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 the electromobility in Austria, focusing specifically on the potential demand for electric vehicles in the automotive market. This works relies on a disaggregate approach, making use of discrete choice behavioral mixture models considering latent variables. Our model allows 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 the electromobility also hold the Austrian market (e.g. proclivity of green-minded 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). In 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 a Park and Ride subscription for one year 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 loading stations. Finally this paper enunciates and successfully tests an alternative approach to deal with 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

The coming scarcity of fossil resources and their negative impact toward the environment have driven the attention of the automobile industry to alternative, more efficient and cleaner propulsion technologies. In addition, more and more restrictive regulations regarding the CO_2 emissions of automobiles and the rising prices of fuel have led to a significant change of the way in which some characteristics of the automobiles are perceived. This way, the interest of the wider public has been driven to less emitting, more efficient and smaller, less consuming engines (Fontaras and Samaras, 2010; Thiel *et al.*, 2014).

This attitudinal change has not only led to a significant adjustment of the 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 on alternative fuel vehicles. This way, during the last decade the car fleet has experienced an important advance of the hybrid electric vehicles (HEV; Jenn *et al.*, 2013). 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, but the market expects a significant advance once these issues may be overcome (Eppstein *et al*., 2011; Lebeau *et al.*, 2012; Shafiei *et al.*, 2012; Hackbarth and Madlener, 2013; among many others).

In this line, numerous governments, such as Japan (Åhman, 2006), the USA (Diamond, 2009) and members of the European Union (Kley *et al.*, 2012) have introduced several incentive policies in order to promote the electromobility, ranging from the development of the charging infrastructure and monetary incentives to the access to express lanes and parking benefits.

Notwithstanding the adoption of electric vehicles is not only driven by economic benefits but also by the environmental concern of the individuals. Although, it may be disputed if electric vehicles are indeed, the most efficient way to reduce CO_2 emissions (Sandy Thomas, 2012; Kasten and Hacker, 2014) several studies have shown 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 have been studied extensively in the past, to our knowledge only one attempt based on disaggregated data have been conducted in Austria (Link et al., 2012). Pfaffenblichler *et al.*, (2009) summarized other attempts to establish the acceptance of electromobility in the country, but the considered 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). Either way, both approaches do not seem to be suitable for reliable prognoses, as the former makes impossible to derive a functional model and the latter attempts to derive the demand for a certain transportation mode (which attributes are unknown for the wider public) based on the characteristics of other alternatives, as the current market share of electric vehicles is very small (Link *et al.*, 2012).

Establishing accurately the future demand for electric vehicles is key issue, not only for the automobile and battery industries but also for the electric markets, as the energy consumption of electric vehicles may have a critical impact on the electric networks (Pieltain Fernández *et al.*, 2011; Schill and Gerbaulet, 2014).

2. DESCRIPTION OF THE DATASET

The data was collected in a web-based survey which was 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. The participation on this experiment was restricted to individuals with a driver's license and an explicit intention to buy a new vehicle within the near future. In total 787 respondents were selected into this subgroup and each respondent was asked to answer 9 independent choice scenarios. No restrictions were applied for the second subgroup which had to respond to the DCE on transport mode choice. Of the 938 respondents in this subgroup 73 individuals gave only incomplete information on their recent trip and thus had to be 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 so as to compound 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 8 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 6 point Likert-type scale:

The following 8 statements were used: (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 the y result in job losses; (g) There are limits to growth which have been or will soon be reached by countries in the industrialized world; (h) I pay attention to the CO_2 footprint of the products I buy.

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

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 the 9 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 loading stations (LS) and policy incentives (IM). Loading station availability varied across three categories (low, medium and high) which were 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 loading 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 customize the choice sets individually. 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 that a certain 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 it can be appreciated, 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 assumed that the error terms follow a EV1 distribution 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, so that 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 has been well established that immaterial non-measurable attitudes also play an important role in the willingness-to-pay for given products or services. In the same line, some variables may have been inaccurately or not completely reported (e.g. income), making necessary to make assumptions about the missing information.

To deal with 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 supposed 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*, which consider the latent variables as explanatory variables and yield as output a positively measured outcome, 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 an adequate identifiability and, more important, it enriches the model incorporating exogenous information, which is in fact closely related with 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 a theoretical support to the model. This way, the measurement equations may take the following shape (if we assume a continuous distribution of the perceptual and attitudinal indicators):

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

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.

