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Does Transport Behavior Influence Preferences for Electromobility?

An Analysis Based on Person- and Alternative-Specific Error Components

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ABSTRACT

The interconnection among different choices by the same decision-maker is fairly well established in the literature. Along this line, this paper aims to identify how preferences for electromobility are affected by mode choices for regular trips. With this purpose in mind, a framework based on person- and alternative-specific error components (covariances) is proposed. The method aims to include individual-specific error components associated with the alternatives of a given experiment into another, and to analyze how the preference for a certain alternative in a given choice situation affects the individual's preferences in another choice situation.

The data for the analysis originates from two discrete choice experiment conducted in Austria during February 2013 (representative sample). Here, individuals were asked to state their preferences in the contexts of transport mode choice and vehicle purchase situations. The results indicate the existence of a strong correlation between the individuals' preferences in both experiments. This way, individuals favoring private transport also favor conventional vehicles over electric alternatives, while individuals preferring public or non-motorized modes ascribe a higher utility to electric vehicles, especially to pure battery electric vehicles.

Keywords: Electric Vehicles, Travel Behavior, Modal Choice, Correlation, Panel Structure, Error Components.

JEL: R40, C35, C50

1. INTRODUCTION

It is a well-established fact that travel preferences and behavior of the individuals are related to other travel-related decisions, such as car ownership or residential location (Golob, 1990; Dieleman *et al.*, 2002, among many others). This correlation may rely on different characteristics of both decisions themselves and of individuals, including potential self-selection biases (Cao *et al.*, 2009; v. Acker and Witlox, 2010), which significantly increases the complexity of the analysis.

In a similar fashion, it may be expected that preferences toward the purchase of electrical cars could also exhibit a correlation with the travel behavior. Several assumptions, based on empirical evidence, support this hypothesis. This way, for instance, it may be expected that green-minded individuals would favor both public transportation (Vredin-Johansson *et al.*, 2006) and electrical vehicles (Daziano and Bolduc, 2013; Jensen *et al.*, 2013), while, at the same time, it may be argued that individuals already driving on a daily basis may be more willing to pay for electric vehicles due to their higher efficiency and lower operational costs (Offer *et al.*, 2010).

The potential demand for alternative powered mobility is well studied (Ehsani *et al.*, 2009; Offer *et al.*, 2010; Eppstein *et al.*, 2011; Lebeau *et al.*, 2012; Hackbarth and Madlener, 2013, among many others). Thus, it is established that it is not only the objective characteristics of the alternatives but also underlying attitudes and perceptions that affect the acceptance of electromobility (Glerum *et al.*, 2013; Jensen *et al.*, 2014; Kim *et al.*, 2014; Bahamonde-Birke and Hannapi, 2015). However, the relation between travel preferences of individuals and their willingness-to-pay for new propulsion technologies is not extensively analyzed. Even when travel preferences are taken into account while

analyzing electromobility preferences, these preferences are normally treated as exogenous information (He *et al.*, 2012).

To conduct this kind of analysis, it is convenient to simultaneously consider travel behavior information and preferences toward electromobility. For this, this work relies on the discrete choice (DC) modeling approach (McFadden, 1974) and considers a simultaneous estimation of DC models on vehicle purchase and on modal choices. An intuitive approach to link both experiments is considering the underlying attitudes affecting both decisions making use of a hybrid discrete choice (HDC) framework (McFadden, 1986; Train *et al.*, 1987, Ben-Akiva *et al.*, 2002), which allows controlling for attitudinal characteristics of the population. However, as it is not possible to identify all attitudes affecting the decisions, the correlation between them may be underestimated. To avoid this problem, the modeling takes advantage of the pseudo-panel structure of the sample (with individuals facing more than one choice situation for each experiment). This way, the correlation among answers provided by the same individual in a given experiment may be incorporated into the other, offering a clear representation of the extent to which one decision is affected by the other.

This paper presents a method to correlate two independent DC experiments, based on stated-preferences (SP), making use of random panel effects (Bhat and Gossen, 2004). Additionally, it identifies the existence of correlation between modal choice and vehicle purchase decisions among the Austrian population; thus the simultaneous consideration of both models increase their explainability and offers clear insights on the way in which both decisions are interconnected.

The rest of the paper is organized as follows. Section 2 presents an overview of the theoretical approach and extends it in order to consider the correlation among different SP-experiments, while Section 3 offers a description of the dataset utilized to test the hypothesis. The results are discussed in section 4 and finally, section 5 summarizes the paper's conclusions.

