Modeling with the unobserved/unobservable

An in-depth analysis of modeling issues concerning the role of attitudes and perceptions in the decision making process

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ZUSAMMENFASSUNG

Hybride Auswahlmodelle mit latenten Variablen zielen darauf ab, immaterielle Attribute der Individuen und der Alternativen, wie z.B. Einstellungen, Wahrnehmungen usw. zu erfassen und dadurch die Vorhersagefähigkeit und den Realismus von diskreten Auswahlmodellen zu erhöhen. Obwohl deren Grundlagen bekannt und etabliert sind, wurden einige technische und theoretische Aspekte noch nicht umfassend untersucht; dies hat zu Kontroversen in der Literatur geführt. Diese Dissertation zielt darauf ab, einige dieser noch unklaren Aspekte zu identifizieren und ausführlich zu analysieren. Dadurch sollten klare Erkenntnisse bezüglich der Modellierung mit latenten Variablen gewonnen und neue methodologische Werkzeuge für angewandte Forscher bereitgestellt werden.

Zunächst wird die Eignung der sequentiellen Schätzung von hybriden Auswahlmodellen diskutiert und es werden Bedingungen zur ihrer Nutzung als second-best-Ansatz abgeleitet. Dazu werden die Unterschiede in der Wirkung zwischen der Darstellung von Einstellungen und Wahrnehmungen durch latente Variablen analysiert. Es kann festgestellt werden, dass die Ersten Ähnlichkeiten mit sozioökonomischen Eigenschaften aufweisen, während die Zweiten den Attributen der Alternativen ähneln. Daher ist es empfehlenswert, systematische Geschmacksvariationen sowie Kategorisierungen zu betrachten. In diesem Sinne wird die Kategorisierung der latenten Variablen untersucht und ein neuer Ansatz zu ihrer Einbeziehung in das Modell vorgeschlagen. Aufgrund theoretischer als auch statistischer Vorteile ist dieser Ansatz den bislang existierenden Alternativen überlegen. Die Hypothese der Stetigkeit von Wahrnehmungs- und Einstellungsindikatoren sowie deren Auswirkungen wird analysiert. Es wird festgestellt, dass bei fehlender Berücksichtigung ihrer diskreten Art verzerrte Ergebnisse auftreten, insbesondere wenn die latenten Variablen eine hohe Variabilität aufweisen. Ferner werden neue methodologische Ansätze vorgeschlagen, um fehlende Einkommensangaben der Befragten zu betrachten bzw. um die Korrelation zwischen Präferenzen des gleichen Individuums in unabhängigen Wahlsituationen anzugehen.

Stichworte: hybride diskrete Auswahlmodelle, latente Variablen, Einstellungen, Wahrnehmungen, Schätzmethoden, Stetigkeit von Indikatoren, latente Klassen, Kategorisierung, Elektrofahrzeuge, fehlende Information, Korrelation, Paneldaten.

ABSTRACT

Hybrid choice models with latent variables aim to capture unobserved attributes of the individuals and the alternatives, such as attitudes, perceptions, etc., increasing the predictive capability and realism of discrete choice models. Even though, their fundaments are fairly well-established, some technical and theoretical issues have not been extensively analyzed, leading to controversies in the literature. This doctoral dissertation aims to identify and analyze some of these methodological issues, offering an in-depth discussion and clear insights on the way these issues should be treated, providing new methodological tools to help applied researchers to successfully develop their own models.

First, the suitability of the sequential estimation of hybrid choice models is discussed, deriving conditions under which sequential estimation is a suitable second-best. The differences between latent constructs representing attitudes and perceptions are established with respect to how the former resemble socio-economic variables, while the latter depict attributes of the alternatives. Hence, considering systematic taste variations as well as categorizations may be advisable, when addressing perceptions and other similar constructs. Along these lines, a new approach to categorize latent variables that exhibits theoretical advantages as well as a better treatment of the error term than existing alternatives is proposed. The hypothesis of continuity of perceptual and attitudinal indicators as well as their implications is also analyzed, establishing that neglecting their nature leads to biased results and that the magnitude of this bias depends on the variability induced into the discrete choice component.

Further, new methodological approaches are proposed to address missing income information and the correlation among the preferences of a given individual in independent choice situations. Both methods are tested in the context of preferences for electromobility.

Keywords: hybrid discrete choice models, latent variables, attitudes, perceptions, estimation, continuity of indicators, latent classes, categorization, electric vehicles, missing information, correlation, panel structure.

RECHTLICHE ERKLÄRUNG

Hiermit versichere ich, dass ich die vorliegende Dissertation selbstständig und ohne unzulässige Hilfsmittel verfasst habe. Die verwendeten Quellen sind vollständig im Literaturverzeichnis angegeben. Die Arbeit wurde noch keiner Prüfungsbehörde in gleicher oder ähnlicher Form vorgelegt.

Francisco J. Bahamonde Birke

Berlin, 9. März 2016

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 About objectivity, subjectivity and decision making

While most children dream of becoming a pilot, an astronaut or a fireman, I always dreamed of becoming a structural engineer. I had pretty clear notions of where I wanted to study and what I wanted to do after graduation. The years went by and I entered the university I always wanted in order to pursue my dream. Everything was going according to plan until my last semester when I had a change of heart. With that my journey in structural engineering came to an end and the one in transportation and behavioral economics began. What had changed? Why did I change my mind? I was still the same person according to all measurable attributes and the environment around me had not changed, but I had walked away from my childhood dream, taking with me a different mindset.

The mechanisms behind decision-making have been largely discussed in the past. In fact, decision theory is an essential area of study in many fields, including psychology, economics, statistics, transportation, and marketing, to name a few. Even though, depending on the field, the complexity of the analysis, and the objectives of the analyst, the problem can be approached from multiple angles and a making variety of assumptions, there is a broad consensus that subjective, unmeasurable elements of decisions play as an important role as do objective measurable attributes in decision making. This way, it may be expected that individuals with different attitudes toward the environment or divergent political views might exhibit different preferences and valuations when facing a choice situation. Along this line, it is expected that the population will also favor an alternative perceived as more comfortable or reliable. Consequently, establishing how decisions are influenced by the intangible attributes of not just choice-makers but also the choice situation, including attitudes, perceptions, values, and mindsets, is critical for the further development of choice theory.

The usual approach in economics with respect to decision-making in economics is to assume that choice-makers aim to maximize their perceived utility. This approach was firstly introduced by Pascal in the 17th century and since then has been continuously extended, refined and revised by many individuals: Bernoulli, Ramsey, Thurstone, von

Neumann, Morgenstern, Lehmann, McFadden, Kahneman and Tverski, among many others. Nevertheless, most specifications only allow for objective measurable characteristics of the individuals (e.g. socio-economic variables) and the alternatives (e.g. price) to be considered, while subjective attributes are assumed to be part of the modeling error (accounting for everything that is ignored by the analyst) or are indirectly captured as part of alternative specific constants. This way, including subjective attributes in models (into the utility) has remained unresolved.

Early approaches to address this problem relied on the use of psychometric data and perceptual mappings. They were included directly into the model in order to improve predictability (Green and Wind; 1973; Recker and Golob; 1976). Further, Hauser and Koppelman (1979) introduced the use of latent factors to correlate stated perceptual rankings. These approaches are, however, criticized for their lack of predictive validity (as psychometric information is not available for non-surveyed individuals). Moreover, the suitability of this approach has been further criticized because indicators tend to be an expression of subjective appreciations rather than causes of behavioral changes (Ben-Akiva *et al.*, 2002). Furthermore, psychometric data and perceptual mappings are highly dependent on the phrasing of survey questions (Tversky and Kahneman, 1981).

Keane (1997) proposed the inclusion of latent attributes in the utility function. According to this approach, these attributes are inferred from individual choices and, hence, the method does not use information beyond the observed choices and the classic objective measurable attributes. But, in this case, it is necessary to assume that the latent variables are specific to the alternatives, while constant over individuals.

Another approach is to use latent classes (Kamakura and Russell, 1989; Bhat, 1997) to identify groups of people exhibiting a distinctive behavior. The main criticism in this case refers to the latent classes not offering a clear picture of the reasons why these classes would behave in a particular way.

By 2015 hybrid discrete choice models dominate the literature in addressing intangible elements (Ashok *et al.*, 2002; Ben-Akiva *et al.*, 2002; Bolduc and Daziano, 2010; v. Acker *et al.* 2013; among many others). Although initially proposed in the 1980s (McFadden, 1986; Train *et al.*, 1987), it was not possible at that time to overcome a series of technical obstacles related to their estimation. With computational progress, however, this approach became a standard tool in discrete choice modeling.

This approach assumes that the underlying unobservable characteristics of the individuals and attributes of the alternatives (represented trough latent variables) affect the expected utility that a given individual ascribes to a certain alternative. Along these lines, it is also assumed that these underlying latent variables also affect the way in which individuals behave, when stating their level of agreement with a set of sentences related or unrelated to the choice situation (psychometric indicators). Finally the approach assumes that the latent variables (accounting for unobserved intangible elements) can be expressed as a function of positively observed characteristics of the individuals and attributes of the alternatives. This way, the model aims to establish a correlation between observed and unobserved variables, in order to quantify their impact in the decision making process. In this framework, the psychometric indicators are no longer used directly into the modeling but are considered a tool to improve the identification of the latent variables.

1.2 Motivation

Even though the fundamentals for the estimation of hybrid discrete choice models are well-established (Walker, 2001; Ben-Akiva *et al.*, 2002) and have been widely known for nearly 15 years, and that many significant technical issues have been resolved over time – such as joint modeling with revealed and stated preferences (Ben-Akiva *et al.*, 2002), identification (Walker *et al.*, 2007; Vij and Walker, 2014), mutually influenced latent constructs (Kamargianni *et al.*, 2014) - other technical issues remained. This way, and despite the proliferation of papers relying on hybrid discrete choice models, an adequate way to consider latent variables, as well as their implications for policy making, has not been well-established (Chorus and Kroesen, 2014). Similarly, many studies rely on sequential estimation (a biased second-best estimation technique), but no attempts have been made to quantify this bias or to establish if the technique is a suitable alternative (Raveau *et al.*, 2010). This is also true for other methodological issues, such as the hypothesis about the continuity of psychometric data, the discrete-continuous use of latent variables and their relation with the latent classes approach, the joint consideration of several independent decisions, the use of latent variables to account for correlation among the answers provided by the same individuals (panel or pseudo-panel data), etc.

Even though identifying and offering alternatives for all of these issues falls largely outside the scope of this doctoral dissertation, some of the most relevant unresolved issues surrounding the estimation of hybrid choice models are identified and analyzed in depth. This way, this work aims to offer clear insights on the way these issues should be treated when modeling with latent variables and to provide methodological tools to help applied researchers to successfully develop their own models.

1.3 Theoretical framework

1.3.1 Random utility theory and the Multinomial Logit model (MNL)

Discrete choice models aims to depict the behavior of a given population facing a discrete choice as accurately as possible. Unlike traditional econometric models, focusing on continuous responses, discrete choice models consider a limited discrete number of possible outcomes, which are defined *a priori* by the analyst. This way, instead of relying on classical optimization algorithms, these models work on the basis of the comparison between available alternatives.

In random utility theory (Thurstone, 1927; McFadden, 1974), it is assumed that individuals q belonging to a population Q behave rationally maximizing their expected utility (subject to any kind restrictions). This way, a given individual q will opt for alternative i among a choice set $A(q)$, if and only if $U_{iq} \geq U_{jq} \;\; \forall \;\; j \in A(q)$.

As it is unrealistic to assume that the modeler is aware of all details affecting the decision making process (or that choice-makers have complete and perfect information), the expected utility is posed as the sum of a representative utility V_{iq} (accounting for all attributes considered by the modeler) and a stochastic term ε_{iq}. This error term stands for all elements relevant to decision that are ignored in the representative utility. Thus, the expected utility can be expressed in the following manner:

$$U_{iq} = V_{iq} + \varepsilon_{iq} \qquad [1.1]$$

This way, a given individual will opt for a certain alternative if and only if:

$$V_{iq} + \varepsilon_{iq} > V_{jq} + \varepsilon_{jq} \qquad \forall j \in A(q) \qquad [1.2]$$

Then, grouping all deterministic components together:

$$V_{iq} - V_{jq} > \varepsilon_{jq} - \varepsilon_{iq} \qquad [1.3]$$

Hence, it is not possible for the modeler to establish which alternative would be selected in a given situation, but only to establish a probability P_{iq}, with which an individual q will opt for an alternative i in his/her choice set. This probability may be expressed as follows:

$$P_{iq} = \Pr\left\{V_{iq} - V_{jq} \geq \varepsilon_{jq} - \varepsilon_{iq},\ \forall\, j \in A(q)\right\} \qquad [1.4]$$

Thus, different assumptions regarding the nature of the error terms will lead to different specifications for this probability and to different kinds of discrete choice models (Train, 2009; Ortúzar and Willumsen, 2011).

Assuming independent and identically distributed (IID) Extreme Value Type 1 (EV1), error terms, leads to the well-known Multinomial Logit (MNL) model (Domencich and McFadden, 1975). Here, the difference ε_{jq} - ε_{iq} follows a Logistic distribution with mean zero and standard deviation σ. Under these assumptions, the probability of choosing alternative i is given by:

$$P_{iq} = \frac{e^{\lambda \cdot V_{iq}}}{\sum_{j} e^{\lambda \cdot V_{jq}}} \qquad [1.5],$$

where λ refers to the scale parameter of the Logistic distribution (and by extension of the Logit model) and relates to the unknown standard deviation σ through the following equation:

$$\lambda = \frac{\pi}{\sigma\sqrt{6}} \qquad [1.6]$$

However, as discrete choice models are based on utility differences, rather than on continuous values, neither the standard deviation nor the scale factor can be identified. Therefore, it is customary to normalize the scale parameter to one, without loss of generalization (Walker, 2002).

Regarding the representative utility, in most cases additive linearity is assumed. This way, the representative utility V_{iq} can be expressed as:

$$V_{iq} = \sum_k \theta_{ki} \cdot X_{kiq} \qquad [1.7],$$

where X represents a given attribute k for the individual q and the alternative i. This specification can be understood as a first-order Taylor expansion of any multi-variable complex function (and therefore it is always valid in the neighborhood of the estimation point); further, if the attributes are also assumed to be linear, the estimated parameters θ_{ik} can be directly interpreted as marginal utilities.

The main advantage of this framework relies on its simplicity allowing, which facilitates the estimation of models, even with limited computational capability. Additionally one of the main properties of the MNLs is the independence of irrelevant alternatives, which implies that the ratio between the probabilities of choosing alternatives i and k does not depend on other alternatives available in the choice set. In fact:

$$\frac{P_{iq}}{P_{kq}} = \frac{e^{\lambda \cdot V_{iq}}}{\sum_{j \in A(q)} e^{\lambda \cdot V_{jq}}} \Bigg/ \frac{e^{\lambda \cdot V_{kq}}}{\sum_{j \in A(q)} e^{\lambda \cdot V_{jq}}} = \frac{e^{\lambda \cdot V_{iq}}}{e^{\lambda \cdot V_{kq}}} \qquad [1.8]$$

This characteristic arises from the assumptions regarding the distribution of the error terms (independent and identically distributed) and is also one of the main limitations of the model, as it does not allow considering correlated alternatives (i.e. correlation among the error terms). Additionally, the model does not allow for heteroscedastic error terms and, as all estimated parameters are considered to be fixed, the model does not allow for stochastic taste variations (Ortúzar and Willumsen, 2011).

Several alternatives have been proposed to overcome these limitations, such as the Nested Logit model (NL, Williams, 1977; Daly and Zachary, 1978) or the Cross-Nested Logit model (CNL, Ben-Akiva and Bierlaire, 1999). More generally, all this structures (including the MNL) can be expressed using the Generalized Extreme-Value framework (GEV, McFadden, 1978). This structure allows for multivariate distribution of the error terms, while retaining a closed-form expression for the choice probabilities.

GEV models as well as Probit models (assuming normally distributed error terms) are not further discussed in the work, as hybrid choice models based on mixing distributions are preferred, but the reader is referred to Walker and Ben-Akiva (2011) for a good discussion.

1.3.2 The Mixed Logit model (ML)

Mixed logit models (Cardell and Dunbar, 1980; Ben-Akiva and Bolduc, 1996) assume that the stochastic component of the model is given by the sum of the previously described, independently identically, EV1 distributed error term (ε_{iq}) and another stochastic element υ_{iq} (mixing distribution) that can follow any distribution. This way, it is not only possible to account for heteroscedasticity and correlation between alternatives (as the additional stochastic elements are not subject to homoscedasticity and no-autocorrelation restrictions), but to consider any desirable functional form. This way, the utility function would be given by:

$$U_{iq} = \sum_k \theta_{ki} \cdot X_{kiq} + \upsilon_{iq} + \varepsilon_{iq} \qquad [1.9]$$

In this case, and opposite to the MNL, the probability of choosing a given alternative cannot be longer depicted through a closed-form expression and it is necessary to integrate the choice probabilities over the probability density function of the mixing distribution. Hence, the probability of selecting a given alternative will take the following form (Train, 2009):

$$P_{i,q} = \int P^*_{iq}(X_{kiq}, \upsilon_{iq}; \theta_{ki}) \cdot f(\upsilon_{iq}) \cdot d\upsilon_{iq} \qquad [1.10],$$

where the first component P^*_{iq} stands for the usual MNL probability (as in [1.5]) and $f(\upsilon_{iq})$ is the probability density function of the error component's term. As this integral cannot normally be analytically resolved, it is necessary to rely on numerical techniques, as numerical integration or the simulated maximum likelihood (McFadden, 1986).

Depending on the assumptions regarding the error terms, the ML framework allows addressing correlation among alternatives, correlation among individuals as well as stochastic taste variations.

1.3.3 Hybrid discrete choice models with latent variables

As previously mentioned, this approach aims to integrate subjective non-measurable valuations in a discrete choice network. Hereby, immaterial constructs, η_{liq}, known as latent variables, are incorporated as part of the utility functions into discrete choice models. These latent variables are supposed to represent subjective elements affecting the decision, such as attitudes, perceptions, values, etc. and are constructed according to a Multiple Indicators Multiple Causes model (MIMiC; Zellner, 1970; Bollen, 1989).

