally, as a linear effect of the wealth over the decision making process is unrealistic, it is convenient to segment the individuals into different categories. Therefore, the latent variable is categorized as proposed by Bahamonde-Birke *et al*. (2014).

Treating the Environmental Concern

As previously noted, empirical evidence suggests that environmental attitudes affects 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.

A factorial analysis reveals that not all of the indicators collected can be linked beyond doubt with greener attitudes. In fact it was only possible to identify a high correlation for five of the statements (a, d, e, f and h). 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.

4. ESTIMATION AND RESULTS

The models were 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. For panel data we increase this number to 10,000 due to computational issues.

Variables that are significant 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. A threshold of 3.4 is chosen so that approximately a third of the sample is categorized as wealthy.

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 €.
FC, MC	Fuel and maintenance cost in € / 100 km., respectively.
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 > 3.4
LSMid, LSHigh	Dummy variables indicating medium or high availability of loading stations for EV.
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".

For the estimation of the model, it is assumed (for identification purposes, without loss of generalization) that the variability of the error terms of the structural equations is uncorrelated and equal to one. Similarly, the error terms of the measurement equations are considered to be uncorrelated. Along the same line, intercepts are only considered in the measurement equations (and not in the structural equations), due to identifiability issues. The scale parameters of both discrete choice models are normalized to the unity and no correlation among the error terms of the alternatives is considered as the behavioral mixture model allows for the capture of behavioral correlation.

Three different models are estimated. First, a classical multinomial logit model (MNL-P) considering the correlation among the answers provided by the same individuals (quasi-panel structure) was calibrated. Additionally, we estimate a behavioral mixture model (MBM1) considering only environmental concerns and a third model (MBM2) considering both environmental awareness and the differences in income following the approach presented in Section 3[3].

The results for the estimated models are presented in Table 2. Linear measurement equations results are presented in the Appendix. 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 affects negatively (at a statistical significance of 10% for a two-tailed test[4]) the likelihood of revealing income. 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 variable wealth itself, it was 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 was not possible to establish a relationship between wealth and 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 (Bolduc *et al.*, 2008; Daziano and Bolduc, 2013; Jensen *et al.*, 2013; Bahamonde-Birke *et al.*, 2014). 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.

[3] For MBM1 and MBM2 the panel structure of the dataset was not taken into account due to computational issues, as this structure requires a particularly high number of draws to achieve convergence.

[4] It is debatable whether a two-tailed test should be conducted as empirical evidence reports lesser propensity to reveal the income among higher socioeconomic groups (Turell, 2000). If a one-tailed test is performed, the statistical significance increases to 5%.

Table 2 – Parameter estimates for the different models.