2. METHODOLOGICAL APPROACH

Under the assumption that individuals are rational decision makers, it can be postulated that individuals facing a set of available alternatives A , will choose the alternative i that maximizes their perceived utility. In accordance with Random Utility Theory (Thurstone, 1927; McFadden, 1974), it is possible to depict this utility (U_i) as the sum of a representative component and an error term (ε), which, under the assumption of additive linearity, leads to the following expression (Ortúzar and Willumsen, 2011):

$$U_i = \beta \cdot X + \varepsilon \quad [2.1],$$

where X is a matrix standing for observed attributes of the alternatives and characteristics of the individuals and β is a vector of parameters to be estimated. If it is assumed for the error terms to be independent EV1 distributed with same mean (for all alternatives) and diagonal homoscedastic covariance matrix (Σ_ε), the choice probabilities will be given by a Multinomial Logit model (Domencich and McFadden, 1975; MNL). Nevertheless, the assumption of independence does not hold, when the observations arise from panel or pseudo-panel data, as in this case the observations associated with the same individual would be correlated.

To approach this problem, it is useful to rely on Mixed Logit models (Cardell and Dunbar, 1980; Ben-Akiva and Bolduc, 1996; ML). Here, it is assumed that the stochastic component of the model would be given but by the sum of the previously described independently identically EV1 distributed error term (ε) and other stochastic element that can follow any distribution. In this case, the utility function would take the following shape:

$$U_i = \beta \cdot X + \eta + \varepsilon \quad [2.2]$$

Here, η is an error component following a given distribution and whose covariance matrix (Σ_η) is not subject to homoscedasticity and no-autocorrelation restrictions (as long as the model is identified). This way, for instance, it can be accounted for correlation between individuals and alternatives. Under these assumptions, the likelihood function may be depicted as follows:

$$L = \int_{\eta} P(y | X, \eta; \beta, \Sigma_{\varepsilon}, \Sigma_{\eta}) \cdot f(\eta | \Sigma_{\eta}) \cdot d\eta \quad [2.3],$$

where the first component stands for the usual MNL probabilities (y is a vector taking a value of 1 if the alternative is selected and 0 otherwise), while the second term represents the distribution of the error term η . As normally this representation will not lead to closed-form expressions for the probabilities, the likelihood function must be integrated over the domain of the stochastic component η , making use of simulated likelihood techniques (McFadden, 1986).

To deal with panel or pseudo panel data it can be assumed that the error component η be common to all answers provided by the same individual (Bhat and Gossen, 2004; Walker

et al., 2007). Thus, the total error would be given by the sum of the i.i.d. EV1 error term and a mixing distribution allowing for capturing the correlation among the choices of the same individual (this approach work well for labelled experiments, but it does not appear to be suitable to address unlabeled data; Daly and Hess, 2010). In this case, the integration must be conducted at individuals' level rather than choices.

Dealing with several SP-Experiments

When addressing two or more independent labelled SP-experiments, whose answers are provided by the same respondents, the situation is not different, as the choices of the same individuals are also correlated.

If the experiments are treated independently, it would suffice to account for the correlation of the answers provided by the same individuals within the experiments (if it is assumed that both experiments consist of more than one choice situations). Thus, the utility functions would take the following shape (when assuming two labelled SP-experiments, each consisting of three alternatives, which is the minimum to assure that the variability of all person- and alternative- specific error components be identified; Walker *et al.*, 2007 - Extending this framework for more SP-Experiments and alternatives is straightforward):

$$\begin{array}{ll}
 U_{11} = \beta_{11} \cdot X + \eta_{11} + \varepsilon_{11} & U_{21} = \beta_{21} \cdot X + \eta_{21} + \varepsilon_{21} \\
 U_{12} = \beta_{12} \cdot X + \eta_{12} + \varepsilon_{12} & U_{22} = \beta_{22} \cdot X + \eta_{22} + \varepsilon_{22} \\
 U_{13} = \beta_{13} \cdot X + \eta_{13} + \varepsilon_{13} & U_{23} = \beta_{23} \cdot X + \eta_{23} + \varepsilon_{23}
 \end{array} \tag{2.4}$$