A MIMiC model is basically a structural equations model where the outcomes represent psychometric indicators (normally attitudinal or perceptual indicators) that are previously collected by the modeler (normally evaluating the level of agreement of the respondent with a carefully designed set of statements). These indicators, I_{ziq}, are supposed to be a measured expression of underlying intangible attributes (e.g. attitudes or perceptions) and are explained by the latent variables through so called measurement equations [1.12]. As the latent variables cannot be directly observed, they are constructed as a function of measurable variables, through structural equations [1.11]. If we assume a linear additive specification for both sets of equations, this framework can be represented in the following manner:

$$\eta_{liq} = \sum_r \alpha_{lri} \cdot s_{riq} + \upsilon_{liq} \qquad [1.11]$$

$$I_{ziq} = \sum_l \gamma_{zli} \cdot \eta_{liq} + \varsigma_{ziq} \qquad [1.12],$$

where r, l, and z refer to exogenous variables, latent variables, and indicators, respectively. α_{lri} and γ_{zli} are parameters to be estimated, while υ_{liq} and ς_{ziq} are error terms. While the former error terms are usually assumed to be normally distributed with mean zero and a given covariance matrix (even though, as shown later, that under certain circumstances it may be advisable to assume a Logistic distribution for them), the distribution of the former depends on the assumptions and on the way the indicators are collected. Although indicators are traditionally assumed to be linear continuous expressions of the latent variables (Vredin-Johansson *et al.*, 2006; Yañez *et al.*, 2010; Daziano and Barla, 2012), this assumption neglects the way in which indicators are usually collected. As the indicators are normally gathered using Likert scales (Likert, 1932), it may be advisable to consider them in an ordinal framework, such as the Ordered Probit or the Ordered Logit model (Greene, 2012; see chapter 4 for a further discussion).

In order to include latent variables into discrete choice models, the utility function depicted in equation [1.7] must be redefined. Again, assuming a linear additive specification, the utility function for alternative i can be written as:

$$U_{iq} = \sum_k \theta_{ki} \cdot X_{kiq} + \sum_l \beta_{li} \cdot \eta_{liq} + \varepsilon_{iq} \qquad [1.13],$$

where β_{li} are parameters to be estimated. It is important to note that including the latent variables does not affect the structure of the error ε_{iq}, but it does indeed affect the overall error structure of the model, as the latent variables consider their own error terms. In fact, replacing [1.11] into [1.13]:

$$U_{iq} = \sum_k \theta_{ki} \cdot X_{kiq} + \sum_l \beta_{li} \cdot \sum_r \alpha_{lri} \cdot s_{riq} + \sum_l \beta_{li} \cdot \upsilon_{liq} + \varepsilon_{iq} \qquad [1.14]$$

As observed from equation [1.15], the addition of this error term (associated with the latent variables) resembles the structure of the ML. Thus, the inclusion of the latent variables is similar to the inclusion of the error component in equation [1.9] (in terms of the error structure; see chapter 2 for a further discussion), meaning that the choice probabilities are no longer given by a closed-form expression. Indeed, the choice probabilities will be given by:

$$P_{i,q} = \int P^*_{iq}(X_{kiq}, \eta_{liq}; \theta_{ki}, \beta_{li}) \cdot f(\eta_{liq}; \alpha_{lri}) \cdot d\eta_{liq} \qquad [1.15],$$

where P^*_{iq} again stands for the MNL probabilities, as described in [1.5], and $f(\eta_{liq},\alpha_{lri})$ is the probability density function of the latent variables. Nevertheless, in this case the modeler is not only interested in the choice probabilities, but also in depicting the stated indicators as accurately as possible. Thus, it is convenient to consider an integrated likelihood function, such as:

$$L = \prod_{q \in Q} \prod_{j \in A(q)} \prod_{z} \int P^{*}_{jq}(X_{kjq}, \eta_{ljq}; \theta_{kj}, \beta_{lj})^{y_{iq}} \cdot P_{zlq}(I_{zjq} \mid \eta_{ljq}; \gamma_{zlj}) \cdot f(\eta_{ljq}; \alpha_{lrj}) \cdot d\eta_{ljq} \quad [1.16],$$

where the first component stands for the probability of observing a given choice j, while the second component accounts for the probability of observing a given indicator. The variable y_{jq} takes the value one if the alternative j is selected by individual q and zero otherwise.

Figure 1.1 offers a graphical representation of a hybrid discrete choice framework.

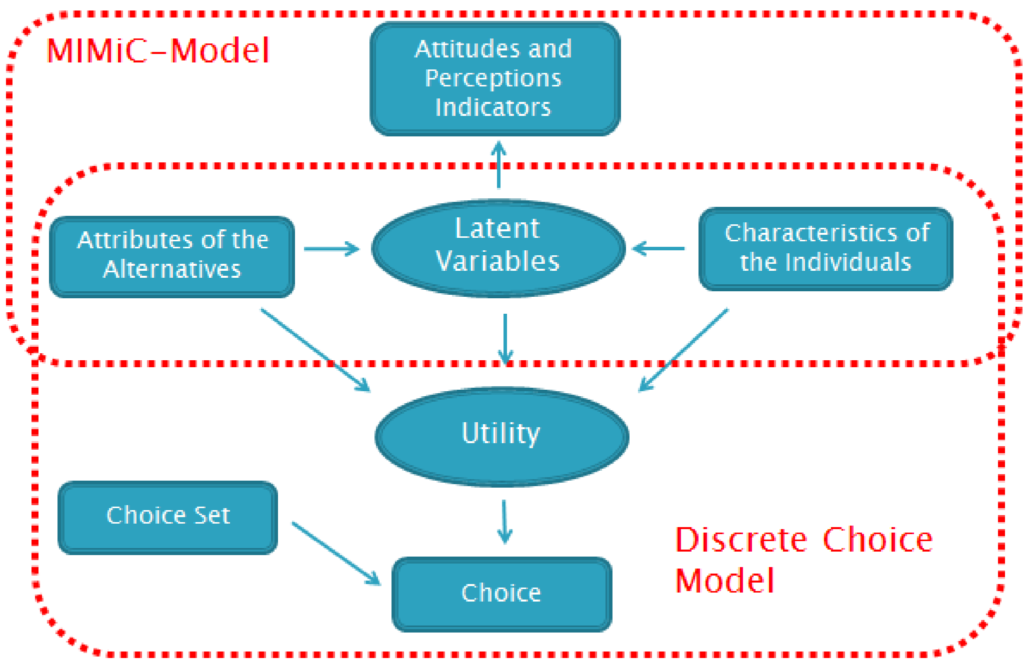

Figure 1.1 – Hybrid discrete choice model with latent variables.

1.3.4 Estimation

Basically the estimation of hybrid discrete choice models can be performed in three different fashions:

1. Sequential estimation.

2. Sequential estimation with integration over the domain of the latent variables.

3. Simultaneous estimation.

The first approach consists of evaluating first the MIMiC model, as an independent problem. Then, the expected values for the latent variables are calculated and incorporated directly into the DC model as fitted deterministic elements. Even though this approach leads to biased results (Ben-Akiva *et al.*, 2002), it was the dominant approach in the early days due to its computational simplicity (Vredin-Johansson *et al.*, 2006; Yañez *et al.*, 2010; v. Acker *et al.*, 2010). Even in 2015, the approach is still used as a second-best alternative, when the number of observations and latent variables lead to prohibitive estimation times if other alternatives are followed.

The second approach is similar to the previous one, but it considers the distribution of the latent variables when computing the choice probabilities. This approach leads to consistent but inefficient estimates, as it does not take into account all the available information (Ben-Akiva *et al.*, 2002). Although Ben-Akiva *et al.* (2002) argue that as in this case it is still necessary to integrate the likelihood function, it could be preferable to estimate the model simultaneously, empirical evidence shows that this approach reduces substantially the estimation time (see chapter 3).

Finally, the simultaneous estimation method leads to unbiased, consistent and efficient estimators, but it is associated with larger computational requirements. Nevertheless, it is the dominant approach (Daly *et al.*, 2012; Hess *et al.*, 2013, among many others), especially when dealing with only a few latent variables.

For both sequential estimation methods, the MIMiC model is estimated independently. In this case, the estimation may be performed via the two-stage least squares regression (Pagan, 1986) or maximizing the likelihood (Goldberger, 1972). Bollen *et al.* (2007) show that both approaches lead to unbiased and efficient estimates, when assuming normally distributed error terms. For the purposes of this work, the maximum likelihood estimation is preferred (when relying on the sequential estimation), because of flexibility (it does not require assuming normally distributed error terms) and consistency issues (due to their error structure, discrete choice models are usually estimated maximizing the likelihood).

For estimating the discrete choice component (or the complete model in the case of the simultaneous estimation), the modeler relies on equation [1.16], whereas the β_{li} are considered as fixed parameters for both sequential methods and the integral is ignored (and replaced by the expected values of the latent variables) when estimating the model without integration.

As previously mentioned, the integral can be computed numerically or via simulation techniques. Numerical integration is the preferred approach when dealing with one or maximum two latent variables, but other alternatives should be favored when addressing more integrals. For the purposes of this work, the simulated maximum likelihood method (SML, McFadden, 1986) is used when considering several latent variables.

The SML approach consists of generating a fixed number (S) of stochastic or pseudo-stochastic draws υ^{*}_{ljq} representing a given distribution. Equation [1.16] is then computed in the following manner:

$$L = \prod_{q \in Q} \prod_{j \in A(q)} \prod_{z} \frac{1}{S} \sum_{s=1}^{S} P^{*}_{jq}(X_{kjq}, \eta_{ljq}; \theta_{kj}, \beta_{lj})^{y_{iq}} \cdot P_{zlq}(I_{zjq} \mid \eta_{ljq}; \gamma_{zlj}) \cdot f(\eta_{ljq}; \alpha_{lrj}, \nu^{*}_{ljq}) \quad [1.17],$$

υ^{*}_{ljq} can be randomly drawn or using low discrepancy sequences, such as the Halton (Halton, 1964) or Sobol (Sobol, 1967) sequences as well as the Modified Latin Hypercube Sampling (MLHS, Hess *et al.*, 2006).

1.3.5 Identification

In general, discrete choice models require fixing at least one parameter associated with the distributions of the error terms in order to allow for identification (normally the scale factor λ). Identification of MIMiC models is a more complicated task as, in this case, the number of, and which, parameters to be fixed will depend on the structure of the model. Stapleton (1978), however, shows that it suffices fixing the variances of the error terms of the structural equations. This approach does not lead to over constrained models.

For further considerations regarding identifiability of discrete choice and hybrid discrete choice models, the reader is referred to Walker *et al.* (2007) and Vij and Walker (2014), respectively.

1.4 Overview of this dissertation

This dissertation is basically based on six original research articles, all focusing on the modeling with hybrid discrete choice models and latent variables accounting for subjective elements, such as attitudes or perceptions. The work conducted during the doctoral studies has led, however, to eleven articles, some of which are not included in this dissertation. Table 1.1 presents an overview of all contributions:

Table 1.1 – Overview of the contributions.

Contribution	***Published / Presented***	***Role / Co-authors***
Verkehrssicherheit und Zahlungsbereitschaft – ein Überblick zum Stand der Forschung.	*Zeitschrift für Verkehrswissenschaft* **84(3)**, 260-287.	Lead authorship, including data collection, analysis and writing the paper. Heike Link and Uwe Kunert.
On the variability of hybrid discrete choice models.	*Transportmetrica A: Transport Science* **10(1)**, 74-88.	Lead authorship, including original idea, generation of the dataset, modeling, analysis and writing the paper.[1] Juan de Dios Ortúzar.
Is Sequential Estimation a Suitable Second Best for Estimation of Hybrid Choice Models?	*Transportation Research Record: Journal of the Transportation Research Board* **2429**, 51-58. Presented *at 93rd Annual Meeting of the Transportation Research Board*, Washington, D.C., USA, 12-16, January, 2014.	Lead authorship, including original idea, generation of the dataset, modeling, analysis and writing the paper. Juan de Dios Ortúzar.
Bewertung der Angebotsmerkmale des Personenfernverkehrs vor dem Hintergrund der Liberalisierung des Fernbusmarktes.	*Zeitschrift für Verkehrswissenschaft* **85(2)**, 107-123. Presented at *Konferenz Verkehrsökonomie und Verkehrspolitik*, Berlin, Germany, 26-27, June, 2014, as Einstellungen, Wahrnehmungen und die Liberalisierung des Fernbusverkehrs in Deutschland.	Lead authorship, including original idea, survey design, data collection, modeling and analysis. Heike Link, Uwe Kunert and Juan de Dios Ortúzar.

[1] The paper was initially submitted prior to starting the doctoral studies.

Contribution	***Published / Presented***	***Role / Co-authors***
Liberalization of the Interurban Coach Market in Germany: Do Attitudes and Perceptions Drive the Choice between Rail and Coach?	Discussion Paper **1415**, DIW-Berlin. Presented at *Kuhmo-Nectar Conference of the International Transportation Economics Association*, Toulouse, France, 4-6, June, 2014, as Liberalization of the interurban coach market in Germany – An attitudinal problem?	Lead authorship, including original idea, survey design, data collection, modeling, analysis and writing the paper. Heike Link, Uwe Kunert and Juan de Dios Ortúzar.
The value of a statistical life in a road safety context – a review of the current literature.	*Transport Reviews* **35(4)**, 488-511.	Lead authorship, including data collection, analysis and writing the paper. Heike Link and Uwe Kunert.
About attitudes and perceptions – finding the proper way to consider latent variables in discrete choice models.	*Transportation* (forthcoming, DOI 10.1007/s11116-015-9663-5). Presented at *3rd hEART Symposium of the European Association for Research in Transportation*, Leeds, UK, 10-12, September, 2014. Preliminary version as Discussion Paper **1474**, DIW-Berlin.	Lead authorship, including original idea, survey design, data collection, modeling, analysis and writing the paper. Heike Link, Uwe Kunert and Juan de Dios Ortúzar.
The potential of electromobility in Austria: Evidence from hybrid choice models under the presence of unreported information.	*Transportation Research Part A: Policy and Practice* **83**, 30-41. Presented at *Kuhmo-Nectar Conference of the International Transportation Economics Association*, Oslo, Norway, 17-19, June, 2015, as The potential of electromobility in Austria. An analysis based on hybrid choice models. Preliminary version as Discussion Paper **1472**, DIW-Berlin.	Lead authorship, including original idea, modeling, analysis and writing the paper. Tibor Hanappi.
Analyzing the continuity of attitudinal and perceptual indicators in hybrid choice models.	Presented at *14th International Conference on Travel Behaviour Research (IATBR)*, Windsor, U.K., 19-23 July, 2015. Currently under review by the Conference Committee for publication in a special issue.	Lead authorship, including original idea, survey design, data collection (of one case study), modeling, analysis and writing the paper. Juan de Dios Ortúzar.
About the categorization of latent variables in hybrid choice models.	Presented at *4th hEART Symposium of the European Association for Research in Transportation*, København, Denmark, 9-11, September, 2015. Currently under review at an international journal.	Lead authorship, including original idea, survey design, data collection (of one case study), modeling, analysis and writing the paper. Juan de Dios Ortúzar.

Contribution	***Published / Presented***	***Role / Co-authors***
Does transport behavior influence preferences for electromobility? An analysis based on person- and alternative-specific error components.	Accepted for presentation at *14th World Conference on Transport Research*, Shanghai, PR China, 10-15, July, 2016. Currently under review at an international journal.	Single author

As previously mentioned and due to thematic cohesion, this dissertation presents only a part of these contributions organized in six different chapters.

1.4.1 Chapter 2: About the sequential estimation as second best[2]

As previously mentioned, the simultaneous estimation method has overtaken the sequential approach as preferred estimation method for hybrid discrete choice models. Notwithstanding, the computational cost of the simultaneous estimation can still be prohibitive when models get more involved and in such cases sequential estimation can still be a potent option. In previous work, Bahamonde-Birke and Ortúzar (2014a) conduct a theoretical analysis that led them to identify a major bias affecting the sequential estimation method and proposed a correction term for the bias induced on the estimated parameters by the variability associated with the latent variables; however, they did not attempt to quantify this induced variability. In this chapter, it is attempted to determine the nature of the variability induced through the latent variables as well as the viability of relying on the sequential estimation method as an alternative (second-best) estimation tool, for cases when the complexity of the specification makes unfeasible to rely on simultaneous estimation.

The results show that the sequential method behaves in an acceptable way (the bias can be avoided through the correction), when the variability associated with the latent variables is low in comparison with the error term of the discrete choice model. On the contrary, when this variability is considerable, the bias correction becomes an intricate matter and appropriate results cannot be guaranteed.

[2] This chapter is based on the article: Bahamonde-Birke, F.J. and Ortúzar, J. de D. (2014). Is Sequential Estimation a Suitable Second Best for Estimation of Hybrid Choice Models? *Transportation Research Record: Journal of the Transportation Research Board* **2429** , 51-58.

1.4.2 Chapter 3: About attitudes and perceptions[3]

This chapter provides an in-depth theoretical discussion about the differences between individual-specific latent constructs (representing attitudes, for example, but also other characteristics such as values or personality traits) and alternative-specific latent constructs (that may represent perceptions) affecting the choice-making process of individuals; it also presents an empirical exercise to analyze their effects. This discussion is important because the majority of papers considering attitudinal latent variables take these as attributes affecting directly the utility of a certain alternative, while systematic taste variations are rarely considered and perceptions are mostly ignored.

The results of a case study show that perceptions may indeed affect the decision making process and that they are able to capture a significant part of the variability that is normally explained by alternative specific constants. Furthermore, the results indicate that attitudes may be a reason for systematic taste variations, and that a proper categorization of latent variables, in accordance with underlying theory, may outperform the customary assumption of linearity.

1.4.3 Chapter 4: About the continuity of attitudinal and perceptual indicators[4]

This chapter addresses the continuity of attitudinal and perceptual indicators in hybrid discrete choice models by comparing the consequences of treating the indicators as continuous or ordinal outcomes, given different assumptions about the way in which these are stated. Based on tradition and for computational reasons, such indicators are predominantly treated as continuous outcomes. This usually neglects their nature (as respondents are normally asked to state their preferences, or level of agreement with a set of statements, using a discrete scale) and may induce important bias.

[3] This chapter is based on the article: Bahamonde-Birke, F.J., Kunert, U., Link, H. and Ortúzar, J. de D. (2016). About attitudes and perceptions – finding the proper way to consider latent variables in discrete choice models. *Transportation* (forthcoming, DOI 10.1007/s11116-015-9663-5).

[4] This chapter is based on the article: Bahamonde-Birke, F.J. and Ortúzar, J. de D. (2015). Analyzing the continuity of attitudinal and perceptual indicators in hybrid choice models. *14th International Conference on Travel Behaviour Research (IATBR)*, Windsor, U.K., 19-23 July, 2015.

An analysis based on simulated data and real data (two case studies) is conducted, finding that the distribution of the indicators (especially when associated with non-uniformly spaced thresholds) may lead to a clear deterioration of the model's predictive capacity, especially when assuming continuous indicators. Along the same line, higher relative variability among the latent variables increases the differences between both approaches (ordinal and continuous outcomes), especially concerning goodness-of-fit of the discrete-choice component. It was not possible to identify a relation between the predictive capacity of both approaches and the amount of available information.

Finally, both case studies using real data show an improvement in overall goodness-of-fit when considering the indicators as ordinal outcomes, but this does not translate in a better predictability of the discrete choices.