The latent variables are then considered into 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).

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 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 may be considered as despicable in contrast with the model's own variability (Bahamonde-Birke and Ortúzar, 2014b).

Treating the Income

In the context of the survey, information was gathered regarding the personal and household net income of the individuals. Given the fact that individuals are very sensitive about this matter, it was allow for the respondents to omit this question, noticing that a 30.02% of the sample did not report this information. A potential alternative to deal with this problem would be to rely on 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 omitting the income behave in a similar way, as the factors leading to the omission of the question are of very different nature.

Another approach would be to impute these variables (Kin *et al.*, 2007), based on other characteristics of the individuals, but it could lead to endogeneity if the likelihood of omitting this question is also driven by the income. In that case, the imputation would be spurious, and therefore it is important to analyze this matter in order to prevent any misspecification.

Finally, it is not clear which kind of income variable (personal or household net income) should be considered into 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, which variable to consider, should rely on theoretical arguments.

To deal with this problem we construct a latent variable called wealth, which is related to both the personal and the household net income, while being explained, at the same time, by a set of characteristics of the individuals. Naturally, this variable was calculated based on the information provided by the individuals reporting the income.

The information provided by the individuals not stating their income (through their omission) was considered making use of a discrete choice framework, as proposed by Sanko *et al.* (2014). For this purpose we introduce a utility function associated with the likelihood of revealing the income, which depends on the characteristics of the individuals and on the latent variable wealth and yields as outcome the probability with which a certain individual will reveal its income. Figure 1 summarizes the way, in which the income is considered into the model:

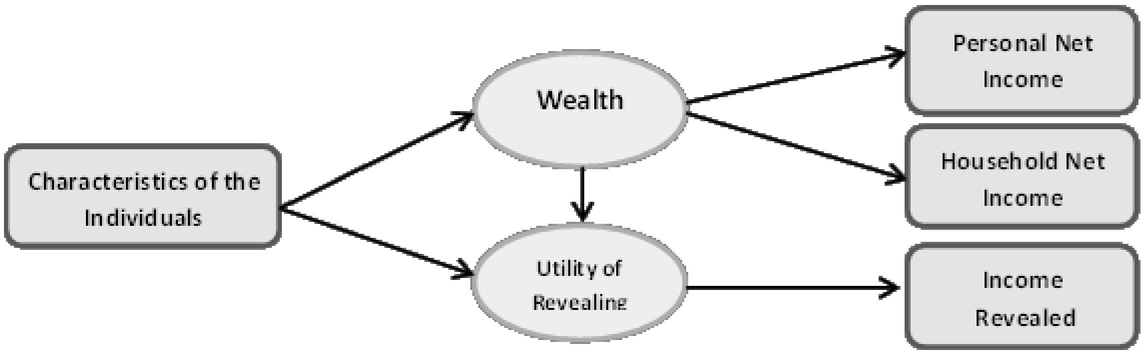

Figure 1 – Treatment of the income.

The personal and the household net income are considered to be a continuous output and the errors of the measurement equations are assumed to be independent normally distributed with mean zero. The error term associated with the utility of revealing the 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 over the decision making process is highly disputable, it is convenient to segment the individuals into different categories. This way, the latent variable is categorized as proposed by (Bahamonde-Birke *et al*., 2014).

Treating the Environmental Concern

As it has been previously stated, the empirical evidence suggests that an environmental attitude 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 being at the same time the cause of the indicators stated in this regard.

A factorial analysis revealed that not all gathered indicators can be linked beyond doubt with a greener attitude. In fact it was only possible to identify a high correlation among five of them (a, d, e, f and h). Notwithstanding an evaluation of the remaining indicators reveals that those are not actually related to the own attitude but rather to an evaluation of the society (b and c) or of the economy (g). Under these circumstances, the latent variable was constructed without taking the latter indicators into consideration.

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 Hypercub Sampling; Hess *et al.*, 2006) draws.

The variables that have been evidenced as relevant for the model are presented in Table 1. As it can be observed, the latent variable "Wealth" has been categorized in order to reflect a potential divergent behavior by wealthier individuals. It has been assumed a threshold of 3.4, so that approx. 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 was assumed (for identifiability 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 were considered to be uncorrelated. In the same line, intercepts were 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 was considered, as the behavioral mixture model allows for the capture of behavioral correlation.