This framework would lead to the following likelihood function (which could easily be split into two independent models):

$$L = \int \int_{\eta_1 \eta_2} P(y_1 | X, \eta_1; \beta_1, \Sigma_{\varepsilon_1}, \Sigma_{\eta_1}) \cdot P(y_2 | X, \eta_2; \beta_2, \Sigma_{\varepsilon_2}, \Sigma_{\eta_2}) \cdot f(\eta_1 | \Sigma_{\eta_1}) \cdot f(\eta_2 | \Sigma_{\eta_2}) \cdot d\eta_1 \cdot d\eta_2 \quad [2.5]$$

In this case, no bias is being induced into the modeling as the observations of the first experiment do not affect the outcome of the other and vice versa. This framework, however, does not allow for considering parameters common to both experiments or for analyzing the existence of a possible correlation among the answers provided in the first and in the second experiments. Nor would it be completely adequate to consider latent variables accounting for factors underlying to both experiments (unless it can be established or assumed that the latent variable is the only source of individual correlation among both experiments).

This issue is of particular importance, as in many cases it may be interesting to analyze the correlation among different decisions, as it would offer a more accurate representation of the population. This correlation may have important implications in terms of policy-making or predictability. Additionally, accounting for correlation may substantially increase the explainability of the joint model.

An alternative to account for this correlation is to assume that the utility functions of given experiment are affected by the correlation among the answers provided by the same individual in another experiment. This way, the first set of utility functions depicted in equation [2.4] would be given by:

$$\begin{aligned} U_{11} &= \beta_{11} \cdot X + \eta_{11} + \varepsilon_{11} + \alpha_{11} \cdot \eta_{21} + \alpha_{12} \cdot \eta_{22} + \alpha_{13} \cdot \eta_{23} \\ U_{12} &= \beta_{12} \cdot X + \eta_{12} + \varepsilon_{12} + \alpha_{21} \cdot \eta_{21} + \alpha_{22} \cdot \eta_{22} + \alpha_{23} \cdot \eta_{23} \\ U_{13} &= \beta_{13} \cdot X + \eta_{13} + \varepsilon_{13} + \alpha_{31} \cdot \eta_{21} + \alpha_{32} \cdot \eta_{22} + \alpha_{33} \cdot \eta_{23} \end{aligned} \quad [2.6]$$

Here, η_{21} , η_{22} and η_{23} represent the person- and alternative-specific error components (PASEC) accounting for correlation among the answers of the same individual, for a given alternative in the second experiment, while α_{jk} are parameters to be calibrated. As the PASECs are constant for all answers associated with the same individual, the model depicted in [2.6] would be unidentified and therefore it is necessary to constrain (without loss of generality) the α parameters of a given alternative; thus the interpretation of the parameters would be similar to the interpretation of alternative specific constants (Ortúzar and Willumsen, 2011) or parameters associated with socio-economic or attitudinal latent variables (Bahamonde-Birke *et al.*, 2014). It is straightforward to extend this framework for the remaining set of utility functions.

Then, the likelihood function for the joint model would be depicted in the following manner:

$$L = \int \int_{\eta_1 \eta_2} P(y_1 | X, \eta_1, \eta_2; \beta_1, \alpha_1, \Sigma_{\epsilon_1}, \Sigma_{\eta_1}, \Sigma_{\eta_2}) \cdot P(y_2 | X, \eta_1, \eta_2; \beta_2, \alpha_2, \Sigma_{\epsilon_2}, \Sigma_{\eta_1}, \Sigma_{\eta_2}) \cdot f(\eta_1 | \Sigma_{\eta_1}) \cdot f(\eta_2 | \Sigma_{\eta_2}) \cdot d\eta_1 \cdot d\eta_2 \quad [2.7]$$

This framework may be extended in order to incorporate latent variables or classes (that may be reason for the existence of correlation). Nevertheless, this approach is clearly more extensive than considering latent variables or classes as the only source of correlation among the answers provided by the same individual, as it allows capturing not only the correlation associated with identified underlying attitudes affecting both choices, but also the correlation related to unidentified characteristics of the individuals.

3. DESCRIPTION OF THE DATASET

The data for the analysis originates from a discrete choice experiment (DCE) conducted in Austria during February 2013 (representative sample), in which the individuals were asked to state their preferences in the context of vehicle purchase situations (Bahamonde-Birke and Hannapi, 2015). 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. 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 assigned to the DCE on transport mode choice. Of the 938 respondents in this subgroup, 73 individuals providing incomplete information were excluded. Both subgroups received 9 independent choice scenarios. In total, 276 individuals took part on both experiments. The survey duration for the individuals responding DCEs was of approx. 30 minutes (as compared to 20 minutes for the remaining 1,173 individuals). Finally, the individuals were presented with a questionnaire covering socio-economic background, mobility behavior and attitudes.