1.4.4 Chapter 5: About the categorization of latent variables[5]

Although hybrid choice models are fairly popular, the way in which different types of latent variables are considered into the utility function has not been extensively analyzed. Latent variables accounting for attitudes resemble socio-economic characteristics and, therefore, systematic taste variations and categorizations of the latent variables should be considered. Nevertheless, categorizing a latent variable is not an easy subject, as these variables are not observed and consequently exhibit an intrinsic variability. Under these circumstances, it is not possibly to assign an individual to a specific group, but only to establish a probability with which an individual should be categorized in given way.

This chapter explores different ways to categorize individuals based on latent characteristics, focusing on the categorization of latent variables. This approach exhibits as main advantage (over latent-classes, for instance) a clear interpretation of the function utilized in the categorization process, as well as taking exogenous information into account. Unfortunately, technical issues (associated with the estimation technique via simulation) arise when attempting a direct categorization.

[5] This chapter is based on the article: Bahamonde-Birke, F.J. and Ortúzar, J. de D. (2015). About the categorization of latent variables in hybrid choice models. *4th hEART Symposium of the European Association for Research in Transportation*, København, Denmark, 9-11, September, 2015.

An alternative to attempt a direct categorization of latent variables (based on an auxiliary variable) is proposed and a theoretical and empirical analysis (two case studies), contrasting this alternative with other approaches (latent variable-latent class approach and latent classes with perceptual indicators approach) conducted. Based on this analysis, it is concluded that the direct categorization is the superior approach, as it offers a consistent treatment of the error term, in accordance with underlying theories, and a better goodness-of-fit.

1.4.5 Chapter 6: About electromobility in Austria and modeling with missing information[6]

This chapter analyzes the impact of the introduction of electromobility in Austria, focusing specifically on the potential demand for electric vehicles in the automotive market. Discrete choice behavioral mixture models considering latent variables are estimated, in order to address the potential demand as well as analyzing the effect of different attributes of the alternatives on the potential market penetration. It is found 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. engine power is not relevant for purely electric vehicles). Along the same line, it is established that some policy incentives would have a positive effect on 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. This work suggests the existence of reliability thresholds concerning the availability of charging stations.

Finally this chapter enunciates and successfully tests an alternative approach to address unreported information regarding income in presence of endogeneity and multiple information sources. It is concluded that, for this case, the presence of endogeneity and correlation makes both classical imputation techniques unsuitable.

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[6] This chapter is based on the article: Bahamonde-Birke, F.J. and Hanappi, T. (2016). The potential of electromobility in Austria. An analysis based on hybrid choice models. *Transportation Research Part A: Policy and Practice* **83**, 30-41.

1.4.6 Chapter 7: About transport behavior, electromobility and person- and alternative-specific error components[7]

The interconnection among different choices by the same decision-maker is fairly well established in the literature. Along this line, this chapter aims to identify how preferences for electromobility are affected by mode choices for regular trips. To this aim, 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 experiments conducted in Austria during February 2013 (representative sample). 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.

Even though this chapter does not consider hybrid discrete choice models directly, it presents an alternative approach to deal with correlation between two independent experiments, outlining its differences with the latent variable approach.

1.5 Concluding remarks

Modeling discrete decisions is a key element in econometrics. It allows for deriving the trade-offs between different attributes, including willingness-to-pays for the improvement of certain features, as well as forecasting the behavior of given population exposed to an

[7] This chapter is based on the article: Bahamonde-Birke, F.J. (2016). Does Transport Behavior Influence Preferences for Electromobility? An Analysis Based on Person- and Alternative-Specific Error

environment differing from the current conditions. For this reason, it is important that these models be as realistic as possible. Nevertheless, subjective elements affecting the decision-making process have normally been ignored when considering choice models. This way, it would have been nearly impossible for a modeler to predict I would never practice as a structural engineer after graduation, starting instead a journey in transportation and behavioral economics. He would have failed to account that my unquiet personality would not have been comfortable in an environment, where design guidelines and construction and security standards dominate over theoretical analysis and creative approaches (although for good reasons).

Along these lines, hybrid discrete choice models with latent variables aim to capture these unobserved elements affecting decisions. This way, unobserved characteristics of the individuals, such as attitudes, values, mindsets, etc. as well as non-measurable attributes of the alternatives, such as perceptions are considered into the modeling, increasing substantially their realism and predictive capability.

This work address several topics related to the estimation of hybrid choice models as well as the use, inclusion and correct interpretation of latent constructs. Further, it proposes new modeling approaches as well offering in-depth analysis of these subjects. This way, it aims to provide new methodological tools, to ease understanding and interpretation of hybrid choice models.

First, the suitability of the sequential estimation as a second-best is discussed, being able to quantify its intrinsic bias as a function of the variability induced on the discrete choice component. In this way, it is possible to perform corrections when the induced variability is low. As a consequence, conditions under which sequential estimation is a suitable second-best are derived.

Further, the differences between person-specific (e.g. attitudes) and alternative- and person-specific (e.g. perceptions) latent constructs as well as their implications are addressed. Furthermore, the way of collecting indictors in order to construct both kinds of latent constructs is discussed. It is possible to establish that alternative- and person-

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specific latent variables resemble attributes of the alternatives while person-specific constructs are similar to socio-economic variables. Therefore, it may advisable to consider systematic taste variations as well as categorizations, when addressing the latter. A case study shows that individuals may be categorized in different groups in accordance with their environmental attitudes, and that more environmentally conscious individuals exhibit a lower subjective value of time.

Along these lines, the categorization of latent variables is explored and a new approach is proposed. The analysis shows that this new method outperforms existent alternatives offering a better treatment of the error term and clear interpretations of the categorized groups in accordance with the underlying theory.

This work also addresses the hypothesis of continuity of perceptual and attitudinal indicators, establishing that neglecting their nature leads indeed to biased results. This bias, however, depends on the variability induced into the discrete choice component through the latent constructs, which is found to be low in our study cases.

Further, the methodology is used to analyze a real case (the adoption of electromobility in Austria), proposing at the same time an innovative approach to deal with missing income information (relying on latent constructs). It is shown that classical approaches, such as imputation or dummy variables, lead to biased results, given the existence of endogeneity. Along these lines, it can be established that a favorable attitude toward the environment affects positively the willingness-to-pay for hybrid, plug-in and fully electric vehicles.

Finally, an analysis about the correlation among preferences of the same individuals in independent choice situations is discussed. Addressing such issues through the latent variable approach is discussed, but it is concluded that alternative approaches may offer a better representation. Hence, a method based on person- and alternative-specific error components is proposed a successfully tested, showing that transport behavior and preferences for electromobility are indeed correlated.

Further research should be oriented to the implementation of the technical contributions proposed in this work as well as analyzing the advantages of the proposed methods in empirical applications. Along these lines, it may be interesting to compare the performance of the person- and alternative-specific error components method and hybrid choice models, when accounting for correlation among different choice situations. From a theoretical perspective, further research is required regarding the interactions among person-specific and alternative- and person-specific latent constructs, as cognitive dissonance may affect the way in which the environment is perceived leading to correlation and complex error structures.

CHAPTER 2[8]

ABOUT THE SEQUENTIAL ESTIMATION AS SECOND BEST

[8] This chapter is based on the article: Bahamonde-Birke, F.J. and Ortúzar, J. de D. (2014). Is Sequential Estimation a Suitable Second Best for Estimation of Hybrid Choice Models? *Transportation Research Record: Journal of the Transportation Research Board* **2429** , 51-58.
Available at http://dx.doi.org/10.3141/2429-06.

2.1 Introduction

Discrete choice models are an essential element in contemporary travel demand modeling and forecasting. Their current state-of-practice considers objective characteristics of the alternatives and the individuals as explanatory variables, and yields as output the choice probabilities of the alternatives included in their choice sets (Ortúzar and Willumsen, 2011; Train, 2009). However, it is well-known that attitudes and perceptions play also a role in the decision making process. The usual approach to take these into account considers the estimation of a Multiple Indicators Multiple Causes (MIMiC) model (Zellner, 1970; Bollen, 1989). Here unobserved, latent, variables are explained by a set of characteristics from the users and the alternatives (through so called structural equations) while explaining, at the same time, a set of perceptual indicators obtained from the individuals (through so called measurement equations). The joint use of MIMiC models and discrete choice (DC) models leads to the state-of-the-art hybrid choice models (Ashok *et al.*, 2002; Ben-Akiva *et al.*, 2002; Bolduc and Daziano, 2010; Raveau *et al.*, 2012).

In the last years, the literature has provided abundant empirical and theoretical evidence about the advantages of this approach and the use of hybrid discrete choice (HDC) models has gained substantial popularity (Yañez *et al.*, 2010; Bahamonde-Birke *et al.*, 2010; Daziano and Bolduc, 2013), among others. In their early days, the most usual form to estimate HDC models was the sequential approach (Yañez *et al.*, 2010; Vredin-Johansson *et al.*, 2010; v. Acker *et al.*, 2013), as this method requires significantly less computational resources and guarantees consistent estimators when integrating over the latent variables (Ben-Akiva *et al.*, 2002) or, at least, just a negligible bias when used without integration (according to the empirical results of Raveau *et al.*, 2010). Nowadays, technical improvements and ever increasing computing power has allowed for extended use of the simultaneous approach, which guarantees consistent, unbiased and efficient estimators (Ben-Akiva *et al.*, 2002; Bolduc and Daziano, 2010). Nevertheless this method is considerably more demanding that the sequential approach and the computational cost can still be prohibitive, especially when working with more complex MIMiC models and a significant number of latent variables (as each latent variable adds a dimension over which the likelihood function must be integrated).

Bahamonde-Birke and Ortúzar (2014a) examined the increase in model variability associated with the direct inclusion of non-observed (estimated) variables, and their own error terms, into the utility function of DC models in a sequential estimation context. They discussed the problem theoretically concluding that although this variability induced bias on the estimated parameters, the bias could be determined and quantified as a function of the error associated with the utility function and the variability induced through the latent variables. However, they did not attempt to quantify this induced variability.

In this chapter we attempt to analyze the nature of the variability induced through the latent variables, which was treated as an unknown variable by Bahamonde-Birke and Ortúzar (2014a). The aim is to analyze both the possibility of correcting the aforementioned bias as well as the viability of relying on the sequential estimation method as an alternative (second-best) estimation tool for cases when the complexity of the model detracts from applying the simultaneous estimation approach.

The rest of the chapter is organized as follows. Section 2.2 summarizes the models and estimation techniques considered. Section 2.3 extends the theory behind the aforementioned bias while section 2.4 sets up an experimental analysis (based on simulated data) to test the findings derived in section 2.3. Section 2.5 discusses the results of the experiment, and section 2.6 reports our conclusions.

2.2 Theoretical background

In Random Utility Theory (Thurstone, 1927; McFadden, 1974), it is assumed that individuals q (belonging to a given market segment Q) are rational decision makers who choose an alternative i (in their set of available alternatives $A(q)$) that maximizes their perceived utility (U_{iq}). In turn, this utility can be described as the sum of a representative component (V_{iq}), considering all attributes that can be observed by a modeler, and an error term (ε_{iq}) describing unknown elements that affect utility but cannot be measured by the observer. In a discrete choice modeling framework, this leads to the following expression (Ortúzar and Willumsen, 2011):

$$U_{iq} = V_{iq} + \varepsilon_{iq} \tag{2.1}$$

Under the assumption that the error terms are independent and identically distributed following an Extreme Value Type 1 (EV1) distribution (with the same mean and variance σ^2), the differences between the utilities associated with the alternatives follow a Logistic distribution with mean zero and scale λ, leading to the well-known Multinomial Logit (MNL) model (Domencich and McFadden, 2015); in this case, the probability of choosing alternative i is given by:

$$P_{iq} = \frac{e^{\lambda \cdot V_{iq}}}{\sum_{j \in A(q)} e^{\lambda \cdot V_{jq}}} \tag{2.2}$$

and λ is inversely related to the standard deviation of the error terms:

$$\lambda = \frac{\pi}{\sigma \sqrt{6}} \tag{2.3}$$

However, this scale parameter cannot be estimated, since any parameters in the representative utility function are multiplied by it (i.e. assuming a linear function as usual), so it is customary to normalize it to one (Walker, 2002).

As mentioned above, the representative utility V_{iq} is a function of attributes that can be measured by the modeler. Usually, DC models just consider level-of-service attributes (X_{kiq}, where k represents the kth attribute) that can be directly observed by the analyst (i.e. travel times and fares) as well as socioeconomic characteristics of the individual. However, when dealing with a HDC model, latent variables (η_{liq}, where l represents the lth latent variable) are also included, but these are immaterial constructs that cannot be directly observed. Assuming a linear specification of the attributes in V_{iq}, so that the estimated parameters θ_{ik} and β_{li} (related to the tangible attributes and latent variables, respectively) can be interpreted as marginal utilities, the representative utility function can be expressed as [2.4].

$$V_{iq} = \sum_k \theta_{ki} \cdot X_{kiq} + \sum_l \beta_{li} \cdot \eta_{liq} \tag{2.4}$$

and the usual approach to identify the latent variables relies on a MIMiC model. This requires additional information about the attitudes and/or perceptions of the individuals (normally gathered in the form of *indicators*). The MIMiC model considers that a group of latent variables, representing attitudes or perceptions, are explained by a set of observable characteristics of the individuals and the alternatives (s_{iqr}), while explaining a set of perceptual indicators. In this manner, the MIMiC model consists of a set of *structural equations* such as [2.5], explaining the latent variables (η_{liq}), and a set of *measurement equations* such as [2.6], which consider the latent variables as inputs to explain the perception/attitudinal indicators (y_{ziq}).

$$\eta_{liq} = \sum_{r} \alpha_{lri} \cdot s_{riq} + \upsilon_{liq} \qquad [2.5]$$

$$y_{ziq} = \sum_{l} \gamma_{lzi} \cdot \eta_{liq} + \varsigma_{ziq} \qquad [2.6]$$

where the indices i, q, r ,l and z refer to alternatives, individuals, exogenous variables, latent variables and indicators, respectively. The error terms υ_{liq} and ς_{ziq} can follow any distribution, but they are typically considered to be Normal distributed with mean zero and a certain covariance matrix. Finally, α_{lri} and γ_{lzi} are parameters to be jointly estimated.

Two approaches have been reported in the literature for the estimation of HDC models. In the simultaneous estimation method (Morikawa *et al.*, 2002; Ashok *et al.*, 2002), both structures (the DC model and the MIMiC model) are considered jointly. As mentioned above, this methodology yields unbiased, consistent and efficient estimators (Ben-Akiva *et al.*, 2002), and for this reason this approach should be preferred. Unfortunately, the method is highly demanding in terms of computational resources and its cost can be prohibitive when dealing with a significant number of latent variables.

As a second best alternative, several researchers (Vredin-Johansson *et al.,* 2006; Yañez, *et al.*, 2010, van Acker *et al.*, 2011), have appealed to the *sequential estimation* method, which divides the problem into two stages, considering first the MIMiC component of the model as an isolated problem to evaluate the expected values of the latent variables. After that, these are incorporated directly into the DC model for estimation.

The sequential estimation can be performed in two ways. First, acknowledging that the estimated latent variables are in fact random variables, so that it is necessary to integrate the likelihood of the DC model over the domain of the latent variables for estimation. These approach guarantees consistent but inefficient results (Ben-Akiva *et al.*, 2002). Even so there are no major reasons to favor this approach over the simultaneous estimation method, as both require integrating the likelihood function yielding computational costs of the same order of magnitude (though the sequential approach is slightly less demanding).

The second way (which is the most popular one to conduct the sequential estimation of HDC models) assumes that the estimated latent variables are in fact deterministic variables. Under this assumption the estimation of the DC model is straightforward (both the specification of the likelihood function and of the required processing power), but it leads to biased and inconsistent estimates for the parameters. As the probability function associated with the logit model is non-linear, it cannot be assumed that the slope of the probability curve is constant over the space over which the density function of the latent variables distributes; hence the probability associated with the expected value of the latent variables is not representative of the probability for the domain, given that similar changes in the value of the latent variables (but in opposite directions), will have a different effect over the choice probabilities ("naïve approach"), as shown in the Figure 2.1 (Train *et al.*, 1987).

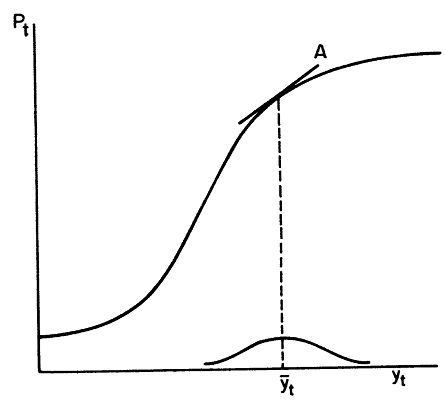

Figure 2.1 – Bias from estimating HDC models using expected values for the latent variables without integration (Train *et al.*, 1987).

When working with this approach, it is usually assumed that increasing the size of the sample can be sufficient to reduce the magnitude of the error, providing acceptable estimators, as long as the variance of the latent variable´s random error is small (Ben-Akiva *et al.*, 2002). In the same line, the empirical evidence suggests, that there are no major discrepancies regarding the ratios of the estimated parameters as well as concerning the marginal rate of substitution between the attributes (Bahamonde-Birke *et al.*, 2010; Raveau *et al.*, 2010).

Nevertheless Bahamonde-Birke and Ortúzar (2014a) were able to identify a major bias, which is not related to sample size but exclusively to the magnitude of the latent variable model´s variability. They found that when estimating a HDC model without considering the variability of the latent variables, an external error source is added directly into the DC model, deflating all estimated parameters according to the following proportion:

$$\tau = \left(1 + \frac{6\sigma_{LV}^2 \cdot \lambda_{DC}^2}{\pi^2}\right)^{-1/2} \qquad [2.7]$$

where σ^2_{LV} represents the error added through the inclusion of estimated non-observed parameters as non-stochastic variables and λ_{DC} stands for model variability related to own error terms of the DC model. They did not propose a way to assess the magnitude of this extra variability (except when dealing with *a priori* known parameters in a controlled environment) and, therefore, expression [2.7] cannot be used to correct the estimates.