Three different models were estimated. First a classical multinomial model (MNP) considering the correlation among the answers provided by the same individuals (panel structure) was calibrated. Additionally we have estimated a behavioral mixture model (MBM1) considering only the environmental concern and a third model (MBM2) considering both the environmental awareness and the differences in income following the approach presented in Section 3. For MBM1 and MBM2 the panel structure of the dataset was not taken into account, due to unsolvable computational issues

The results for the estimated models are presented in Table 2. Due to space constraints we do not include the results for the linear measurement equations, which can be found in the Appendix 1. The results of the t-test for statistical significance are presented in parenthesis. The final value for the log-likelihood is also reported, but it does not provide a significant insight into the wellness-of-fit of the different models, as the number of measurement equations considered varies between them.

As it can be observed on Table 2, the wealth affects negatively (at a statistical significance of 10% for a two-tailed nest[2]) the likelihood of revealing the income. This way, imputing the income directly would have led to spurious results due to the presence of endogeneity. 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 on a full time basis are more likely to earn higher incomes. Similarly, a urban or a suburban residence and the number of automobiles are positively correlated with the wealth. Finally, married individuals tend to exhibit a higher income. It was not possible to establish a relation between wealth and gender or age.

In relation with environmental concern our results support the thesis that male and younger individuals care less about the environment than their female and older counterparts, respectively. These findings are in line with the 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 a more ecological attitude, while individuals living in Vienna

[2] It is a debatable point, 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	MNP		MBM1		MBM2[3]	
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*	0.423	*(0.64)*	-0.0771	*(-0.37)*	0.0762	*(0.36)*
ASC_PHEV	*Utility PHEV*	-0.0551	*(-0.08)*	-0.455	*(-2.08)*	-0.393	*(-1.77)*
ASC_EV	*Utility EV*	-1.73	*(-2.14)*	-0.979	*(-3.26)*	-0.837	*(-2.76)*
PP	*Utility CV*	-1.89	*(-5)*	-1.14	*(-9.39)*	-1.38	*(-9.06)*
PP	*Utility HEV*	-2.36	*(-24.27)*	-1.71	*(-24.12)*	-2.06	*(-16.62)*
PP	*Utility PHEV*	-2.38	*(-20.37)*	-1.75	*(-20.81)*	-2.01	*(-15.56)*
PP	*Utility EV*	-1.62	*(-10.44)*	-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*	-31.2	*(-12.09)*	-17.6	*(-9.22)*	-17.6	*(-9.24)*
FC	*Utility CV, HEV; PHEV, EV*	-31.5	*(-20.68)*	-18.9	*(-16.37)*	-18.6	*(-16.11)*
PS	*Utility CV*	0.0557	*(3.98)*	0.0285	*(5.75)*	0.0289	*(5.84)*
PS	*Utility HEV*	0.0503	*(9.02)*	0.0338	*(8.31)*	0.0335	*(8.23)*
PS	*Utility PHEV*	0.0528	*(8.92)*	0.0373	*(8.5)*	0.037	*(8.41)*
PS	*Utility EV*	0.00666	*(1.28)*	0.00272	*(0.71)*	0.00278	*(0.73)*
*PS * Male*	*Utility CV*	-0.0191	*(-3.51)*	-0.0164	*(-4.2)*	-0.0161	*(-4.13)*
*PS * Male*	*Utility HEV*	-0.0161	*(-2.88)*	-0.0145	*(-3.41)*	-0.0145	*(-3.39)*
*PS * Male*	*Utility PHEV*	-0.015	*(-2.66)*	-0.0136	*(-3.17)*	-0.0134	*(-3.11)*
*PS * Male*	*Utility EV*	-0.00575	*(-0.98)*	-0.00606	*(-1.36)*	-0.00572	*(-1.28)*
MidAge	*Utility HEV*	-0.171	*(-0.6)*	-0.27	*(-2.6)*	-0.307	*(-2.93)*
MidAge	*Utility PHEV*	-0.276	*(-0.97)*	-0.393	*(-3.74)*	-0.399	*(-3.77)*
MidAge	*Utility EV*	-0.768	*(-2.1)*	-0.665	*(-4.74)*	-0.703	*(-4.91)*
Old	*Utility HEV*	-1.23	*(-3.73)*	-1.01	*(-7.08)*	-0.953	*(-6.78)*
Old	*Utility PHEV*	-1.59	*(-4.77)*	-1.27	*(-8.48)*	-1.24	*(-8.4)*
Old	*Utility EV*	-2.35	*(-5.6)*	-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*	0.00529	*(10.11)*	0.00329	*(8.11)*	0.00327	*(8.07)*
LSMid	*Utility EV*	0.312	*(1.76)*	0.164	*(1.26)*	0.165	*(1.26)*
LSHigh	*Utility EV*	1.02	*(6.34)*	0.694	*(5.75)*	0.692	*(5.72)*
IM3	*Utility EV*	0.499	*(3.62)*	0.235	*(2.25)*	0.233	*(2.23)*
Sigma CV	*Utility CV*	-2.82	*(-21.56)*	-		-	
Sigma PHEV	*Utility HEV*	-1.05	*(-7.18)*	-		-	
Sigma HEV	*Utility PHEV*	0.965	*(6.81)*	-		-	
Sigma EV	*Utility EV*	-2.45	*(-15.81)*	-		-	
Log-likelihood		**-5 130.4**		**-16 627.3**		**-20 207.7**	