Variable	Equation	MNL-P		MBM1		MBM2[5]	
Married	*S.E. LV Wealth*	-		-		**1.02**	*(10.11)*
HighSkill	*S.E. LV Wealth*	-		-		**0.56**	*(3.98)*
MidSkill	*S.E. LV Wealth*	-		-		**0.263**	*(2.37)*
FullTime	*S.E. LV Wealth*	-		-		**0.692**	*(7.85)*
Suburban	*S.E. LV Wealth*	-		-		**0.169**	*(1.76)*
Urban	*S.E. LV Wealth*	-		-		**0.367**	*(3.74)*
NCars	*S.E. LV Wealth*	-		-		**0.714**	*(13.08)*
NewCar	*S.E. LV Wealth*	-		-		**0.429**	*(5.14)*
Constant	*Utility Reveal Income*	-		-		**0.485**	*(2.6)*
LV Wealth	*Utility Reveal Income*	-		-		**-0.1**	*(-1.62)*
Male	*Utility Reveal Income*	-		-		**0.542**	*(4.42)*
Old	*Utility Reveal Income*	-		-		**0.659**	*(4.02)*
MidAge	*Utility Reveal Income*	-		-		**0.506**	*(3.68)*
Vienna	*S.E. LV Green*	-		**-0.133**	*(-2)*	**-0.155**	*(-2.29)*
Male	*S.E. LV Green*	-		**-0.275**	*(-4.56)*	**-0.301**	*(-4.99)*
HighSkill	*S.E. LV Green*	-		**0.571**	*(6.46)*	**0.548**	*(5.99)*
MidSkill	*S.E. LV Green*	-		**0.345**	*(4.76)*	**0.336**	*(4.53)*
Old	*S.E. LV Green*	-		**0.636**	*(7.47)*	**0.614**	*(7.14)*
MidAge	*S.E. LV Green*	-		**0.385**	*(5.32)*	**0.379**	*(5.19)*
Carsharing	*S.E. LV Green*	-		**0.652**	*(4.77)*	**0.619**	*(4.56)*
CarUser	*S.E. LV Green*	-		**-0.337**	*(-6.57)*	**-0.364**	*(-6.98)*
ASC_CV	*Utility CV*	**0**	*(fixed)*	**0**	*(fixed)*	**0**	*(fixed)*
ASC_HEV	*Utility HEV*	**0.605**	*(0.82)*	**-0.0771**	*(-0.37)*	**0.0762**	*(0.36)*
ASC_PHEV	*Utility PHEV*	**0.0831**	*(0.12)*	**-0.455**	*(-2.08)*	**-0.393**	*(-1.77)*
ASC_EV	*Utility EV*	**-1.61**	*(-1.91)*	**-0.979**	*(-3.26)*	**-0.837**	*(-2.76)*
PP	*Utility CV*	**-1.61**	*(-3.75)*	**-1.14**	*(-9.39)*	**-1.38**	*(-9.06)*
PP	*Utility HEV*	**-2.5**	*(-24.7)*	**-1.71**	*(-24.12)*	**-2.06**	*(-16.62)*
PP	*Utility PHEV*	**-2.27**	*(-20.63)*	**-1.75**	*(-20.81)*	**-2.01**	*(-15.56)*
PP	*Utility EV*	**-1.64**	*(-10.58)*	**-1.29**	*(-12.66)*	**-1.63**	*(-10.05)*
*PP * Wealthy*	*Utility CV*	-		-		**0.506**	*(2.78)*
*PP * Wealthy*	*Utility HEV*	-		-		**0.705**	*(3.82)*
*PP * Wealthy*	*Utility PHEV*	-		-		**0.596**	*(3.08)*
*PP * Wealthy*	*Utility EV*	-		-		**0.694**	*(3.19)*
MC	*Utility CV, HEV; PHEV, EV*	**-30.9**	*(-12)*	**-17.6**	*(-9.22)*	**-17.6**	*(-9.24)*
FC	*Utility CV, HEV; PHEV, EV*	**-31.6**	*(-20.69)*	**-18.9**	*(-16.37)*	**-18.6**	*(-16.11)*
PS	*Utility CV*	**0.0492**	*(3.18)*	**0.0285**	*(5.75)*	**0.0289**	*(5.84)*
PS	*Utility HEV*	**0.0516**	*(9.1)*	**0.0338**	*(8.31)*	**0.0335**	*(8.23)*
PS	*Utility PHEV*	**0.0507**	*(8.7)*	**0.0373**	*(8.5)*	**0.037**	*(8.41)*
PS	*Utility EV*	**0.00695**	*(1.34)*	**0.00272**	*(0.71)*	**0.00278**	*(0.73)*
*PS * Male*	*Utility CV*	**-0.0179**	*(-3.25)*	**-0.0164**	*(-4.2)*	**-0.0161**	*(-4.13)*
*PS * Male*	*Utility HEV*	**-0.0147**	*(-2.58)*	**-0.0145**	*(-3.41)*	**-0.0145**	*(-3.39)*
*PS * Male*	*Utility PHEV*	**-0.0143**	*(-2.53)*	**-0.0136**	*(-3.17)*	**-0.0134**	*(-3.11)*
*PS * Male*	*Utility EV*	**-0.00512**	*(-0.87)*	**-0.00606**	*(-1.36)*	**-0.00572**	*(-1.28)*
MidAge	*Utility HEV*	**-0.295**	*(-0.96)*	**-0.27**	*(-2.6)*	**-0.307**	*(-2.93)*
MidAge	*Utility PHEV*	**-0.35**	*(-1.26)*	**-0.393**	*(-3.74)*	**-0.399**	*(-3.77)*
MidAge	*Utility EV*	**-0.895**	*(-2.42)*	**-0.665**	*(-4.74)*	**-0.703**	*(-4.91)*
Old	*Utility HEV*	**-1.51**	*(-4.17)*	**-1.01**	*(-7.08)*	**-0.953**	*(-6.78)*
Old	*Utility PHEV*	**-1.72**	*(-5.14)*	**-1.27**	*(-8.48)*	**-1.24**	*(-8.4)*
Old	*Utility EV*	**-2.83**	*(-6.16)*	**-1.9**	*(-9.15)*	**-1.86**	*(-9.08)*
LV Green	*Utility HEV*	-		**0.594**	*(5.29)*	**0.559**	*(5.02)*
LV Green	*Utility PHEV*	-		**0.564**	*(4.88)*	**0.539**	*(4.76)*
LV Green	*Utility EV*	-		**1.06**	*(6.31)*	**1.05**	*(6.28)*
RA	*Utility EV*	**0.0053**	*(10.09)*	**0.00329**	*(8.11)*	**0.00327**	*(8.07)*
LSMid	*Utility EV*	**0.318**	*(1.78)*	**0.164**	*(1.26)*	**0.165**	*(1.26)*
LSHigh	*Utility EV*	**1.04**	*(6.42)*	**0.694**	*(5.75)*	**0.692**	*(5.72)*
IM3	*Utility EV*	**0.5**	*(3.61)*	**0.235**	*(2.25)*	**0.233**	*(2.23)*
Sigma CV	*Utility CV*	**-2.81**	*(-21.95)*	-		-	
Sigma PHEV	*Utility HEV*	**-1.45**	*(-13.96)*	-		-	
Sigma HEV	*Utility PHEV*	**0**	*(fixed)*	-		-	
Sigma EV	*Utility EV*	**-2.35**	*(-15.46)*	-		-	
Log-likelihood		**-5 110.1**		**-16 627.3**		**-20 207.7**	