2.3 Quantifying the extra variability

When considering only the expected values of the latent variables the analyst is also adding an external source of error directly into the DC model to be estimated, so that the total discrepancy between the representative and perceived utility corresponds to the sum of the error term underlying the DC model and an extra error coming from the MIMiC model. In fact, replacing [2.4] and [2.5] in [2.1] we get:

$$U_{iq} = \sum_k \theta_{ki} \cdot X_{kiq} + \sum_l \beta_{li} \cdot \left(\sum_r \alpha_{lri} \cdot s_{riq} + \upsilon_{liq} \right) + \varepsilon_{iq} \qquad [2.8]$$

When estimating a HDC model using the sequential estimation method, the analyst assumes the existence of a single error term but this is, in fact, greater than the usual error term associated with the DC model. This new error term can be represented in the following manner:

$$\varepsilon_{(HDC)iq} = \sum_l \beta_{li} \cdot \upsilon_{liq} + \varepsilon_{(DC)iq} \qquad [2.9]$$

where $\varepsilon_{(HDC)iq}$ is the total error considered in the sequential estimation, while $\varepsilon_{(DC)iq}$ stands for the error term associated with the underlying discrete choice component of the model, as required when following the simultaneous approach. As a consequence, the model variability can be expressed as follows:

$$\sigma^2_{HDC} = \sigma^2_{DC} + \sum_l \beta_l^2 \cdot \sigma_l^2 \qquad [2.10]$$

where $\sigma_{HDC}{}^2$ represents the model variability considered in the estimation, $\sigma_l{}^2$ is the variability associated with the error terms of the MIMiC model´s structural equations and $\sigma_{DC}{}^2$ stands for the variability of the underlying discrete choice model. To simplify the notation, from [2.10] onwards we assume, without loss of generality, that a given latent variable only affects the utility of a single alternative. If we consider that the parameters b_i are deterministic and known *a priori* β_l^2 are deterministic and known *a priori*, $\sum_l \beta_l^2 \cdot \sigma_l^2$ stands for the induced variability $\sigma^2{}_{LV}$ considered by Bahamonde-Birke and Ortúzar (2014a) in equation [2.7].

If we assume that the error terms of the MIMiC model´s structural equations (υ_{liq}) follow a distribution which is equal to the difference between two IID EV1 distributions with different variance, it can be shown that both the underlying DC model and the HDC model to be sequentially estimated can be represented as Logit models. If this is not so, the crux of the argument does not change but the mathematics and interpretation of results would get much more involved. Also, theoretically the whole estimation of HDC models using the sequential estimation method would neglect the hypotheses of the Logit model; even so, empirical experience (Bahamonde-Birke *et al.*, 2010; Raveau *et al.*, 2010), provides evidence sustaining that this neglect does not have major implications over the estimates. Then, under the above assumption, equation [2.10] can be simply written as:

$$\frac{\pi^2}{6\cdot\lambda_{HDC}^2}=\frac{\pi^2}{6\cdot\lambda_{DC}^2}+\sum_l \beta_l^2\cdot\sigma_l^2 \qquad [2.11]$$

where λ_{DC} and λ_{HDC} are the scale parameters of the Logit models associated with underlying DC model and the HDC model to be estimated, respectively. The β_l parameters, in turn, stand not for the parameters associated with the underlying DC model, but for the estimated parameters of the HDC model estimated sequentially; therefore, they are also deflated by its scale parameter, so that:

$$\beta^*{}_l=\frac{\lambda_{HDC}}{\lambda_{DC}}\cdot\beta_l \qquad [2.12]$$

where $\beta^*{}_l$ are the parameters associated with the underlying DC model. Hence, equation [2.11] can be rewritten in terms of the parameters associated with the underlying DC model (again under the assumption that the β_l parameters are deterministic and *a priori* known variables), which are those that would be recovered if the problem was approached properly (without the induction of bias):

$$\frac{\pi^2}{6\cdot\lambda_{HDC}^2}=\frac{\pi^2}{6\cdot\lambda_{DC}^2}+\frac{\lambda_{HDC}^2}{\lambda_{DC}^2}\cdot\sum_l \beta^{*2}_l\cdot\sigma_l^2 \qquad [2.13]$$

Working on equation [2.13], the scale parameter λ_{HDC} can be isolated as a function of λ_{DC} and $\beta^*{}_l$:

$$\lambda_{HDC}=\sqrt{\frac{-\frac{\pi^2}{6\cdot\lambda_{DC}^2}+\sqrt{\frac{\pi^4}{6^2\cdot\lambda_{DC}^4}+\frac{4\cdot\pi^2}{6\cdot\lambda_{DC}^2}\cdot\sum_l \beta^{*2}_l\cdot\sigma_l^2}}{\frac{2}{\lambda_{DC}^2}\cdot\sum_l \beta^{*2}_l\cdot\sigma_l^2}} \qquad [2.14]$$

Figure 2.2 presents a graphical representation of the relation between λ_{HDC} and λ_{DC} (which actually represents the deflation of the parameters) following [2.14] as a function of the artificially induced variability $\sum_l \beta_l^{*2}\cdot\sigma_l^2$ for different values of λ_{DC}.

As can be seen, λ_{HDC} is equal to λ_{DC} when no variability is added (as expected), and gets smaller in comparison with λ_{DC} when the induced error increases, both in relative (smaller λ_{DC}) and in absolute terms. The relation tends asymptotically to zero for all values of λ_{DC}.

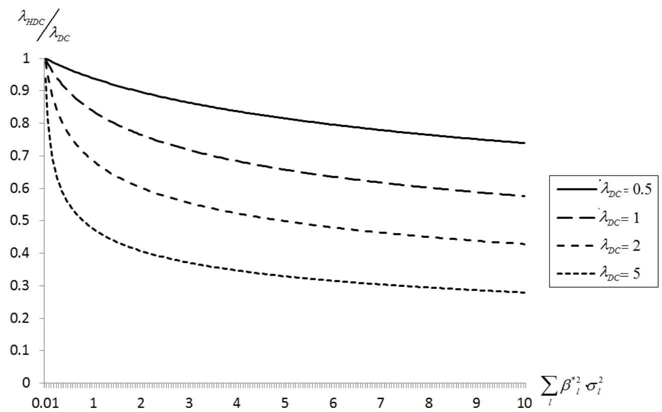

Figure 2.2 – Relation between λ_{HDC} and λ_{DC}.

As stated in the previous section, all estimated parameters of a DC model are deflated by the scale parameter λ. As this parameter is inversely related with the standard deviation of the error terms [2.3], it is clear that higher variability should imply smaller estimates, which is consistent with our findings and with the fact that a model affected by greater error terms is less informative (the smaller the parameter estimates, the more the estimated model tends to the equiprobable model). Hence, the sequential estimation of HDC models increases model variability and deflates the estimates, affecting the choice probabilities and decreasing artificially the model's goodness-of-fit.

One could suggest correcting the estimated parameters using equation [2.14] and fixing λ_{DC} to one (to emulate the results of the simultaneous estimation). However this strategy suffers from theoretical problems and equation [2.14] is not useful in practice. First, it must be acknowledged that as the β^*_l parameters are unknown (they should be estimated), they are not available to perform a correction (in contrast, the σ_l values are known deterministic variables, as the modeler has to fit the variances associated with the MIMiC model´s structural equations to guarantee identification (Stapleton, 1978). Further, the β^*_l parameters, which we had considered as fixed known deterministic variables, are in fact stochastic. This further increases the variability induced into the model and the increment depends on the nature of the model and the dataset. Hence, the result presented in [2.14] can only be understood as an upper limit and the real deflation associated with the use of the sequential estimation should probably be larger.

2.4 An experimental analysis

To analyze our findings and to test how much the real deflation differs from the result derived above, we devised an experimental analysis based on simulated data. This allows to examine the research subject in a context free of undesired effects, while at the same time enabling to determine the magnitude of the theoretically expected deflation (the upper limit of λ_{HDC} or the lower limit of the deflation), as the real parameters are an input of equation [2.14]. Following the tradition of Williams and Ortúzar (1982), we generated 15 different samples, each of 25,000 simulated individuals, behaving in a compensatory manner in accordance with different utility functions.

We considered a MIMiC model specification based on three explanatory variables, two latent variables and three perceptual indicators, though certain parameters were fixed at zero in some specifications, excluding latent variables or perception/attitudinal indicators from the modeling. Regarding the specification of the utility function, we considered two alternatives, each represented as the sum of one observed variable, a latent variable and an error term. The structure used in the generation of the dataset was the following:

$$U_{iq} = \theta_i \cdot X_{iq} + \beta_i \cdot \eta_{iq} + \varepsilon_{iq}$$

$$\eta_{iq} = \alpha_{1i} \cdot s_{1q} + \alpha_{2i} \cdot s_{2q} + \alpha_{3i} \cdot s_{3q} + \upsilon_{iq}$$

$$y_{zq} = \gamma_{zi} \cdot \eta_{iq} + \gamma_{zi} \cdot \eta_{iq} + \varsigma_{zq} \qquad [2.15]$$

which is a simplified form of the structure presented in the equations [2.4], [2.5] and [2.6], where the sub-index i stands for an alternative, z for an indicator and q for an individual. This notation is consistent with the sub-indices in Table 2.1.

All three explanatory variables (s_{ri}) were generated taking random draws from independent continuous uniform distributions, between zero and one, for each individual. The error terms of the measurement equations (ς_{zq}) are distributed Normal with zero mean and unit variance. To vary the magnitude of the error induced over the utility function, the error terms associated with the structural equations of the MIMiC model (υ_{iq}) have different variances, distributed Normal with zero mean and standard deviation σ_i. The observed variable (X_{iq}) taking part on the utility function was generated taking draws form a Normal distribution with mean 3.0 and standard deviation 1.4 for alternative one, and mean 4.0 and standard deviation 1.2 for alternative two. We fixed to one all parameters associated with the utility function and the scale parameters of the error terms associated with them, to simplify the evaluation of the bias. The values of the MIMiC model´s parameters for each sample, as well as the standard deviations σ_i of the error terms υ_{iq} are also presented in Table 2.1. To dismiss potential misspecifications in the data generation process we estimated the model for all samples following the simultaneous approach, observing that the data was indeed properly recovered.

Table 2.1 – Parameters used in the generation of the MIMiC model.

Sample	α_{11}	α_{21}	α_{31}	α_{12}	α_{22}	α_{32}	γ_{11}	γ_{12}	γ_{21}	γ_{22}	γ_{31}	γ_{32}	σ_1	σ_2
1	3	2	-1	0	0	0	0.7	0	0.5	0	0	0	1	0
2	3	2	-1	0	0	0	0.7	0	0.5	0	0	0	5	0
3	3	2	-1	0	0	0	0.7	0	0.5	0	0	0	2	0
4	3	2	-1	0	0	0	0.7	0	0.5	0	0	0	0.5	0
5	3	2	-1	0	0	0	0.7	0	0.5	0	0	0	0.2	0
6	0.5	0.2	0.3	0	0	0	3	0	1.5	0	0	0	1	0
7	0.5	0.2	0.3	0	0	0	3	0	1.5	0	0	0	5	0
8	0.5	0.2	0.3	0	0	0	3	0	1.5	0	0	0	2	0
9	0.5	0.2	0.3	0	0	0	3	0	1.5	0	0	0	0.5	0
10	0.5	0.2	0.3	0	0	0	3	0	1.5	0	0	0	0.2	0
11	3	2	0	0	2	3	0.7	0	0.5	0.5	0	0.7	1	1
12	3	2	0	0	2	3	0.7	0	0.5	0.5	0	0.7	2	2
13	3	2	0	0	2	3	0.7	0	0.5	0.5	0	0.7	0.5	2
14	3	2	0	0	2	3	0.7	0	0.5	0.5	0	0.7	2	0.5
15	3	2	0	0	2	3	0.7	0	0.5	0.5	0	0.7	0.5	0.5

2.4 Results and discussion

Using the sequential approach (without integration over the domain of the latent variables) we estimated HDC models for all the samples, following the exact specification used in the generation of the dataset. As expected, the parameters associated with the MIMiC part of the model were properly recovered, and there is no statistical evidence to reject the hypothesis of equality between the estimates and the target values for any parameter of all 15 samples (at a confidence level of 5%). The results obtained from the estimation of the DC models for the 15 samples are presented on Table 2.2. The notation is that used in equation [2.15] and the standard deviation of the estimates is shown in brackets. We have also included the expected induced variability $\sum_l \beta_l^{*2} \cdot \sigma_l^2$ as well as the value for λ_{HDC} calculated in accordance to equation [2.14], considering that the λ_{DC} parameter was fixed to one. The calibration of the DC models was performed using Biogeme (2003).

From Table 2.2 it is clear that the estimates obtained from the sequential approach are affected by the variability associated with the estimates of the latent variables, and it is not possible to recover the target values without performing a correction. Acknowledging this issue is important as, in some cases, the estimates are deflated by as much as three times their real values, affecting substantially the choice probabilities and the predictive capability of the models.

To ease following the situation discussed, in Figure 2.3 we provide a graphic representation of the estimated parameters together with the proposed correction curve, given the different induced variabilities. The horizontal axis of the graph uses a logarithmic scale.

In relation to the proposed expression for the λ_{HDC} parameter, the empirical results indicate that there are not major discrepancies between the suggested upper limit for λ_{HDC} and the real deflation affecting the estimates. In fact, it is not possible to detect significant differences between this upper limit and the real deflation, as long as the induced variability does not exceed a magnitude of two. Over this value the differences tend to increase in conjunction with the added variability and our proposed value cannot be considered a proper predictor of the deflation.

Table 2.2 – Estimation results of the DC model.

Sample	**β_1**	**β_2**	**η_1**	**η_2**	$\sum_l \beta_l^{*2} \cdot \sigma_l^2$	**λ_{HDC}**
1	0.870 (0.0135)	0.876 (0.0125)	0.866 (0.0173)	-	1	0.837
2	0.306 (0.00884)	0.317 (0.00796)	0.321 (0.0114)	-	25	0.475
3	0.636 (0.0112)	0.628 (0.0103)	0.629 (0.0140)	-	4	0.684
4	0.968 (0.0145)	0.954 (0.0135)	0.956 (0.0174)	-	0.25	0.939
5	0.988 (0.0139)	1.00 (0.0139)	1.05 (0.0182)	-	0.04	0.988
6	0.871 (0.0176)	0.846 (0.0125)	0.840 (0.0894)	-	1	0.837
7	0.295 (0.0135)	0.291 (0.00869)	0.183 (0.0993)	-	25	0.475
8	0.645 (0.0155)	0.623 (0.0107)	0.642 (0.0864)	-	4	0.684
9	0.922 (0.0183)	0.963 (0.0135)	1.01 (0.0863)	-	0.25	0.939
10	0.979 (0.0186)	0.983 (0.0138)	0.918 (0.0791)	-	0.04	0.988
11	0.747 (0.0127)	0.763 (0.0125)	0.783 (0.0166)	0.772 (0.0166)	2	0.765
12	0.504 (0.0103)	0.514 (0.0102)	0.502 (0.0141)	0.482 (0.0141)	8	0.602
13	0.618 (0.0114)	0.634 (0.0112)	0.637 (0.0153)	0.621 (0.0153)	4.25	0.677
14	0.639 (0.0115)	0.638 (0.0113)	0.630 (0.0154)	0.612 (0.0149)	4.25	0.677
15	0.901 (0.0320)	0.884 (0.0312)	0.832 (0.0388)	0.871 (0.0387)	0.5	0.896

As a consequence, a correction based on this upper limit can be attempted and it should provide acceptable results when working with a small induced variability. Although this correction is not 100% reliable – for instance the results obtained for sample 1 are slightly biased (in terms of the magnitude) even after correcting the estimates and standard deviations – it provides clearly better estimates than working directly with the estimation results, making it possible to recover most target values. Even in those cases affected by a high variability (more than two in our tests) a correction of the deflation using this upper limit offers clearly better results for forecasting (although still biased) than dealing with the original values.

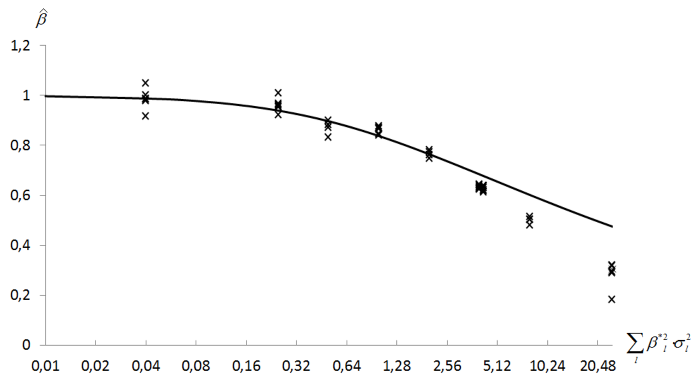

Figure 2.3 – Estimated parameters and expected deflation.

As stated before, the result presented in [2.14] cannot be used in practice since the β^*_l parameters are unknown, but an alternative formulation based on the model estimates β_l can be proposed working over expression [2.11]. In that case, the λ_{HDC} parameter may be expressed as a function of λ_{DC} and the β_l .

$$\lambda_{HDC} = \frac{\lambda_{DC}}{\sqrt{1+\frac{6\cdot\lambda_{DC}^2\cdot\sum_l \beta_l^2\cdot\sigma_l^2}{\pi^2}}} \qquad [2.16]$$

However, it is important to proceed very carefully when dealing with this formulation, as the β_l parameters are also deflated by the λ_{HDC} parameter, so that the inclusion of over-deflated estimates (as can be expected, since we are working with an upper limit for λ_{HDC}) could lead to an underestimation of the general deflation. Moreover, it is important to state that in this specification, the input variables are also stochastic estimates, implying that the λ_{HDC} parameter is of the same nature.

To illustrate this situation, we have computed $\boldsymbol{\lambda_{HDC}}$ following the alternative formulation for our 15 samples. The results are shown in Table 2.3. As expected, the proposed form provides a good proxy for $\boldsymbol{\lambda_{HDC}}$, when the deflation is small, but underestimates the latter (even more), when the induced variability gets larger.

Table 2.3 - Comparison of deflation estimators.

Sample	λ_{HDC} **[2.14]**	λ_{HDC} **[2.16]**
1	0.837	0.829
2	0.475	0.624
3	0.684	0.714
4	0.939	0.937
5	0.988	0.987
6	0.837	0.837
7	0.475	0.814
8	0.684	0.707
9	0.939	0.930
10	0.988	0.990
11	0.765	0.759
12	0.602	0.793
13	0.677	0.808
14	0.677	0.806
15	0.896	0.905

Finally, it is important to acknowledge, that in line with the previous empirical evidence, the relation between the estimated parameters as well as the marginal rates of substitution between the attributes do not appear to be affected by any bias and the target values are properly recovered, despite the use of the sequential estimation method (the only exception could be the value associated with the latent variable in sample 7, but the large standard deviation associated with this estimate prevents rejecting any hypothesis of equality).

2.6 Conclusions

The estimation of HDC models following the sequential estimation approach is still widely used as a second-best estimation tool, because of the high computational costs of the simultaneous estimation method, especially when working with several latent variables. Notwithstanding, the estimators associated with this methodology are biased and inconsistent, as the estimates for the latent variables are introduced into the DC model as deterministic (observed) variables, inducing an extra error into the model. As the estimators are inconsistent, this bias cannot be reduced by increasing the size of the sample.

We expanded the theoretical analysis of Bahamonde-Birke and Ortúzar (2014a) to quantify the magnitude of this bias and to propose a correction term for the estimates. However, we were only able to identify an upper limit for the scale parameter associated with the deflation caused by the direct inclusion of the latent variables into the DC model.