For this analysis, only the 276 individuals responding to both questionnaires are taken into account. 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 age and gender structure, but also regarding to Austria's nine federal states and the degree of urbanization (rural, sub-urban and urban).

The DCE on modal choice (DCE-MC) considered four labelled choice alternatives: private transportation (PV), public transportation - bus (PT-B), public transportation - train (including urban trains, PT-T) and non-motorized transportation (NMT). The PT alternative was described in terms of the free flow time (FFT), congestion time (CT), parking (PRK), toll (TL) and fuel expenses (FE), while both public transportation alternatives were depicted in terms of the travel time (TT), fare (TCK), interval (INT) and number of transfers (NT). The NMT alternative was characterized by its travel time and was subsequently subdivided in walking (WLK), cycling (BCL) and electric bicycles (EBC), so that each choice situation would present only one NMT alternative (although electric bicycles are technically motorized vehicles, they were considered as part of the NMT alternative, as they are considered to be closely related to other NMT sub-alternatives); hence, the sub-divisions of the NMT alternative cannot be considered to be labelled alternatives, but rather attributes of the labelled alternative NMT. Additionally, information regarding the last trip (with the same purpose and destination) was gathered, so that it is possible to construct an inertia variable (IN); this information, however, is only disaggregated at the level of private, public or non-motorized transportation, thus both public transport alternatives (PT-B and PT-T) are associated with the same inertia variable.

The DCE on vehicle purchase (DCE-VP) 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 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).

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.

4. ESTIMATION AND RESULTS

As equations [2.5] and [2.7] do not exhibit closed-form expressions, the estimation is performed via simulation making use of PythonBiogeme (Bierlaire, 2003). To compute the simulated likelihood, 1,000 MLHS (Modified Latin Hypercube Sampling; Hess *et al.*, 2006) draws are utilized. Table 1 presents an overview of the variables that were found to be significant for the matters of the study.

First, independent models for both experiments were calibrated taking the correlation within individuals into account (equation [2.5]). Subsequently, correlation terms among both experiments were introduced. For the purposes of this study, it was assumed that only the correlation among the answers in the modal choice experiment would affect the vehicle purchase experiment, and not vice versa. The hypothesis behind this reasoning is that individuals are familiar with modal choice decisions, and therefore a particular set of attitudes, perceptions and values (for which it is not being controlled) has been developed

over time. Hence, this particular mindset may affect other (slightly related) decisions. In the case of the DCE on vehicle purchase considering electric vehicles (whose participation in the market is still very low; Jenn *et al.*, 2013), the modeler is dealing primarily with a hypothetical decision; thus attitudes, perceptions and values affecting this decision arise from other experiences and no particular mindsets related to this specific choice situation have been developed yet.

Table 1 – Definition of the variables considered in the model.

Variable	Definition
<i>Male</i>	Dummy variable indicating masculine gender.
<i>Old</i>	Dummy variable indicating individuals older than 60 years
<i>MidAge</i>	Dummy variable indicating individuals older than 35 years, but no older than 60 year.
<i>IN</i>	Inertia variable in DCE-MC.
<i>FFT, CT</i>	Free flow time and congestion time for PV in DCE-MC in min., respectively.
<i>PRK, TL, FE</i>	Parking, toll and fuel expenses for PV in DCE-MC in €, respectively.
<i>TT, INT</i>	Travel and interval time for PT-B, PT-T or NMT in DCE-MC in min., respectively.
<i>TCK</i>	Fare for individual ticket for PT-B or PT-C in DCE-MC in €.
<i>NT</i>	Number of transfers for PT-B or PT-T in DCE-MC.
<i>WLK, BCL, EBC</i>	Subdivision of the NMT alternative in DCE-MC: walking, cycling and electric bicycle, respectively.
<i>PP</i>	Purchase Price in DCE-VP in $\text{€} \cdot 10^4$.
<i>FC, MC</i>	Fuel and maintenance cost in DCE-VP in $\text{€} / 100 \text{ km.}$, respectively.
<i>PS</i>	Power of the engine in DCE-VP in hp.
<i>RA</i>	Driving range in DCE-VP in km.
<i>IM2, IM3, IM4</i>	Dummy variables indicating the execution of the respective policy incentive in DCE-VP.
<i>Sigma</i>	Variability of the person- and alternative-specific covariances (η_{xy} for U_{xy} in eq. [2.6]).
$\alpha\text{-PV}$	Impact of person-specific covariance of alternative PV in DCE-VP (α_{xy} in eq. [2.6]).
$\alpha\text{-PT-B}$	Impact of person-specific covariance of alternative PT-B in DCE-VP.
$\alpha\text{-PT-T}$	Impact of person-specific covariance of alternative PT-T in DCE-VP.
$\alpha\text{-NMT}$	Impact of person-specific covariance of alternative NMT in DCE-VP.