[3] Given the complex structure of the likelihood function, it was not possible to obtain 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 despicable for all estimations.

are not as concerned about the environment as the individuals living in smaller cities or in the countryside. As it can be expected, the attitude toward the ecology is reflected in the use of automobiles: green-minded individuals tend to rely more on the carsharing and drive less to their main occupational activity.

This green attitude impacts on the preferences for electromobility. Despite the fact that it is not clear, whether electric vehicles would offer a better ecological performance than conventional vehicles, green-minded individuals ascribe a higher utility to automobiles with electric engines. However, this favoritism does not impact all technologies equally and the pure electric vehicles are preferred. Older individuals show themselves to be more reluctant in regard to the adoption of the electromobility.

As it can be expected, higher fuel and maintenance costs impact negatively on the utility ascribed to a certain alternative and it is not possible to identify a statistically different valuation of these two features. In the same line, the purchase price affects also negatively the utility associated with a given alternative. It is noteworthy that the disutility of the purchase price is smaller for wealthier individuals, which is in line with our expectations.

Regarding the power of the engines, it was possible to establish that this feature is important and affects positively the utility when the analyzed alternative considered at least one conventional motor. When the propulsion is purely electric this effect vanishes. Interestingly, women show a statistically significantly higher willingness-to-pay for bigger engines than their masculine counterparts.

A longer driving range and a high availability of loading stations impact positively on the utility ascribed to pure electrical vehicles. This contrasts with the fact that an intermediate level of availability is not significantly better than a low availability of loading stations (at least, in the more complex models). This phenomenon can be understood in light of the fact that this level of service would still not offer a high reliability and individuals would still be reliant upon loading their automobiles at home, suggesting the existence of reliability thresholds.

In regard to policy incentives, it was only possible to identify an increase of the willingness-to-pay for electrical cars associated with investment subsidies to support private loading 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 - despite the fact, that the parameters associated with the model considering the panel structure (MNP), are deflated by larger λ (more informative), due to the nature of the error terms - , meaning than including additional information does not affect significantly the relations 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 the electromobility is one of the major challenges concerning the automobile industry. Its gradual adoption will be undoubtedly a milestone for the future development of the electrical, automotive and infrastructure markets. However, its impact will depend on the characteristics of the alternatives provided to the population. Our research focusses on the effects of these attributes and provides a model to quantify their impact as well as the potential of the electromobility.

It was possible to establish, that many of the usual assumptions regarding the electromobility are also applicable to the Austrian market. This way, the reluctance of older people and the proclivity of ecological-minded individuals are proven to be true. In a similar fashion, it was possible to establish that the engine power has no major effect when dealing with purely electrical vehicles; on the contrary an increased driving range and loading station availability as well as effective policy incentives can indeed favor the adoption of the new technology. Regarding the latter, our research supports the thesis, that the inclusion of policy incentives must be properly evaluated, as some policies may have an important cost for the government and no major effect over the adoption of alternative fuel vehicles. Similarly, a middle level of availability of loading stations should not have a significant effect (in contrast with a low availability). The finding suggests the existence of reliability thresholds concerning the loading infrastructure.

Finally, this paper also presents 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.

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APPENDIX

Appendix 1 – Parameter estimates for the linear measurement equations.

Variable	Equation	MNL[4]	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)

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