In the same line, we conducted an empirical experiment (based on simulated data) to analyze how much the real deflation differed from the quantifiable upper limit (bottom limit of the deflation), observing that the discrepancies were negligible for small induced variability. Hence, we argue that this upper limit is a good predictor for the real deflation when the induced variability is low and behaves appropriately as a correction term. When the induced error gets larger the upper limit underestimates the real deflation and therefore, the correction term is not able to guarantee unbiased estimators.

We argue that performing this correction is highly recommended when approaching the estimation problem sequentially, as it corrects or diminishes (depending on the magnitude of the induced error) a significant bias affecting the predictive capability of the estimated models. Notwithstanding, and in accordance with other studies, our findings show that the marginal rates of substitution between the attributes are not actually affected by the estimation technique. Therefore our study supports the thesis that sequential estimation of HDC models is a suitable second best alternative when the focus is centered on finding marginal rates of substitution or willingness-to-pay measures.

On the contrary, when the analyst expects to use the model for forecasting and for evaluation of choice probabilities, the suitability of the estimation technique must be properly evaluated. So, if the induced error associated with the variability of the latent variables is relatively small in comparison with the error terms intrinsic to the DC model, the estimation methodology should work in an acceptable manner if the correction term suggested in this chapter is applied. If this is not the case, other alternatives should be favored.

Finally, it is important to remember that the most important reason to opt for the sequential over the simultaneous estimation method are the high computational costs associated with the inclusion of several latent variables. Unfortunately, it can be expected that the inclusion of several latent variables will imply the introduction of higher induced variability into the DC model, causing the appearance of larger bias, detracting from the advantages of our simplified technique, making it a less suitable alternative.

CHAPTER 3[9]

ABOUT ATTITUDES AND PERCEPTIONS

[9] This chapter is based on the article: Bahamonde-Birke, F.J., Kunert, U., Link, H. and Ortúzar, J. de D. (2015). About attitudes and perceptions – finding the proper way to consider latent variables in discrete choice models. *Transportation* (forthcoming, DOI 10.1007/s11116-015-9663-5).
Available at http://dx.doi.org/10.1007/s11116-015-9663-5.

3.1 Introduction

The last decades have seen discrete choice models (DCM) become a key element in travel demand modeling and forecasting (Ortúzar and Willumsen, 2011). Their current state-of-practice considers objective characteristics of the alternatives and the individuals as explanatory variables, and yield as output individual probabilities of choice between different alternatives. It is also well known that *individual specific latent attributes* (i.e. attitudes) and *alternative specific latent attributes* (i.e. perceptions) play a role in the decision making process. The usual approach to take these into account considers the estimation of Multiple Indicator Multiple Cause (MIMiC) models, as suggested by Bollen (1989). The joint use of MIMiC models and DCM leads to state-of-the-art hybrid discrete choice (HDC) models (Ashok *et al.*, 2002; Ben-Akiva *et al.*, 2002; Bolduc and Daziano, 2010).

The transport literature has provided abundant empirical and theoretical evidence about the advantages of the HDC approach and the use of these models has gained popularity (v. Acker *et al.*, 2011; Bahamonde-Birke *et al.*, 2010; Raveau *et al.,* 2012; Daziano and Bolduc, 2013; Paulssen *et al.*, 2014; among others). Notwithstanding, *attitudes* and *perceptions* are usually not differentiated, ignoring that both may be expressions of different value judgments. While *attitudes* express a characteristic of the individuals toward life, society, etc. and are intrinsically related to them, *perceptions* are exclusively related to the way certain alternatives are perceived. Thus, an *attitude* resembles an individual's socio-economic characteristic, while a *perception* is intrinsically associated with an alternative[10]. This difference has important implications and the way in which both should be treated in a DCM is completely different. In turn, this issue affects not only the way in which latent variables (LV) are estimated but almost all hypotheses concerning them. Hence, different assumptions ma have an effect on both the way the LV

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[10] Formally speaking these definitions do not only apply to attitudes and perceptions but to all kinds of individual-specific and alternative-specific latent attributes, respectively. Nevertheless, in this work we focus on attitudes and perceptions, as these are the most representative ones. We are grateful to an unknown referee for pointing this out to us.

are constructed through the MIMiC model as well as on the manner in which these constructs are reflected in the utility function of the DCM.

This chapter aims to provide an in-depth discussion about the different ways to treat LV in DCMs. We discuss the implications of the latent constructs being individual or alternative specific and different approaches to deal with them. Along this line, we conduct an empirical experiment to test the aforementioned approaches (e.g. analyzing attitudinal LV in continuous and categorized fashions, or considering interactions between attitudinal LV and attributes of the alternatives). Furthermore we discuss strategies to deal with perceptual indicators that depend on different attributes of the alternatives; the latter allows constructing perceptual LVs that are sensitive to changes in the alternatives.

The rest of the chapter is organized as follows. Section 3.2 offers a theoretical overview of HDC models, while Section 3.3 presents the above-described discussion. Section 3.4 describes an experiment carried out to test the hypotheses of the previous section, and its results are discussed in section 3.5. Finally, section 3.6 summarizes our conclusions.

3.2 Theoretical background

Under the assumption of rational decision makers, it can be postulated that individuals q facing a set of available alternatives $A(q)$, will choose the alternative i that maximizes their perceived utility. In a Random Utility Theory framework (Thurstone, 1927; McFadden, 1974), it is possible to represent this utility as the sum of a representative component (V_{iq}) and an error term (ε_{iq}). When considering a Hybrid Discrete Choice (HDC) modeling framework (Ben-Akiva *et al.*, 2002), the modeler attempts to depict abstract attributes as measurable variables in order to include them as part of the systematic utility. Hereby, immaterial constructs, known as latent variables (η_{liq}), are also included into the modeling. These variables are supposed to represent attitudes and/or perceptions (or other unobservable characteristics) of the individuals and, as cannot be directly observed, they must be constructed as a function of other positively observed variables. The usual approach to construct these latent variables (LV) relies on a MIMiC structure (Zellner, 1970; Bollen, 1989). Here, the LV are explained by a set of characteristics of the individuals and the alternatives (s_{iqr}), through so called *structural equations*, while explaining, at the same time, a set of attitudinal and/or perceptual indicators (I_{ziq}), previously gathered from the individuals, through so called *measurement equations*. If we assume a linear distribution for the indicators, this framework can be represented through the following equations:

$$\eta_{liq} = \sum_r \alpha_{lri} \cdot s_{riq} + \upsilon_{liq} \qquad [3.1]$$

$$I_{ziq} = \sum_l \gamma_{zli} \cdot \eta_{liq} + \varsigma_{ziq} \qquad [3.2]$$

where the indices i, q, r, l and z refer to alternatives, individuals, exogenous variables, latent variables and indicators, respectively. The error terms υ_{liq} and ς_{ziq} can follow any distribution but they are typically assumed to distribute Normal with mean zero and a certain covariance matrix. Finally, α_{lri} and γ_{zli} are parameters to be jointly estimated.

If we assume a linear specification in V_{iq}, the utility function can be expressed as [3.3].

$$U_{iq} = \sum_k \theta_{ki} \cdot X_{kiq} + \sum_l \beta_{li} \cdot \eta_{liq} + \varepsilon_{iq} \qquad [3.3]$$

Under the assumption that the error terms ε_{iq} in [3.3] are independent and identically distributed (IID) Extreme Value Type 1 (EV1), the differences between the utilities associated with the alternatives follow a Logistic distribution, leading to the well-known Multinomial Logit (MNL) model (Domencich and McFadden, 1975).

The estimation of both parts of the model should be performed simultaneously, as a sequential estimation considering first the MIMiC part as an isolated system and evaluating afterwards the expected values for the LV cannot guarantee consistent and unbiased estimators (Train *et al.*, 1987; Ben-Akiva *et al.*, 2002). However, empirical evidence sustains the thesis that the sequential estimation produces no major discrepancies regarding the ratios between the estimated parameters and, therefore, the marginal rates of substitution (Raveau *et al.*, 2010; Bahamonde-Birke *et al.*, 2010). Nevertheless

Bahamonde-Birke and Ortúzar (2014a, 2014b) prove that the estimators may indeed be affected by a significant deflation bias (affecting all estimated parameters).

An intermediate path between the simultaneous and classical sequential estimation consists of estimating the model sequentially, but taking into account the variability of the LV. Despite the fact that this approach also requires integrating over the domain of the LV, it offers significant advantages in terms of computational costs. This approach leads to consistent but inefficient estimators (Ben-Akiva *et al.*, 2002) and avoids the bias described by Bahamonde-Birke and Ortúzar (2014b).

When estimating the model simultaneously, or sequentially integrating over the domain of the LV, the process is usually performed by simulated maximum likelihood, employing random draws to depict the probability distributions associated with the LV (Ben-Akiva *et al.*, 2002; Bierlaire, 2003).

3.3 Attitudes, perceptions and latent constructs in choice modeling

Prior to discussing the different ways in which LV may be considered in a HDC-model, it is necessary to understand the difference between individual-specific (e.g. attitudes, but also other characteristics such as values or personality traits, etc.) and alternative-specific latent attributes (e.g. perceptions). The former may be considered as a mind-set or a tendency to act in a particular way based on the individual's experience and temperament (Allport, 1935; Pickens, 2005). Therefore, in our approach indicators representing individual-specific latent constructs depend only on the individuals and are considered constant for all alternatives. Thus, one set of attitudinal indicators would be enough to describe the individual in question. Contrariwise, perceptions (although closely related to attitudes) may be interpreted as the process by which individuals experience their environment (Lindsay and Norman, 1972) and depend, therefore, on both the person and the stimuli (Pickens, 2005). As a corollary, perceptual indicators should be a function of both the individual and the alternatives. Even more, any variation in the alternatives may lead to a different valuation of them, as every detail may affect the way in which the population perceives the various alternatives. Therefore, in order to analyze the role of perceptions and perceptual indicators, it is necessary to gather a new set of indicators for every alternative (defined as every possible combination of attributes) that the individual faces.

This issue can lead to a significant increase in the information collected in the experiment, as normally the alternatives would consist of different attributes that are subject to variations. Therefore, it is mandatory to make certain simplifying assumptions. First, it may be assumed that certain attributes will not affect the way in which a given alternative is perceived and, consequently, this dimension may be excluded from the design (e.g. price may not affect accessibility indicators). Second, it can be assumed that the model is valid across individuals (avoiding the need that all of them state their perceptions for every combination of possible attributes, as long as some are faced with the remaining combinations).

Once the indicators are gathered it is possible to construct the latent variables. Obviously, attitudinal variables will be related to attitudinal indicators and *vice versa*. Thus, while attitudinal variables must be solely explained by characteristics of the individuals (as no variation across alternatives will be observed), perceptions should be explained also by the attributes of the different alternatives in the experimental design.

On the few examples when perceptual indicators are considered, researchers just allow one attribute of the alternatives to vary and then adjust independent alternative-specific models (one model per indicator set) that depend exclusively on the characteristics of the individuals (e.g. Yañez *et al.,* 2010). These models are, therefore, insensitive to changes in the alternatives; moreover, as the model does not depend on the stimuli, it is disputable if it can adequately treat actual perceptions.

Alternatively, different sets of indicators, associated with different combinations of attributes describing an alternative, may be treated jointly. This allows observing variation associated with these alternative-related attributes, and the model would be no longer indifferent to the stimuli. Although such an integrated HDCM would offer a poorer goodness-of-fit, as no *ad-hoc* model is being estimated for each independent attribute (or combination of attributes, if more than one dimension is allowed to vary), it should reflect how certain attributes affect perceptions in a more adequate manner. If one follows this approach, it is possible to gather more than one set of indicators per person (associated with different combinations of the alternative's attributes). In this case, correlation among the responses provided by the same individuals should be taken into account.

Kamargianni and Polydoropoulou (2014) provide a good example in this regard by using the characteristics of the individuals' living environment as explanatory variables to explain the perception of walkability. Even though they did not attempt to analyze directly how changes in the attributes affected the perceptions of specific individuals (gathering more than one set of perceptual indicators per individuals, for instance), nor if these attributes could be linked undoubtedly to the specific alternative, their approach appears appropriate to deal with alternative-specific latent constructs.

Finally, the treatment of both kinds of variables (*attitudes* and *perceptions*) in the DCM should not be equal, as some attitudes, just as socio-economic variables (which affect the way in which the attributes of the alternatives are perceived), should be incorporated through systematic taste variations and not linearly into the utility function.

Against this background, we distinguish three kinds of LV, which will be treated in our case study (see Section 3.4):

a) *Non-alternative related individual-specific latent attributes (e.g. attitudes)*: Most researchers working with HDC models consider this kind of variables (Bolduc and Daziano, 2010; Jensen *et al.,* 2014, among many others). They represent general attitudes of the individuals toward their social and physical environment, such as a more ecological mind-set or a higher valuation of social status. Even when using variables that may be understood as perceptions, such as comfort and security, the modeler is, in fact, dealing with a non-alternative related attitude, as in this case the variable stands for the importance assigned by the individual to a given aspect and not to the perception of the alternative itself (Daziano, 2012). Thus, inferences such as "Alternative A is perceived as more comfortable" would not be accurate, but rather, "Individuals caring for comfort favor alternative A", which is not equivalent. Chorus and Kroesen (2014) argue (in our opinion rightly) that this kind of models does not allow deriving policy implications, as these attitudinal variables are intrinsic characteristics of the individuals (like sex or age) and therefore not sensitive to changes in the alternatives (longitudinal data could be an exception, as it allows capturing how attitudes may change depending on external circumstances, and thus deriving policy implications). In the same line, Chorus and Kroesen (2014) criticize the causal relation between attitudes and choices, as attitudes and stated attitudinal indicators may be indeed affected by the individual's choices (e.g. the stated attitude toward the comfort provided by a given alternative, may depend on whether the alternative is selected). However, this criticism may be substantially reduced if no direct link can be established between indicators and choices. In that case, both would be indeed an expression of deeper underlying attitudes, such in the case of environmental attitudes, political views, values, and so on.

As these variables resemble socio-economic characteristics, to identify the DCM they must be considered together with alternative specific attributes in the utility function. However, in most reported cases they are just considered in conjunction with alternative specific constants (Vredin-Johansson *et al.,* 2006; Bolduc *et al.*, 2008); this restriction may neglect important aspects of the decision, as it can be expected that individuals with different attitudes toward life exhibit a different valuation of the attributes of the alternatives, and therefore systematic taste variations should be allowed for (Ortúzar and Willumsen, 2011, page 279).

Furthermore, similar to socio-economic variables, it is not clear that *attitudes* should have a linear impact on utility. Therefore, a categorization of the LV should be considered. For instance, it is plausible that a low or intermediate appraisal of security (or safety) may have no effect whatsoever over the decision, but a high concern could lead to a significantly different valuation. If this were the case, treating the variable linearly would not properly reflect individual behavior.

Categorizing the LV offers also significant advantages in terms of flexibility, as it allows estimating different utility functions for every category, resembling a latent class model, but expanding it in order to account for the behavioral information. This categorization may be performed using a latent variable-latent class structure (Hess *et al.*, 2013) or attempting a direct categorization (i.e. a dummy variable that takes a positive value if the LV surpasses a certain threshold).

b) *Alternative related individual-specific latent attributes (e.g. attitudes)*: These variables are similar to those above, with the exception that attitudes are unequivocally related to a given alternative. Thus, they must be considered in conjunction with the alternative specific constants. For instance, Daziano and Barla (2012) allowed for the effect of a favorable predisposition toward automobiles or transit systems in this way. As in the previous case, systematic taste variations (within the same alternative) and a possible categorization should also be analyzed.

c) *Alternative-specific latent attributes (e.g. perceptions)*: These variables are alternative related (i.e. they exhibit a different valuation depending on the alternative considered) and as such they resemble observed attributes such as price or travel time; hence, both kinds of variables (observed and alternative-specific latent attributes) should be treated in the same fashion. In this case, both alternative specific and generic estimators may be considered.

   These variables allow evaluating how changes in alternatives may affect the perceptions, and thus the choices. As in this case the perceptions and indicators are driven by exogenous attributes of the alternatives, causality issues as described by Chorus and Kroesen (2014) may be overcome.

Regarding the model's identifiability, necessary and sufficient conditions have not yet been developed. Therefore, most studies relying on HDC models achieve identification by not letting some explanatory variables impact the utility of a given alternative, both directly and through a latent variable (Bhat, 2014)[11]. This is indeed a sufficient but highly restrictive condition and, especially when dealing with perceptual LV, the modeler may be forced to employ the same attributes in the structural equations as well as in the utility functions to represent behavior properly (e.g. air conditioning may have an effect over perceived comfort, but still have a direct impact on the decision due to other considerations). Under these circumstances identification must be analyzed on a case-by-case basis (see Vij and Walker, 2014, for a good discussion about the identifiability of HDC models).

[11] The authors are aware that some papers have relaxed this restrictive condition (e.g. Atasoy *et al.*, 2010 or Kamargianni *et al.*, 2014), but the majority of papers on HDC just rely on it.

3.4 Case study

Departing from usual practice (which typically considers only *attitudes*), we designed an experiment considering both attitudinal and perceptual indicators in a transport choice framework. This allowed us testing for the appropriate manner to consider both kinds of LV in a DCM, regarding the underlying theoretical concerns.

We conducted a stated choice (SC) experiment where respondents were asked to choose between different interurban public transport alternatives in Germany (regional[12] and intercity trains, and interurban coaches). The experiment was carried out in three waves (January 2014, March 2014 and April/May 2014), contacting both students and employees from two universities in Berlin (the Technische Universität Berlin and the Humboldt-Universität zu Berlin), as well as employees of member institutions of the Leibniz-Gemeinschaft[13]. After data cleaning the survey yielded a total of 1,832 responses.

The questionnaire had four parts. In the first, respondents were asked to describe the main characteristics (fare, travel time, number of transfers, etc.) of their last trip with the regional and intercity trains of Deutsche Bahn. Respondents were also asked to state their general experience of traveling with Deutsche Bahn. It was considered that attributes such as fare or travel time, would have no effect over the indicators (which was confirmed in a pilot study), but that the number of transfers or the transport mode could. Participants were required to state their level of agreement with the statements below, using a ten-point Likert scale which ranged from strongly disagree (1) to strongly agree (10), provided that the trip might be carried out with both transport modes (regional and intercity trains) and considering a given number of transfers (which was equivalent to that reported in the previous module, to ensure that respondents had previously faced the combination of attributes).

[12] Regional trains should not be confused with commuter rail. In Germany, regional trains operate over long interurban distances, stopping more and over shorter distances than intercity trains. It is possible to travel across the country using only regional trains.
[13] The Leibniz-Gemeinschaft is one of the shelter associations of publicly funded research institutes in Germany.