The results for the estimated models are presented in Table 2 (DCE-MC) and Table 3 (DCE-VP). Even though the models were estimated jointly, the results for both experiments are presented separated for layout purposes. The model on the right (Independent Model) corresponds to the model estimated according equation [2.5], while the model on the left (Correlated Experiments) was estimated in accordance with equation

[2.7]. The results of the t-test for statistical significance are presented in parenthesis. The final value for the overall log-likelihood is also reported.

Table 2 – Parameter estimates for the DCE-MC

Variable	Equation	Independent Model	Correlated Experiments
<i>ASC_PV</i>	<i>Utility PT-B</i>	0 (<i>fixed</i>)	0 (<i>fixed</i>)
<i>ASC_PT-B</i>	<i>Utility PT-B</i>	-0.971 (-1.87)	-0.392 (-0.44)
<i>ASC_PT-T</i>	<i>Utility PT-T</i>	-1.86 (-3.31)	-1.1 (-1.17)
<i>ASC_WLK</i>	<i>Utility NMT</i>	-3.05 (-3.43)	-2.89 (-2.83)
<i>ASC_BCL</i>	<i>Utility NMT</i>	-3.64 (-4.07)	-3.49 (-3.39)
<i>ASC_EBC</i>	<i>Utility NMT</i>	-1.06 (-1.09)	-0.99 (-0.8)
<i>Inertia</i>	<i>Utility PV</i>	0.613 (1.29)	1.33 (1.73)
<i>Inertia</i>	<i>Utility PT-B</i>	0.8 (1.61)	0.939 (1.42)
<i>Inertia</i>	<i>Utility PT-T</i>	1.52 (2.79)	1.41 (1.84)
<i>Inertia</i>	<i>Utility NMT</i>	3.31 (4)	2.17 (2.75)
<i>FFT</i>	<i>Utility PV</i>	-0.116 (-10.24)	-0.118 (-10.32)
<i>CT</i>	<i>Utility PV</i>	-0.141 (-14.63)	-0.141 (-14.53)
<i>TT</i>	<i>Utility PT-B</i>	-0.104 (-11.39)	-0.105 (-11.34)
<i>TT</i>	<i>Utility PT-T</i>	-0.0841 (-8.82)	-0.0852 (-9.04)
<i>TT</i>	<i>Utility NMT</i>	-0.146 (-13.15)	-0.143 (-13.64)
<i>INT</i>	<i>Utility PT-B</i>	-0.0277 (-2.3)	-0.026 (-2.14)
<i>INT</i>	<i>Utility PT-T</i>	-0.0465 (-3.47)	-0.0465 (-3.56)
<i>TL</i>	<i>Utility PV</i>	-0.264 (-7.16)	-0.266 (-7.14)
<i>PRK</i>	<i>Utility PV</i>	-0.29 (-7.66)	-0.292 (-7.76)
<i>FE</i>	<i>Utility PV</i>	-0.145 (-1.38)	-0.125 (-1.27)
<i>TCK</i>	<i>Utility PT-B</i>	-0.34 (-8.55)	-0.35 (-8.74)
<i>TCK</i>	<i>Utility PT-T</i>	-0.313 (-8.19)	-0.322 (-8.62)
<i>NT</i>	<i>Utility PT-B</i>	-0.403 (-5.58)	-0.42 (-5.77)
<i>NT</i>	<i>Utility PT-T</i>	-0.56 (-7.33)	-0.561 (-7.43)
<i>MidAge</i>	<i>Utility NMT</i>	1.65 (2.15)	2.24 (3.02)
<i>Old</i>	<i>Utility NMT</i>	1.79 (2.39)	1.66 (2.93)
<i>Sigma PV</i>	<i>Utility PV</i>	2.65 (12.71)	2.8 (15)
<i>Sigma PT-B</i>	<i>Utility PT-B</i>	0.492 (2.11)	-0.943 (-6.88)
<i>Sigma PT-T</i>	<i>Utility PT-T</i>	-1.25 (-5.95)	-0.941 (-5.43)
<i>Sigma NMT</i>	<i>Utility NMT</i>	3.24 (9.49)	3.27 (11.06)
<i>Log-likelihood</i>	<i>Overall</i>	-3,791.8	-3,759.1

As can be observed from Table 2 the current transportation modes appear to play a significant role in the preferences stated by the individuals in the DCE, with the current choice favored over competing alternatives (inertia variables). Along this line, current preferences for non-motorized transportation have a stronger impact than the inertia associated with public and private transportation (the latter is not even significant at confidence level of 5%).