[5] Given the complex structure of the likelihood function, and the estimation technique (simulated maximum likelihood), minor discontinuity issues arise making impossible to achieve a perfect convergence of the optimization routines for this model. Different algorithms as well as several starting points were analyzed, noticing that all arrive at the same value for the log-likelihood and the parameter estimates do not differ in more than ±1%. In terms of the statistical significance, the differences between the parameters are completely negligible for all estimations.

The results thus 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 equally impact all technologies alike, as pure electric vehicles are preferred. Older individuals are more reluctant in regard to the adoption of the electromobility.

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. At the same time, the purchase price also negatively affects the utility associated with agiven alternative. It is noteworthy that 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 vanishes. Interestingly, women show a statistically significantly higher willingness-to-pay for bigger engines than do men.

A greater range and 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 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 a Park and Ride subscription (IM2) or a one-year-ticket for public transportation (IM4).

Finally, it is important to mention that the analysed features are quite orthogonal across the different models meaning than including additional information does not significantly affect the relationship between the attributes of the alternatives (except when considering an interaction with another attribute or in the case of socioeconomic characteristics) 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 currently hot topic in 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 information. Our results support the validity of this approach and the existence of endogeneity in regard to the decision of revealing the income making unsuitable the classical imputation techniques.

It is possible to establish that many of the typical assumptions regarding electromobility apply to the Austrian market, with the reluctance of older people and the proclivities of environmentally-minded individuals proven true among Austrians. In a similar fashion, it is established that engine power does not have a major effect when dealing with purely electrical vehicles; adoption of new technology automobiles depends on an increased driving range and charging station availability as well as effective policy incentives. 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 major impact on the adoption of alternative fuel vehicles. Similarly, 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.

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APPENDIX

Appendix 1 – Parameter estimates for the linear measurement equations.

Variable	Equation	MNL[6]	MBM1		MBM2	
LV Wealth	*M.E. Household Net Income*	-	-		$0.784*10^3$	*(19.87)*
Constant	*M.E. Household Net Income*	-	-		$0.748*10^3$	*(6.47)*
St.Dev.	*M.E. Household Net Income*	-	-		$0.564*10^3$	*(11.17)*
LV Wealth	*M.E. Personal Net Income*	-	-		$0.435*10^3$	*(17.52)*
Constant	*M.E. Personal Net Income*	-	-		$0.76*10^3$	*(7.84)*
St.Dev.	*M.E. Personal Net Income*	-	-		$0.856*10^3$	*(39.12)*
LV Green	*M.E. EcAwareness*	-	-0.567	*(-24.27)*	-0.563	*(-24.04)*
Constant	*M.E. EcAwareness*	-	2.58	*(48.82)*	2.55	*(47.24)*
St.Dev.	*M.E. EcAwareness*	-	0.676	*(40.53)*	0.677	*(40.25)*
LV Green	*M.E. LocalFood*	-	-0.683	*(-25.87)*	-0.683	*(-25.97)*
Constant	*M.E. LocalFood*	-	2.37	*(38.19)*	2.34	*(36.51)*
St.Dev.	*M.E. LocalFood*	-	0.707	*(36.77)*	0.705	*(36.53)*
LV Green	*M.E. EcoFriendly*	-	-0.805	*(-24.58)*	-0.803	*(-24.11)*
Constant	*M.E. EcoFriendly*	-	2.97	*(40.41)*	2.93	*(38.76)*
St.Dev.	*M.E. EcoFriendly*	-	0.89	*(37.98)*	0.89	*(37.58)*
LV Green	*M.E. Protection*	-	-0.419	*(-13.42)*	-0.417	*(-13.33)*
Constant	*M.E. Protection*	-	3.36	*(72.03)*	3.33	*(70.78)*
St.Dev.	*M.E. Protection*	-	1.05	*(51.28)*	1.05	*(51.25)*
LV Green	*M.E. CO2Footprint*	-	-0.788	*(-24.97)*	-0.78	*(-24.7)*
Constant	*M.E. CO2Footprint*	-	3.51	*(48.22)*	3.47	*(46.72)*
St.Dev.	*M.E. CO2Footprint*	-	0.892	*(38.88)*	0.897	*(39.17)*

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