I was able to relax during the trip (y_{11})	***Relax***
I felt secure from thefts and losses (y_{12})	***Security***
Traveling with heavy luggage was (would have been) uncomplicated (y_{13})	***Luggage***
The departure time was reliable (y_{14})	***Departure***
The arrival time was reliable (y_{15})	***Arrival***
It was possible to use the travel time productively (y_{16})	***Productivity***
The station was easily accessible (y_{17})	***Station***
Purchasing the ticket was uncomplicated (y_{18})	***Tickets***

Respondents were also asked to state their level of agreement with these statements under the assumption that a bus carrier with no transfers would offer the service.

The second part of the survey gathered travel behavior data as well as indicators related to traveler's attitudes toward current political issues discussed in Germany, stating their level of agreement with the following sentences using again a 10 point Likert scale:

I agree with the nuclear power phase-out (y_{21})	***NuclearPhaseOut***
Environment protection is more important than economic growth (y_{22})	***Environment***
I am willing to pay a 25% surcharge on my electric bill to reduce CO_2 emissions from coal power plants (y_{23})	***ElectricSurcharge***
Highway tolls should be introduced to compensate CO_2 emissions (y_{24})	***HighwayTolls***
Automobiles with higher engine power should pay more taxes (y_{25})	***CarTax***
Investing on the development of high-speed trains should be encouraged (y_{26})	***HSTrains***
New highways or additional lanes to the existing ones should be built (y_{27})	***Highways***
New high-speed rail lines should be built (y_{28})	***RailLines***
I agree with the introduction of speed limits on highways (y_{29})	***SpeedLimits***

The third part of the questionnaire was the SC experiment itself. Respondents were required to choose between a first (pivotal) alternative, representing the trip previously described, and a new travel alternative (either the same mode or a different one). Altogether, respondents were confronted with twelve choice situations; the first six used a pivotal alternative based on a trip with Deutsche Bahn regional trains and the last six considered a trip with Deutsche Bahn intercity trains. Alternatives were described in terms of their travel time, fare, number of transfers, mode of transport - regional trains (RE), intercity trains (FVZ) and coaches (LB) - and a safety level, represented through the number of severely injured passengers and the number of fatalities in the overall network over a year for each mode (this value was highest for the coach alternative[14]). The appendix A presents a translated sample screen of the SP-experiment.

The attribute levels of the alternatives were optimized maximizing the D-efficiency for a pivotal design as proposed by Rose et al. (2008). As it was not possible to personalize the attribute levels during the survey, they were fixed *a priori* based on the average levels of the attributes. These average levels, as well as the priors used for computing the D-error, were established in accordance with models previously estimated, based on the answers gathered during the pre-test of the survey (48 individuals).

Finally, the fourth part of questionnaire requested socioeconomic information about the respondents.

3.5 Model estimation

3.5.1 Model structure

To establish the structure of the MIMiC model, the indicators were analyzed using factor analysis to guarantee a correct specification of the LV (Atasoy *et al.*, 2010). This way, it was possible to identify three components (with an eigenvalue greater than 1) explaining 70% of the variance of the perceptual indicators (y_{11} to y_{18}). In the same way, it was possible to establish that two factors (with an eigenvalue greater than 1) captured 54% of the variability associated with the attitudinal indicators (y_{21} to y_{29}). Table 3.1 presents the rotated component matrices for both types of indicators.

On the basis of these results, we constructed two generic and three alternative-specific LV (shown in bold in Table 3.1[15]). The first was identified as *Comfort*, as it was related to indicators such as ease of access, relaxation, or an environment that was comfortable enough to be used productively. The second component was called *Stress-free*, as it was

[14] Because of the way the statistic was provided, as well as to avoid minuscule numbers, it was necessary to use numbers for the overall network.

[15] It is necessary to rely on heuristic criteria to define the structure of the LV model. This way, we used a Varimax rotation – to ease the identification of each variable with a single factor – and associated the indicators with a given latent construct when the absolute value of the loading factor was greater than 0.5.

associated with situations causing tension during the trip, such as worrying about the luggage or personal security. The third component was identified as *Reliability*.

Table 3.1 – Rotated component matrix of perceptual and attitudinal Indicators.

Indicator	Comfort	StressFree	Reliability
Relax	**0.548**	**0.591**	0.171
Security	0.144	**0.782**	0.132
Luggage	0.061	**0.810**	0.178
Departure	0.117	0.245	**0.892**
Arrival	0.280	0.125	**0.867**
Productivity	**0.663**	0.432	0.099
Station	**0.810**	0.064	0.177
Tickets	**0.711**	0.059	0.153

Indicator	Green	TrainFan
NuclearPhaseOut	**0.688**	-0.029
Environment	**0.726**	-0.074
ElectricSurcharge	**0.704**	0.030
HighwayTolls	**0.658**	0.214
CarTax	**0.686**	0.192
HSTrains	0.114	**0.860**
Highways	**-0.546**	0.365
RailLines	0.046	**0.891**
SpeedLimits	**0.610**	0.082

In the case of the attitudinal indicators, the first component was associated with having a *Green* attitude, including a negative predisposition toward automobiles (y_{24}, y_{25}, y_{27} and y_{29}). The second component related to individuals who had a great appreciation for the development of trains and rail lanes (for this reason, this LV was called *TrainFan*). These results are interesting for our analysis as it was possible to identify a generic (*Green*) and an alternative related (*TrainFan*) attitude.

3.5.2 MIMiC model components

Given the complex structure and size of the dataset (1,832 individuals; 3,900 sets of perceptual indicators; eight latent variables – two generic and three alternative-specific variables[16] - and 13,138 observed decisions), it was not computationally possible to perform a simultaneous estimation of the HDC model[17]. In addition, we wanted to analyze the effect of attitudinal LV both as continuous or as categorized variables, which complicated the structure of the model even more.

[16] For each choice situation the alternative-specific LV depends on the alternatives. Therefore we have three LV (*Comfort*, *Stress-free* and *Reliability*) associated with the *status quo* alternative and another three related to the new option offered to the individual.

[17] We attempted it using *PythonBiogeme*, but observed that the optimization algorithm interrupted the computation without reaching convergence after approximately three weeks (*unsuccessful linesearch*).

Therefore, a sequential estimation considering the own variability of the LV and integrating over their domain was attempted. Thus, the MIMiC model was estimated first and the latent variables considered in the DCM component were constructed according to these estimates. In fact, it was necessary to estimate two different MIMiC models, one for the attitudinal variables and another for the perceptual indicators.

The first only considered individual characteristics as explanatory variables. Figure 3.1 presents the final structure of the selected model (several specifications considering additional socio-economic variables and other combinations of those shown were also considered), and Table 3.2 its estimated parameters.

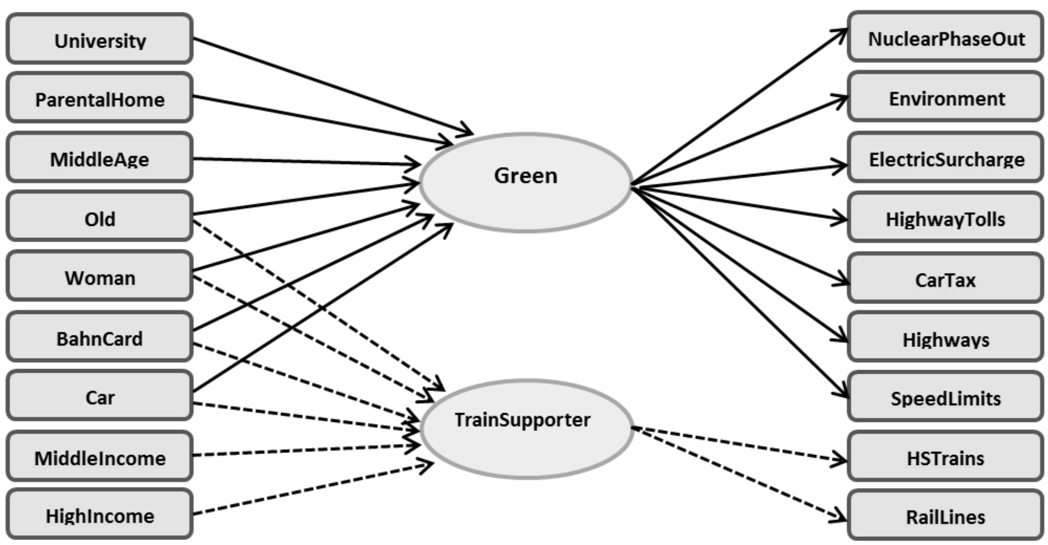

Figure 3.1 – Structure of the attitudinal MIMiC model.[18]

The second MIMiC model was estimated for the perceptual indicators. In this case, not only the characteristics of the individuals but also the attributes of the transport modes were considered as explanatory variables. It is also important to consider interactions between these two kinds of variables, as different population groups may perceive differently the attributes of the alternatives (i.e. systematic taste variations).

It is important to note, that the model cannot be subdivided based on alternatives, as we are calibrating an integrated perceptual model, where the transport mode and the number of transfers do not describe the alternatives but are considered as further attributes. The

[18] The different line types are only used to ease the understanding of the figure.

Table 3.2 – Estimated parameters for the attitudinal MIMiC model.

Explanatory Variable	Estimate	t- statistic	Attitudinal Indicator	Estimate	t- statistic
Green Attitude			***Green Attitude***		
University	0.258	4.134	*NuclearPhaseOut*	1.463	44.416
ParentalHome	-0.181	-2.815	*Environment*	1.178	49.917
MiddleAge	0.298	6.124	*ElectricSurcharge*	1.666	51.02
Old	0.497	3.713	*HighwayTolls*	2.14	51.02
Woman	0.287	5.917	*CarTax*	1.628	46.489
BahnCard	0.334	6.565	*Highways*	-1.053	-37.228
Car	-0.524	-10.075	*SpeedLimits*	2.282	51.902
TrainFan			***TrainFan***		
Old	0.282	2.048	*HSTrains*	2.088	49.695
Woman	-0.282	-5.639	*RailLines*	2.12	49.937
BahnCard	0.333	6.356			
Car	-0.058	-1.116*			
MiddleIncome	0.141	2.807			
HighIncome	0.128	1.66**			

(*)The variable was kept in the model as it is considered a policy variable and has the proper sign.
(**) As the signs of the estimators were known *a priori*, a one-tailed test was performed ($\alpha_{5\%}$ =1.645).

structure of the estimated model is shown in Figure 3.2. Here, *Losses* and *Accidents* indicate that the individual had suffered material losses during a trip in the past or had been involved in a train accident, respectively. The number of transfers is represented by a discrete variable ranging between zero and four, while *BusUser* indicates whether the individual had undertaken at least one trip using coach services during the last three years. Again identifiability was achieved by constraining the variance of the LV and the estimation was performed maximizing the likelihood. The estimation results are presented in Table 3.3.

Altogether, there were 13,138 observations available for estimation. The potential correlation between the responses of a given individual (panel effect) was considered but not included in the final models since it was not statistically significant[19]. The latent variables *Green* and *TrainFan* were considered both linearly and categorized in two different levels. We attempted a direct categorization, with the dummies $Green_{(+67\%)}$ and

[19] A plausible explanation for the absence of correlation among the repeated responses of each individual relies in the fact that the alternatives presented were not related to a specific transport mode.

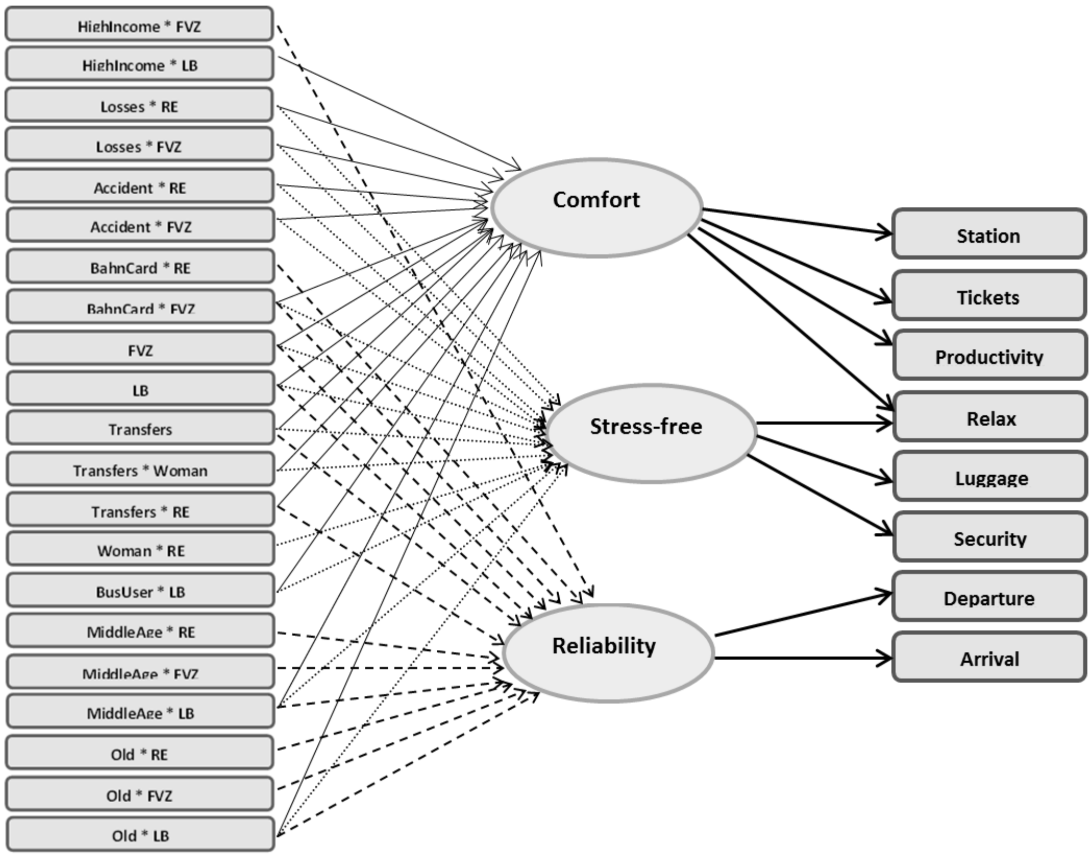

Figure 3.2 – Structure of the perceptual MIMiC model.

TrainFan$_{(+67\%)}$ taking a positive value with the probability of the original LV being greater than a given threshold ψ_l. Thresholds were fixed to represent the fact that individuals belonged to the upper third of the population (regarding the distribution of these two LV). As mentioned above, estimation was performed sequentially using PythonBiogeme (Bierlaire, 2003), integrating over the domain of the latent variables, so that the reported value for the log-likelihood refers only to the discrete choice component of each model. This takes the following form when the LV are considered as continuous variables:

$$L = \int_{\eta} P(y \mid X, \eta; \beta, \theta, \varepsilon) \cdot f(\eta \mid s; \alpha, \upsilon) \cdot d\eta \qquad [3.4]$$

Table 3.3 – Estimated parameters for the perceptual MIMiC model.

Explanatory Variable	Estimate	t-statistic	Attitudinal Indicator	Estimate	t- statistic
Comfort			***Comfort***		
*HighIncome * LB*	-0.249	-2.958	*Station*	1.403	64.12
*Losses * RE*	-0.28	-3.577	*Ticket*	1.136	57.733
*Losses * FVZ*	-0.173	-2.028	*Productivity*	1.935	72.199
*Accident * RE*	-0.243	-3.527	*Relax*	1.36	62.262
*Accident * FVZ*	-0.217	-2.816			
*BahnCard * FVZ*	0.341	7.199			
FVZ	0.471	12.704			
LB	-0.907	-23.639			
Transfers	-0.161	-8.05			
*Transfers * Woman*	-0.06	-1.765*			
*Transfers * RE*	0.059	2.448			
*BusUser * LB*	0.338	8.011			
*MiddleAge * LB*	-0.282	-5.917			
*Old * LB*	-0.522	-3.796			
Stress-free			***Stress-free***		
*Losses * RE*	-0.539	-6.808	*Relax*	0.719	36.669
*Losses * FVZ*	-0.468	-5.403	*Luggage*	2.119	72.975
*Accident * RE*	-0.188	-2.704	*Security*	1.546	64.834
*Accident * FVZ*	-0.246	-3.162			
*BahnCard * FVZ*	0.283	5.928			
FVZ	0.311	8.35			
LB	0.399	10.674			
Transfers	-0.12	-5.965			
*Transfers * Woman*	-0.144	-4.193			
*Woman * RE*	-0.207	-4.56			
*BusUser * LB*	0.104	2.438			
*MiddleAge * LB*	-0.128	-2.67			
*Old * LB*	-0.462	-3.327			
Reliability			***Reliability***		
LB	-0.227	-6.209	*Departure*	2.115	72.855
FVZ	0.063	1.724*	*Arrival*	2.284	74.573
Transfers	-0.158	-7.921			
*Transfers * Woman*	-0.099	-2.934			
*HighIncome * FVZ*	-0.173	-2.07			
*BahnCard * RE*	0123	4.155			
*BahnCard * FVZ*	0.083	2.583			
*BusUser * LB*	0.185	1.773*			
*MiddleAge * RE*	0.133	2.974			
*MiddleAge * FVZ*	0.083	1.754*			
*MiddleAge * LB*	-0.103	2.185			
*Old * RE*	0.133	0.974**			
*Old * FVZ*	0.166	1.212**			
*Old * LB*	-0.347	-2.536			

(*) As the signs of the estimators were known *a priori*, a one-tailed test was performed ($\alpha_{5\%}$ =1.645).

(**) In spite of their low significance the variables were kept in the model as both the signs and magnitudes of the estimated parameters were consistent with the values obtained for the other age-related estimators.

or the following one when a latent variable η_c is categorized

$$L = \int_{\eta} P(y \mid X, \eta, 0; \beta, \theta, \varepsilon) \cdot f(\eta \mid s, \alpha, \upsilon) \cdot d\eta \cdot P(d\eta_c < \psi \mid s, \alpha, \upsilon)$$
$$+ \int_{\eta} P(y \mid X, \eta, 1; \beta, \theta, \varepsilon) \cdot f(\eta \mid s, \alpha, \upsilon) \cdot d\eta \cdot P(d\eta_c \geq \psi \mid s, \alpha, \upsilon) \quad [3.5]$$

Table 3.4 presents the estimation results for five different specifications; all are good models easily surpassing the typical test of being better that their market shares reference model (Ortúzar and Willumsen, 2011, pages 281-283). The first (*Linear LV*) considers all LV (generic and alternative-specific) in a linear fashion. The second (*Categorical Green*) categorizes the latent variable *Green*, while the third (*Categorical LV*) explores categorized specifications for both attitudinal LV. The fourth (*No Stress-free*) is similar to model *Categorical Greene* but ignores *Stress-free* (found not statistically significant in the second model[20]). Finally, the fifth (*No Perceptual*) ignores all perceptual LV.