The travel time associated with non-motorized alternatives has a stronger negative effect than in the case of private and public transportation. Further, it may be established that the

travel time using transit systems (especially trains) have a lesser impact on the utility than the travel time by private vehicles, with congestion time being perceived as more displeasing than free flow time. These findings are in line with the literature (Quarmby, 1967; Caussade *et al.*, 2005; Wardman *et al.*, 2012, among many others).

Table 3 – Parameter estimates for the DCE-VP

Variable	Equation	Independent Model	Correlated Experiments
<i>ASC CV</i>	<i>Utility CV</i>	0 (<i>fixed</i>)	0 (<i>fixed</i>)
<i>ASC_HEV</i>	<i>Utility HEV</i>	1.28 (1.35)	0.807 (1.01)
<i>ASC_PHEV</i>	<i>Utility PHEV</i>	0.595 (0.63)	-0.13 (-0.14)
<i>ASC_BEV</i>	<i>Utility BEV</i>	-0.744 (-0.61)	-1.75 (-1.48)
<i>PP</i>	<i>Utility CV</i>	-2.36 (-3.53)	-2.17 (-3.05)
<i>PP</i>	<i>Utility HEV</i>	-2.71 (-15.35)	-2.56 (-14.57)
<i>PP</i>	<i>Utility PHEV</i>	-2.3 (-11.88)	-2.37 (-11.79)
<i>PP</i>	<i>Utility BEV</i>	-1.81 (-6.86)	-1.98 (-6.81)
<i>MC</i>	<i>Utility CV, HEV; PHEV, BEV</i>	-32.8 (-7.82)	-32.9 (-7.83)
<i>FC</i>	<i>Utility CV, HEV; PHEV, BEV</i>	-33.5 (-13.38)	-32.9 (-13.11)
<i>PS</i>	<i>Utility CV</i>	0.0675 (3.02)	0.0525 (2.27)
<i>PS</i>	<i>Utility HEV</i>	0.0504 (5.38)	0.0434 (4.57)
<i>PS</i>	<i>Utility PHEV</i>	0.0466 (4.67)	0.0445 (4.42)
<i>PS</i>	<i>Utility BEV</i>	0.00488 (0.52)	0.00463 (0.49)
<i>PS * Male</i>	<i>Utility CV</i>	-0.0227 (-2.5)	-0.0134 (-1.44)
<i>PS * Male</i>	<i>Utility HEV</i>	-0.0147 (-1.53)	-0.0105 (-1.07)
<i>PS * Male</i>	<i>Utility PHEV</i>	-0.0184 (-1.9)	-0.0141 (-1.44)
<i>PS * Male</i>	<i>Utility BEV</i>	-0.00175 (-0.17)	-0.00267 (-0.26)
<i>MidAge</i>	<i>Utility HEV</i>	-0.513 (-0.97)	-0.191 (-0.46)
<i>MidAge</i>	<i>Utility PHEV</i>	-0.49 (-0.96)	-0.298 (-0.52)
<i>MidAge</i>	<i>Utility BEV</i>	-1.48 (-2.19)	-1.07 (-1.21)
<i>Old</i>	<i>Utility HEV</i>	-1.09 (-1.98)	-1.15 (-2.71)
<i>Old</i>	<i>Utility PHEV</i>	-1.14 (-2.13)	-1.51 (-2.72)
<i>Old</i>	<i>Utility BEV</i>	-3.13 (-4.25)	-3.45 (-3.84)
<i>RA</i>	<i>Utility BEV</i>	0.00514 (5.8)	0.00538 (5.87)
<i>LSMid</i>	<i>Utility BEV</i>	0.154 (0.52)	0.184 (0.6)
<i>LSHigh</i>	<i>Utility BEV</i>	0.807 (2.97)	0.843 (2.98)
<i>IM3</i>	<i>Utility BEV</i>	0.424 (1.86)	0.416 (1.77)
<i>Sigma CV</i>	<i>Utility CV</i>	-2.34 (-12.56)	-0.585 (-1.23)
<i>Sigma HEV</i>	<i>Utility HEV</i>	-0.773 (-4.04)	-0.775 (-4.15)
<i>Sigma PHEV</i>	<i>Utility PHEV</i>	0.535 (2.31)	0.533 (2.51)
<i>Sigma BEV</i>	<i>Utility BEV</i>	-2.39 (-9.78)	-2.14 (-9.72)
<i>a-PV</i>	<i>Utility CV</i>	- (-)	0.2 (3.41)
<i>a-PV</i>	<i>Utility HEV</i>	- (-)	0 (<i>fixed</i>)
<i>a-PV</i>	<i>Utility PHEV</i>	- (-)	-0.0268 (-0.44)
<i>a-PV</i>	<i>Utility BEV</i>	- (-)	-0.23 (-2.08)
<i>a-PT-B</i>	<i>Utility CV</i>	- (-)	-1.06 (-3.74)
<i>a-PT-B</i>	<i>Utility HEV</i>	- (-)	0 (<i>fixed</i>)
<i>a-PT-B</i>	<i>Utility PHEV</i>	- (-)	0.613 (2.78)
<i>a-PT-B</i>	<i>Utility BEV</i>	- (-)	0.833 (2.77)
<i>a-PT-T</i>	<i>Utility CV</i>	- (-)	-1.43 (-3.86)
<i>a-PT-T</i>	<i>Utility HEV</i>	- (-)	0 (<i>fixed</i>)
<i>a-PT-T</i>	<i>Utility PHEV</i>	- (-)	0.46 (1.79)
<i>a-PT-T</i>	<i>Utility BEV</i>	- (-)	1.06 (2.7)
<i>a-NMT</i>	<i>Utility CV</i>	- (-)	-0.333 (-4.23)
<i>a-NMT</i>	<i>Utility HEV</i>	- (-)	0 (<i>fixed</i>)
<i>a-NMT</i>	<i>Utility PHEV</i>	- (-)	0.0752 (1.29)
<i>a-NMT</i>	<i>Utility BEV</i>	- (-)	0.325 (3.42)
<i>Log-likelihood</i>	<i>Overall</i>	-3,791.8	-3,759.1