Two of the three perceptual indicators were found to be statistically significant. Thus, both the perception of reliability and comfort affect utility positively. On the contrary, the perception of a stress-free travel appears not to be statistically significant in the decision making process.

Note that when the perceptual attributes are omitted, the mode specific constants become highly significant (model *No Perceptual*). However, when perceptions are integrated they capture a large part of the variability previously ascribed to them and these become either not significant (Regional Train), or their impact on the decision decreases (Coach). This is accompanied by a significant improvement in goodness-of-fit.

These findings are in accordance with theory: the mode specific constants normally capture the omitted information regarding a specific alternative, but when perceptions are considered, this information is enriched and the importance of these constants decreases.

[20] At a 5% significance level (1.645) performing a one-tailed test as estimator signs were known *a priori*.

Table 3.4 – Estimated parameters for the discrete choice model.

Variable	Linear LV	Categorical Green	Categorical LV	No Stress-free	No Perceptual
Inertia	0.415 (10.25)	0.43 (9.92)	0.465 (6.36)	0.443 (9.21)	0.363 (13.22)
Coach (LB)	-0.741 (-3.42)	-0.768 (-3.37)	-0.592 (-2.51)	-0.626 (-3.01)	-1.47 (-12.46)
Regional Train (RE)	0.0201 (0.19)	0.0338 (0.31)	0.134 (0.98)	-0.0147 (-0.14)	-0.407 (-9.28)
Travel Time	-0.0233 (-12.12)	-0.0332 (-10.97)	-0.0384 (-6.04)	-0.0341 (-9.85)	-0.0266 (-16.25)
Travel Time * LV Green	0.00892 (6.05)	-	-	-	-
Travel Time * LV Green $_{(+67\%)}$	-	0.0266 (7.89)	0.0311 (5.25)	0.0271 (7.31)	0.0206 (9.04)
Ln(Price) * Very Low Income	-6.77 (-14.5)	-7.09 (-13.71)	-8.17 (-6.64)	-7.34 (-11.97)	-5.91 (-28.69)
Ln(Price) * Low Income	-5.95 (-13.52)	-6.23 (-12.8)	-7.13 (-6.47)	-6.46 (-11.34)	-5.1 (-24.3)
Ln(Price) * Middle Income	-4.65 (-10.71)	-4.85 (-10.36)	-5.56 (-5.92)	-5.04 (-9.41)	-3.89 (-14.49)
Ln(Price) * High Income	-3.5 (-7.24)	-3.69 (-7.22)	-4.15 (-5.01)	-3.83 (-6.85)	-2.9 (-8.18)
Safety Level	-0.00519 (-4.78)	-0.00545 (-4.8)	-0.00616 (-4.01)	-0.00556 (-4.63)	-0.00419 (-4.77)
Transfers	-0.355 (-7.85)	-0.369 (-7.94)	-0.434 (-4.7)	-0.418 (-8.78)	-0.49 (-17.65)
Comfort	0.661 (3.47)	0.679 (3.41)	1.15 (3.03)	0.84 (3.9)	-
Reliability	0.368 (1.69)	0.395 (1.68)	0.145 (0.61)	0.354 (1.51)	-
Stress-free	0.204 (1.4)	0.236 (1.56)	0.23 (1.39)	-	-
FVZ * TrainFan	0.54 (3.25)	0.554 (3.19)	-	0.575 (3.2)	0.625 (5.52)
FVZ * TrainFan $_{(+67\%)}$	-	-	-0.176 (-1.02)	-	-
Log-Likelihood	-7 424.26	-7 412.27	-7 416.37	-7 413.75	-7 443.77

Regarding the attitudinal LV, we found that the generic attitude *Green* affects the way in which travel time is perceived (i.e. it was possible to identify a systematic taste variation related to this attitude). The variable is statistically significant both when considered linearly and when it is categorized, reflecting the importance of the systematic taste variation. However, when the variable is categorized (*Green*$_{+67\%}$) the model gets a substantially superior goodness-of-fit (models *Categorical Greene* and *Stress-free*), suggesting a considerably better representation of behavior. This finding is in line with the perception that shorter travel times imply higher speeds and, therefore, more CO_2 emissions and a larger damage to the environment. Also, the fact that the effect of *Greene* is not linear, is in agreement with the notion that only highly environmentally concerned individuals are willing to accept larger travel times to reduce ecological harm.

When considering interactions between continuous LV and travel time or travel expenses, assessing the value of travel time gets more involved as the latent variables do not drop out of the equation when deriving the utility over travel time or cost. Therefore, the value of time will depend on the attitudes of the individuals and to obtain a societal value of time it would be necessary to integrate over all individuals. When a LV is considered in a categorized fashion, the analysis is straightforward and similar to the one performed, when working with latent classes, and the same applies for demand elasticities.

Finally, as expected, our alternative related attitude (*TrainFan*) is statically significant in conjunction with intercity trains (FVZ). It was possible to detect a social group of train enthusiasts willing to favor the railways. However, this favoritism does not extend to regional trains. In this case, a model considering the variable in a categorized fashion (e.g. model *Categorical Variables*) does not outperform the linear specification. It was not possible either to identify a systematic taste variation within the alternative intercity trains.

3.6 Conclusions

The significant technical and methodological improvements in the estimation of HDC models during the last decade have not led to a significantly better understanding of the way in which perceptions affect the decision making process, as these aspects are mostly ignored by modelers. Even in the case of attitudes, which have been widely studied, the specification of latent variables has tended to be fairly simplistic and rarely departs from the linearity assumptions (fortunately latent class models have been an alternative in this regard), while the analysis of systematic taste variations in association with attitudes appears to be practically inexistent.

This reticence may be related to deeper concerns about artificial constructs, such as latent variables and the information that can be acquired from them. Nevertheless, it should not be forgotten that we, as modelers, aim to depict reality in the best way possible and, therefore, if we decide to work with latent variables, we should guide our efforts to represent the decision making process and the way in which the different variables take part in it as accurately as possible.

This chapter ponders about the different ways in which attitudes and perceptions may affect the decision making process and derives practical recommendations about data collection and estimation issues. Basically, individual-specific latent attributes (e.g. attitudes) resemble socio-economic characteristics of the individuals, and thus they should be treated in a similar fashion. Hence, exploring alternatives as systematic taste variations (in conjunction with observable attributes of the alternatives) or through a categorization is highly recommended. Alternative-specific latent attributes (e.g. perceptions), on the other side, should be treated in a similar manner to the attributes of the alternatives. Along the same line, it is important for perceptual models, to consider the attributes of the alternatives as explanatory variables, to properly reflect the way in which perceptions arise in the population and to remain sensitive to changes in the alternatives.

With regard to the collection of perceptual indicators, it is important that questionnaire design allows capturing variability in the indicators associated with changes in the alternatives. Attempting to analyze how various combinations of alternative attributes may affect a perceptual indicator, may lead to a significant increase in the information required; so, it is important to rely on a careful survey design and to determine *a priori* which attributes are relevant to the perception.

We conducted an empirical analysis to test our hypotheses. This gave evidence sustaining the notion that perceptions may affect the way in which individuals ascribe utility to a certain alternative. In the same line, our empirical experiment suggests that perceptions may explain a significant portion of the variability normally captured by alternative specific constants, offering significant improvements in model goodness-of-fit. Also, our results support our hypotheses that *attitudes* may indeed be related to systematic taste variations and that attitudinal latent variables should be treated in the same manner as socio-economic variables.

Although we were able to identify systematic taste variations with our data, as well as a categorization for latent variables that outperformed the linearity assumption, this does not imply that every attitudinal latent variable should be considered in this way. Prior to estimation, or even better prior to constructing the experiment, the analyst should study which variables take part in the decision making process and decide the way in which they should be considered in accordance with underlying theory.

Although not treated in this chapter, interactions among attitudes and perceptions represent an issue that should be considered in further research, as cognitive dissonance might affect the way in which different alternatives are perceived, leading to correlation and more complex error structures.

CHAPTER 4[21]

ABOUT THE CONTINUITY OF ATTITUDINAL AND PERCEPTUAL INDICATORS

[21] This chapter is based on the article: Bahamonde-Birke, F.J. and Ortúzar, J. de D. (2015). Analyzing the continuity of attitudinal and perceptual indicators in hybrid choice models. *14th International Conference on Travel Behaviour Research (IATBR)*, Windsor, U.K., 19-23 July, 2015.

4.1 Introduction

The study of unobserved latent variables is a hot topic nowadays. When it cannot be assumed that the outcome satisfies the property of continuity (as in the case of discrete, ordinal or nominal variables), the modeler usually relies on unobserved continuous constructs; this way, it is assumed that the underlying factors, represented through latent variables, explain the observed non-continuous output.

Discrete choice (DC) modeling (McFadden, 1974) is a special case of dealing with nominal variables. Here, it is assumed that individuals face a set of alternatives associated with a particular underlying utility function that depends on both the characteristics of the individuals and the alternatives' attributes. Observed choices are considered to be the result of a maximization process, where individuals opt for the alternative associated with the highest expected utility.

An important limitation of this framework is that it only allows for observed variables to impact utility. The effort of combining discrete choice models with other unobserved latent variables, accounting for unobserved factors that may be relevant in the decision making process, such as attitudes and perceptions, led at the 80s to propose the first versions of hybrid discrete choice (HDC) models (McFadden, 1986; Train *et al.*, 1987), an approach currently based on the Multiple Indicators Multiple Causes (MIMiC) model (Zellner, 1970; Bollen, 1989). Here it is assumed that latent variables (associated with attitudes and perceptions) explain a set of indicators previously gathered from the individuals (through so called *measurement equations*), while being explained by a set of characteristics from the users and the alternatives (through so called *structural equations*). HDC modeling basically consists in the use of latent constructs associated with a MIMiC model as explanatory variables in a DCM framework.

Despite not having a great impact in its origins (mainly due to computational issues), HDC modeling was revitalized during the last decade (Ben-Akiva *et al.*, 2002). Since then, the approach has gained popularity and has become a standard tool in travel behavior research (v. Acker *et al.*, 2011; Ashok et al., 2002; Raveau *et al.*, 2012; Alvarez-Daziano and Bolduc, 2013; Bahamonde-Birke and Ortúzar, 2014a; among many others).

Notwithstanding, the indicators are usually considered as a linear continuous expression of the latent variables (Vredin-Johansson *et al.*, 2006; Bahamonde-Birke and Ortúzar, 2014b; Yañez *et al.*, 2010; Alvarez-Daziano and Barla, 2012). This approach may induce an important bias, as respondents are normally asked to state their preferences, or level of agreement with a set of statements, using a discrete scale (Likert, 1932). Even if the modeler allows for the individuals to state continuous indicators, it is highly doubtful whether respondents would take this into consideration and decimal numbers may be underrepresented in favor of integers. Even more, it is a debatable point if the individual considers equally all values in the scale, as simplifying heuristics (Tversky and Kahneman, 1974) may cause some levels to be ignored (leading for instance to an overrepresentation of the extremes and the midpoint).

Therefore, the indicators should not be treated as discrete outcomes, but rather as ordinal ones (Daly *et al.*, 2012). However, the impact of considering the indicators as ordinal outcomes has major implications in terms of computational costs, as model estimation gets considerable more involved, especially when considering specifications not leading to close-forms expressions for the probabilities, such as Ordered Probit model (OPM). That is the reason why researchers considering ordinal indicators, tend to rely on the Ordered Logit model (OLM; Daly *et al.*, 2012; Hess *et al.*, 2013).

4.2 Theoretical background

When considering a MIMiC model, the analyst assumes the existence of latent variables, which are a function of positively observed explanatory variables and, eventually, of other latent constructs (Kamargianni *et al.*, 2014; Link, 2015). This way, the above-mentioned structural equations may take the following form (assuming a linear specification):

$$\eta = \alpha_X \cdot X + \alpha_\eta \cdot \eta^* + \upsilon \qquad [4.1]$$

Here, η and η^* are vectors describing sets of jointly dependent endogenous latent constructs, X a set of exogenous observed explanatory variables and υ an error term that can follow any distribution, but is usually assumed to be normally distributed with mean zero and a given covariance matrix Σ_η. α_x and α_η are matrices of parameters to be estimated.

In a MIMiC structure, this set of equations will always be unidentified (it is mandatory), so that it is necessary to consider it in conjunction with a measurement equations set. The latter may be described in the following manner (again assuming a linear specification):

$$I = \gamma_X \cdot X + \gamma_\eta \cdot \eta + \varsigma \qquad [4.2]$$

where I is a vector of exogenous indicators and ς an error term, the distribution of which will depend on the assumptions regarding the indicators. Finally γ_x and γ_η are matrices of parameters to be estimated.

Sufficient and necessary conditions for identification of the equations' sets are well-known (Bollen, 1989) and it is necessary to constrain either some parameters or the variance associated with the error terms of the structural equations[22] (which is preferred in this work, given the fact that it simplifies selecting the parameters to be constrained). That being the case, the model can be estimated maximizing the likelihood function (once the structural equations have been reduced):

$$L = \int_\eta P(I \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) \cdot f(\eta \mid X, \eta^*; \alpha, \upsilon) \cdot d\eta \qquad [4.3]$$

As mentioned in the previous section, for the sake of simplicity as well as for historical reasons (the first models relying on this structure were based on that assumption; Morikawa *et al.*, 1996; Ben-Akiva *et al.*, 2002) the indicators have been considered continuously distributed. This way, assuming normally distributed error terms with mean zero and a diagonal covariance matrix Σ_I for the measurement equations, the probability in equation [4.3] can be depicted in the following manner:

$$P(I \mid X, \eta; \alpha, \gamma, \upsilon) = \frac{1}{\sigma_I} \phi\left(\frac{I - \gamma_X \cdot X - \gamma_\eta \cdot \eta}{\sigma_I}\right) \qquad [4.4]$$

[22] It is important to notice that it only applies when working with more than one measurement equations. In other case it is necessary to impose one additional constrain.

where σ_I are the elements in the diagonal of Σ_I and are parameters to be estimated. ϕ stands for the pdf of the standard normal distribution.

When the indicators are no longer considered to be a continuous response, but ordinal variables (as they indeed are), equation [4.4] does not longer apply. In this case the probability of observing a given output would be given by:

$$\begin{aligned} &P(I = n \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) = P(\psi_{n-1} < \gamma_X \cdot X + \gamma_\eta \cdot \eta \leq \psi_n \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) \\ &= P(\psi_n < \gamma_X \cdot X + \gamma_\eta \cdot \eta \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) - P(\psi_{n-1} < \gamma_X \cdot X + \gamma_\eta \cdot \eta \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) \end{aligned} \quad [4.5]$$

Here, Ψ are thresholds to be estimated and n describes a given level of the ordinal variable *I*. This has *m* different levels of *I*, $\Psi_0 = -\infty$ and $\Psi_\mu = \infty$, with the intermediate thresholds increasing monotonically. Depending on the specification of the error term ς, which is normally assumed to be either normally or logistically distributed, with mean zero and diagonal covariance matrix Σ_I, equation [4.5] will lead to an OPM or OLM framework, respectively.

Combining a MIMiC model with a DC framework (considering latent variables into the utility function of one or more alternatives) leads to a HDC model, where under the assumption of additive linearity, the utility functions may be described in the following fashion:

$$U_j = \beta_X \cdot X + \beta_\eta \cdot \eta + \varepsilon \quad [4.6]$$

where β_x and β_η are vectors of parameters to be estimated and ε an error term that is usually assumed to follow an EV1 distribution with the same mean for all alternatives and a given covariance matrix. If the covariance matrix is considered to be diagonal, the choice probabilities will be given by a Logit model; if not the choice situation will be described by other member of the Generalized Logit family (for identifiability purposes some components of the covariance matrix must be constrained without loss of generality; Walker *et al.*, 2007). A given alternative *j* will be selected if $U_j > U_k \ \forall\ k \neq j$; in this case the dummy variable y_j takes a positive value. The likelihood function for the integrated framework will then take the following form:

$$L = \int_{\eta} P(I \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) \cdot P(y \mid X, \eta; \alpha, \beta, \varepsilon, \upsilon) \cdot f(\eta \mid X, \eta^{*}; \alpha, \upsilon) \cdot d\eta \qquad [4.7]$$

Observing equation [4.7], it is clear that the discrete choice component of the HDC model can be considered as just another measurement equation for the integrated framework, with the difference that its output is discrete and not ordinal. Moreover, when working with only one indicator, it would be enough to constrain the variances of the structural equations, as the discrete choice component will provide the additional information required to identify the model as it would be another indicator.

4.3 Simulation exercise

The main objective of this work is to compare the consequences of treating the indicators as continuous or ordinal outcomes, given different assumptions and distributions regarding the way in which they are stated. As both specifications cannot be directly compared statistically (given the underlying assumptions), we will conduct a qualitative analysis based on the likelihood for the overall model and for the discrete choice component only (which is the part, we aim to reproduce as accurately as possible[23]). Along the same line, we want to analyze if both specifications are affected by other characteristics of the sample, such as the variability of the structural equations (the importance of the stochastic part relative to the deterministic part which is independent of the normalization), the distribution of the indicators and the number of observations.

For that reason, we conducted first a simulation exercise. This allows us to analyze the aforementioned effects in a controlled environment (free of undesired effects) as well as to vary the characteristics we want to examine, when generating the samples.

[23] Focusing the analysis on parameter recovery is not expedient as magnitudes depend on the normalization, which is in turn, affected by the fact that in the estimation we are neglecting the assumptions used in the generation of the database.

4.3.1 Generation of the datasets

Following Williams and Ortúzar (1982) we generated different samples of simulated individuals behaving compensatory in a binomial Logit framework, according to the following structural and utility equations:

$$\eta = \alpha_1 \cdot X_{\eta 1} + \alpha_2 \cdot X_{\eta 2} + \alpha_3 \cdot X_{\eta 3} + \alpha_4 \cdot X_{\eta 4} + \upsilon \qquad [4.8]$$

$$\Delta U = \beta_{X1} \cdot X_1 + \beta_\eta \cdot \eta - \beta_{X2} \cdot X_2 + \varepsilon \qquad [4.9]$$

Here, $X_{\eta 1}$ follows a discrete uniform distribution across the population, taking the values 0 and 1 (or, alternatively, Bernoulli distributed with q = 0.5). Similarly, $X_{\eta 2}$ follows a discrete uniform distribution in the range [0; 2]. $X_{\eta 3}$ and $X_{\eta 4}$ are assumed to be continuous uniformly distributed across the sample in the ranges [0; 2] and [0; 3], respectively. Finally, $X_{\eta 3}$ and $X_{\eta 4}$ follow normal distributions N(4, 2) and N(8, 1.5), respectively.

All α and β parameters were fixed to 1 (to ease the comparison of the results). The error term of the reduced utility function is independent and identically distributed following a Logistic distribution with mean 0 and scale parameter 1 (in accordance with the binomial Logit framework) for all observations. Regarding the distribution of υ we considered it to be normally distributed with mean 0 and three different cases (named Case 1, Case 2 and Case 3), which differ only on the variability of the parameter by assuming standard deviations equal to 0.5, 1 and 2, respectively.