The interval time (normally associated with the waiting time for public transportation) is associated with a lesser disutility than the travel time, which may be related to the fact that transit systems in Austria operate on schedule, and therefore higher interval times are associated rather with less flexibility (regarding departure time) than with larger waiting periods.

Regarding travel expenses, it is observed that toll and parking fees are perceived as much more discouraging than fuel costs (with the parameter associated with the latter not being statistically significant). However, the disutility associated with toll and parking fees is less than the disutility associated with tickets for public transportation. Given the fact that it was allowed for multiple time and money parameters to be calibrated (related to different transportation modes and features) there is no uniform value of time (VoT), but it ranges between 23€-26 €/hr. for private transportation and 15€-18 €/hr. for public transportation.

The number of transfers has a significant negative impact for both public transportation alternatives, while it can be established that middle-aged and older individuals favor non-motorized alternatives. A statically significant correlation among the answers provided by the same individuals was identified for all alternatives.

In general, major differences between the estimates following both approaches cannot be established. The main differences are related to changes in the ASCs and inertia variables (which are more sensitive to changes when using an alternative-specific correlation structure) as well as to a significant increase of the variability of the PASEC associated with the alternative TP-B.

The estimates for the DCE-VP (Table 3) are in line with the results reported by Bahamonde-Birke and Hanappi (2015) using the complete database for the DCE-VP

experiment (in this case, only the answers provided by the 276 individuals responding both questionnaires are being used). This way, it is possible to identify significant disutilities associated with the purchase price - opposite to Bahamonde-Birke and Hanappi (2015), this sample does not allow identifying a higher price disutility associated with BEVs-, a similar impact of both kinds of operational costs (fuel and maintenance costs), a positive impact of the engine power for all alternatives considering a conventional motor that does not extend to pure electric vehicles. Similarly, it can be established that women value increases in the engine power more than men do (a one-tailed test on statistical significance is performed as the sign is known *a priori*) or than older individuals ascribe a lesser utility to electric vehicles. In the case of middle-aged individuals only a disutility associated with pure electric vehicles can be statically identified.

For this sample, the willingness-to-pay for an extended driving range is slightly less than reported by Bahamonde-Birke and Hanappi (2015), ranging between 27 €/km and 28 €/km (depending on the model). It is observed that only one incentive policy (investment subsidies supporting private charging stations) has a significant impact on the adoption of BEVs. Along this line a high availability of charging stations have a positive effect, while a medium availability is statistically no different from poor availability.

Concerning the comparison between the model considering independent experiments and the one taking the correlation into account, it may be concluded that the main differences are (as in the previous case) associated with the ASCs and the PASECs. While the PASECs are all significant for the independent model, for the correlated model it can be observed that the variability of the PASEC of alternative PV is substantially smaller, not being statistically different from zero (the variability of the PASECs does not exhibit significant differences between models for the remaining alternatives). Nevertheless, in

this case the differences between parameter estimates appear to be larger than in the previous case. It may be explained by the fact that in this experiment, the impact of the correlation observed in the DCE-VP is being considered directly into the utility functions.

Finally, it can be established that the correlation among the answers provided by the same individual in the DCE on modal choice has a significant effect on the answers provided in the DCE-VP, as most of the parameters accounting for correlation across experiments are statistically significant. Therefore, it can be concluded that the transport behavior indeed influences the preferences for electromobility. Additionally, a substantial increase of the predictive capability is observed with the goodness-of-fit of the model accounting for correlation clearly outperforming the independent model (the likelihood-ratio test for equal predictive capability can be easily rejected).

Table 4 presents an overview of the effect of the PASECs of the DCE-MC on the utility functions of the DCE-VP. Here, the estimated parameters (α_{jk}) are multiplied by variability (absolute value) of the PASECs in order to offer a better representation of the extent, to which the utility functions of the DCE-VP are affected by these error component.

Table 4 – Impact of the PASECs of the DCE-MC on the DCE-VP

	<i>PV</i>	<i>PT-B</i>	<i>PT-T</i>	<i>NMV</i>
<i>Sigma</i>	2.8	0.943	0.941	3.27
<i>CV</i>	0.56	-1.0	-1.35	-1.09
<i>HEV</i>	0*	0*	0*	0*
<i>PHEV</i>	-0.08**	0.58	0.43**	0.25**
<i>BEV</i>	-0.64	0.79	0.99	1.06

*Reference alternative

** α parameters not statistically different from zero

As can be observed, individuals favoring private transportation (PV) in the modal choice experiment tend to favor conventional vehicles in the vehicle purchase experiment as well. Along this line, these individuals tend to dislike BEVs. Contrariwise individuals favoring public transportation or non-motorized alternatives ascribe a higher utility to BEVs and a

relative disutility to CVs. It is not possible to identify a statistically significant correlation among travel behavior and preferences between HEVs and PHEVs (except in the case of PT-B users favoring PHEV). This is in line with our expectations, as HEVs and PHEVs are usually perceived as similar alternatives.

These findings are in line with the assumption that individuals concerned about the environment may favor both public or non-motorized transportation and electric vehicles.

5. CONCLUSIONS

It is well documented in the literature that apparently independent choices may be interconnected by underlying attitudes, preferences, perceptions or values of the decision-makers. This way, it may be expected, for instance, that choices such as residential location or travel behavior exhibit a high correlation with car ownership. Along this line, it may be expected for correlation to arise every time choices of the same individuals are being modelled.

This paper proposes and successfully tests a method to treat correlation among the answers provided by the same individuals in independent stated-choice experiments. The method relies on person- and alternative-specific error components (covariances) and aims to include individual-specific error components associated with the alternatives of a given experiment into another. This way, it is possible to analyze how the favoritism of given individual for a certain alternative in a given experiment affects the preferences of the same individual in another choice situation. This approach overcomes some shortcomings of alternative treatments, such as controlling for underlying attitudes (e.g. through latent variables or latent classes), as it allows for capturing the entire effect and not only the part associated with the modelled attitudes.

This framework is utilized in order to analyze whether the transport behavior influence preferences for electromobility. The results show that the preferences for electromobility are strongly affected by the choices for the transportation mode of regular trips. Thus, it is possible to determine that individuals favoring private transportation also favor conventional vehicles over electric alternatives (and especially over pure battery electric vehicles). On the contrary, individuals preferring public or non-motorized transportation ascribe a higher utility to electric vehicles, especially to pure battery electric vehicles.

As a possible explanation for the phenomena may rely on underlying environmental attitudes, it would be interesting to analyze how the correlation between both decisions would be affected, when the modeler controls for this environmental attitude (for instance, using latent variables or latent classes). Further research should be conducted in this direction.

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