We also considered two indicators the measurement equations of which are simply the sum of a latent variable η and an error term ς, which distributes standard Normal. However, the situation is not as simple as by using a Likert-scale we only allow for the stated indicators to take integer values between 1 and 5. Therefore, it is necessary to define the way to relate this continuous equation to discrete indicators. We considered six different cases:

a) Case A: This corresponds to the simplest assumption, i.e. normalizing the results of the measurement equations, so that all are contained between 0 and 5, and then associating the results contained in the different quintiles of the distribution to the respective level of the indicators. This case resembles the assumptions behind treating the indicators as continuous variables.

b) Case B: Thresholds are established, so that the levels of the indicators have a uniform distribution.

c) Case C: As above, but the distribution of the levels follows a discrete approximation of an inverted triangular distribution. This case attempts to depict an overrepresentation of the extremes.

d) Case D: As above, but the distribution of the levels follows a discrete approximation of a triangular distribution. This case attempts to depict an overrepresentation of the intermediate levels.

e) Case E: As above, but the distribution of the levels follows a discrete approximation of an exponential function of the form:

$$f(x) = \frac{e^x - 1}{e - 2}$$

f) Case F: As above, but the distribution of the levels follows a discrete approximation of an exponential function of the form:

$$f(x) = e - e^x$$

Figure 4.1 represents graphically the different cases considered.

Altogether we generated 18 different samples of 25,000 pseudo-individuals. Additionally, and in order to test the influence of sample size we simulated populations of 5,000; 1,000 and 500 individuals. In this case we considered all six distributions for the indicators, but only Case 2 regarding the variability of the structural equations.

4.3.2 Estimation results

Our first interest was the influence of the indicators' distribution as well as of the variability of structural equations on the model results. With this goal we estimated

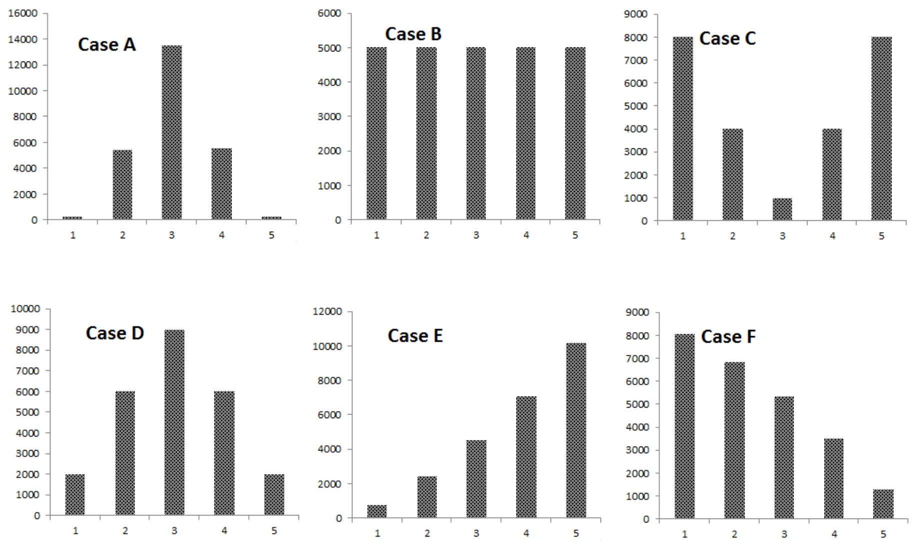

Figure 4.1 – Considered distributions for the indicators. Simulation exercise[24].

models for the 18 full-size samples, considering two different specifications: in the first one, we treated the indicators as continuous outputs and assumed that the error terms of the measurement equations distributed Normal; in the second specification, we considered the indicators to be of an ordinal nature and assumed logistically distributed error terms for the measurement equations; this leads to an OLM specification. Even though given the fashion in which the data was generated it would be more appropriate to consider an OPM specification, we opted for the logistic distribution, as this is the most common assumption when dealing with ordinal indicators in HDC models (given its computational advantages).

The models were estimated simultaneously using PythonBiogeme (Bierlaire, 2003). Taking advantage of the fact that we are dealing with only one latent variable the log-likelihood was computed via numerical integration. Table 4.1 presents results for the overall model for all cases analyzed. The upper results correspond to the assumption of discrete indicators while the inferior ones are related to the continuous specification.

[24] The actual distribution of the indicators considered in Case A depends on the variability of the structural equations. The distribution presented in Figure 4.1 corresponds to Case 1A (slight variability).

Table 4.1 – Goodness-of-fit of the overall model. Simulation exercise.

	Case A	*Case B*	*Case C*	*Case D*	*Case E*	*Case F*
Case 1	**-44,560.6**	**-69,244.4**	**-63,194.6**	**-61,367.4**	**-58,165.0**	**-63,240.4**
	-44,520.5	**-76,888.0**	**-88,821.7**	**-62,045.2**	**-66,678.6**	**-69,676.9**
Case 2	**-46,874.2**	**-72,506.4**	**-66,258.0**	**-64,676.7**	**-61,426.4**	**-66,457.5**
	-46,886.0	**-79,939.7**	**-91,551.2**	**-65,347.4**	**-69,365.6**	**-72,582.8**
Case 3	**-49,234.6**	**-74,317.8**	**-68,402.9**	**-66,808.3**	**-63,671.9**	**-68,478.3**
	-48,140.6	**-79,794.7**	**-91,524.9**	**-66,060.2**	**-69,402.5**	**-72,704.8**

As can be observed, the log-likelihood depends strongly on the distribution of the indicators. In line with our expectations, a greater relative variability in the structural equations affects negatively the log-likelihood of the estimated model. Regarding the estimation's assumptions, the discrete specification appears to clearly outperform the assumption of continuous indicators, when the distribution of the indicators is not linearly related to the continuous results of measurement equations (Case A). Additionally this former distribution provides the best overall fit, notwithstanding the assumptions considered in the estimation. The worst goodness-of-fit is associated with Case C (overrepresentation of the extremes), which is the case departing the most from the assumptions of Case A.

To offer a better comparison between both assumptions for the indicators, Table 4.2 presents the results for the logarithm of direct likelihood ratio (DLR; upper cell). The table also shows the logarithm of the DLR between both approaches considering the DC component of the model only (the likelihood of the model estimated under the OLM assumption is considered in the numerator of the DLR).

Table 4.2 – DLR between both approaches under different variability.

	Case A	*Case B*	*Case C*	*Case D*	*Case E*	*Case F*
Case 1	**-40.13**	**7,644.5**	**2,5627.3**	**677.8**	**8,513.6**	**6,436.6**
	-0.045	**1.577**	**3.391**	**0.096**	**3.044**	**1.665**
Case 2	**11.79**	**7,433.3**	**25,293.2**	**670.7**	**7,939.2**	**6,125.3**
	612.7	**604.4**	**621.1**	**599.1**	**652.3**	**609.3**
Case 3	**-1,094.1**	**5,476.9**	**23,122.0**	**-748.1**	**5,730.6**	**4,226.5**
	1,910.9	**1,823.8**	**1,900.4**	**1,800.6**	**1,892.2**	**1,838.8**

As mentioned before, the OLM specification clearly outperforms the continuous assumption in cases B, C, E and F, while the results are not conclusive for cases A and D (which present the most similar distribution of all considered cases). Nevertheless, the gap appears to diminish (or increase in favor of the continuous assumption), when the relative variability of the structural equation increases.

More telling than the overall log-likelihood, however, is to consider only the log-likelihood associated with the DC component of the model; first, this part is equal in both specifications and second, when considering a HDC, the focus remains on predicting the observed choices as accurately as possible and not the indicators. In this case, we cannot observe any significant difference when the relative variability of the structural equations is small but the gap increases dramatically as this variability gets larger (in opposition to the log-likelihood of the overall model). This finding applies to all distributions considered for the indicators.

Regarding the number of observations available for estimation, we have calibrated models considering different sample sizes, as described in the previous section. Table 4.3 presents the results for the logarithm of the direct likelihood ratio for the overall model and for the DC component. The results are normalized by the number of observations in order to make them comparable (the results are normalized to 500 observations).

Table 4.3 – Log-DLR between both approaches under different sample sizes.

# of Obs.	*Case A*	*Case B*	*Case C*	*Case D*	*Case E*	*Case F*
500	**5.184**	**164.732**	**513.641**	**14.134**	**184.892**	**142.275**
	13.318	**13.035**	**13.444**	**12.724**	**13.653**	**13.293**
1,000	**8.263**	**167.259**	**537.652**	**17.707**	**170.015**	**147.154**
	17.193	**17.094**	**17.385**	**16.877**	**16.264**	**17.151**
5,000	**-1.014**	**148.560**	**513.535**	**11.458**	**155.781**	**125.595**
	10.410	**10.335**	**10.667**	**10.124**	**14.082**	**10.497**
25,000	**0.236**	**148.666**	**505.863**	**13.414**	**158.785**	**122.506**
	12.253	**12.089**	**12.423**	**11.982**	**13.045**	**12.185**

As can be appreciated, there is no clear tendency regarding the goodness-of-fit and the number of observations used in the estimation. Moreover the gap between both approaches (for the overall model and for the DC component only) appears to stay constant, notwithstanding the number of observations.

Finally it must be remarked that, in this particular case, the convergence velocity of the continuous approach was about 50% superior, but it depends on the model structure and the starting values of the parameters.

4.4 Case study 4.1 – Electromobility in Austria

To provide further information for our analysis, we repeated our experiment considering real data. Our first case study comes from the DEFINE project and a web-based survey conducted in Austria during February 2013. The sample is representative for the Austrian society.

The survey considered a SP-experiment and was set in the context of choosing between different options of electromobility (for details see Bahamonde-Birke and Hanappi, 2016). The vehicle purchase experiment used 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 was described by the following attributes: purchase price (PP), power (PS), fuel costs (FC) and maintenance costs (MC). In addition to these attributes, the EV was further characterized 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), and a one-year-ticket for public transport (IM4).

Additionally, attitudinal indicators related to the degree of agreement with eight different sentences were collected. Bahamonde-Birke and Hanappi (2016) considered the following five of them to construct a latent variable related to the environmental attitude of the individuals: "*I am an ecologically aware person*" (EcAwareness), "*I pay attention to regional origins when shopping foods and groceries*" (LocalFood), "*I buy ecologically* *friendly products*" (EcoFriendly), "*Environmental protection measures should be enacted even if they result in job losses*" (Protection) and "*I pay attention to the CO2 footprint of the products I buy*" (CO2Footprint). The level of agreement was stated using a six points Likert scale. Figure 4.2 describes the distribution of the indicators and Table 4.4 presents an overview of the variables that are relevant to our study[25].

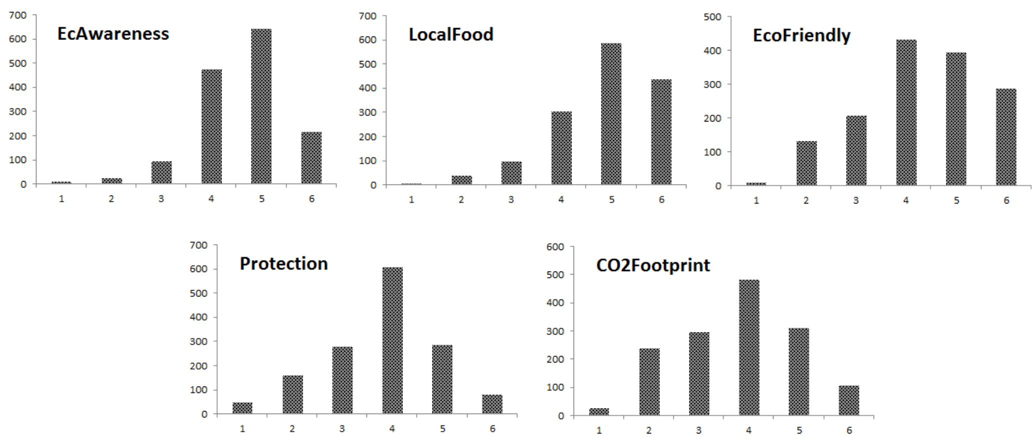

Figure 4.2 – Considered distributions for the indicators. Case study 4.1.

As can be observed from Figure 4.2, the distribution of the indicators is quite variable. In some cases the mode is given by one of the central points (4), while in other the upper third is overrepresented, departing from the assumptions of the hypothesis of continuity. The shape of the distributions differs from the shapes considered in our simulation exercise, but broadly tend to depict an overrepresentation of the intermediate levels.

We estimated two models following the approaches presented in the previous section. Again, taking advantage of having just one latent variable, the log-likelihood was computed using numerical integration. The results for the models assuming continuous (MCT1) and ordinal indicators (OLM1) are presented in Table 4.5. The results of the t-test for statistical significance are presented in parenthesis and the log-likelihood for the

[25] Bahamonde-Birke and Hanappi (2016) considered further variables and also estimated more involved models than the one considered in this study. For the purposes of this work, this specification is considered appropriate, as additional complexity would only add noise to our analysis as well as computational complexity. Bahamonde-Birke and Hanappi (2016) considered the attitudinal indicators to be a continuous expression of the latent variable.

overall model as well as for DC component is also reported (the results for the measurement equations are omitted, as they are not suitable for comparison).

Table 4.4 – Definition of the variables considered in the model. Case study 4.1.

Variable	***Definition***
MidSkill	Dummy variable indicating a career and technical education.
HighSkill	Dummy variable indicating a college education or higher.
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.
LSMid, LSHigh	Dummy variables indicating medium or high availability of loading stations for EV.
LV Green	Latent variable Green.
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".

As can be observed, the differences between the parameters obtained following both approaches are minor and not statistically different. Nevertheless and in line with our expectations, the most notable differences are related to the structural equations and the parameters associated with the latent variable in the DC model. The overall goodness-of-fit of the model considering ordinal indicators is much higher than the adjustment of the model neglecting the discrete nature of the indicators. Nevertheless, it does not translate into a better goodness-of-fit for the DC-component. Even more, the model considering continuous indicators predicts the choices stated by the individuals slightly better, which is counterintuitive as this model neglects the nature of the indicators. The difference between both models is however rather small and it cannot be concluded that one model would predict choices consistently better than the other. The situation resembles the cases with low relative variability of the latent variables in the simulation exercise.

Table 4.5 – Parameter estimates. Case study 4.1.

Variable	*Equation*	*MCT1*[26]		*OLM1*	
Vienna	*S.E. LV Green*	-0.135	*(-2.01)*	0.138	*(2.04)*
Male	*S.E. LV Green*	-0.286	*(-4.72)*	0.302	*(5.01)*
HighSkill	*S.E. LV Green*	0.599	*(6.64)*	-0.591	*(-6.58)*
MidSkill	*S.E. LV Green*	0.346	*(4.72)*	-0.342	*(-4.68)*
Old	*S.E. LV Green*	0.621	*(7.24)*	-0.608	*(-7.13)*
MidAge	*S.E. LV Green*	0.384	*(5.27)*	-0.374	*(-5.17)*
Carsharing	*S.E. LV Green*	0.634	*(4.59)*	-0.645	*(-4.62)*
CarUser	*S.E. LV Green*	-0.346	*(-6.67)*	0.356	*(6.85)*
ASC_CV	*Utility CV*	0	*(fixed)*	0	*(fixed)*
ASC_HEV	*Utility HEV*	-0.079	*(-0.38)*	-0.0744	*(-0.36)*
ASC_PHEV	*Utility PHEV*	-0.456	*(-2.09)*	-0.454	*(-2.09)*
ASC_EV	*Utility EV*	-0.954	*(-3.21)*	-0.928	*(-3.16)*
PP	*Utility CV*	-1.14	*(-9.4)*	-1.13	*(-9.42)*
PP	*Utility HEV*	-1.71	*(-24.11)*	-1.71	*(-24.13)*
PP	*Utility PHEV*	-1.75	*(-20.82)*	-1.75	*(-20.84)*
PP	*Utility EV*	-1.29	*(-12.7)*	-1.28	*(-12.77)*
MC	*Utility CV, HEV, PHEV, EV*	-17.5	*(-9.22)*	-17.5	*(-9.22)*
FC	*Utility CV, HEV, PHEV, EV*	-18.9	*(-16.37)*	-18.8	*(-16.39)*
PS	*Utility CV*	0.0284	*(5.76)*	0.0284	*(5.77)*
PS	*Utility HEV*	0.0338	*(8.32)*	0.0338	*(8.34)*
PS	*Utility PHEV*	0.0373	*(8.51)*	0.0373	*(8.54)*
PS	*Utility EV*	0.00269	*(0.71)*	0.00268	*(0.71)*
*PS * Male*	*Utility CV*	-0.0163	*(-4.21)*	-0.0163	*(-4.21)*
*PS * Male*	*Utility HEV*	-0.0144	*(-3.4)*	-0.0143	*(-3.38)*
*PS * Male*	*Utility PHEV*	-0.0136	*(-3.17)*	-0.0135	*(-3.16)*
*PS * Male*	*Utility EV*	-0.00605	*(-1.36)*	-0.006	*(-1.36)*
MidAge	*Utility HEV*	-0.266	*(-2.57)*	-0.256	*(-2.5)*
MidAge	*Utility PHEV*	-0.389	*(-3.72)*	-0.379	*(-3.66)*
MidAge	*Utility EV*	-0.652	*(-4.71)*	-0.632	*(-4.68)*
Old	*Utility HEV*	-0.997	*(-7.06)*	-0.982	*(-7.06)*
Old	*Utility PHEV*	-1.26	*(-8.48)*	-1.25	*(-8.5)*
Old	*Utility EV*	-1.86	*(-9.17)*	-1.82	*(-9.28)*
LV Green	*Utility HEV*	0.591	*(5.3)*	-0.58	*(-5.29)*
LV Green	*Utility PHEV*	0.558	*(4.88)*	-0.546	*(-4.87)*
LV Green	*Utility EV*	1.03	*(6.23)*	-0.991	*(-6.36)*
RA	*Utility EV*	0.00326	*(8.14)*	0.00325	*(8.18)*
LSMid	*Utility EV*	0.163	*(1.25)*	0.165	*(1.27)*
LSHigh	*Utility EV*	0.694	*(5.78)*	0.693	*(5.8)*
IM3	*Utility EV*	0.233	*(2.25)*	0.232	*(2.25)*
Log-likelihood Overall Model		-16,620.586		-16,202.677	
Log-likelihood DC Component		-6,625.468		-6,626.086	

[26] Even though we considered the same specification reported by Bahamonde-Birke and Hanappi (2016), the results may exhibit minor variations given the estimation technique (numerical integration as opposed to simulated maximum likelihood).

4.5 Case study 4.2 – Modal choice in Germany

In this SP experiment respondents were asked to choose between different interurban public transport alternatives in Germany (regional and intercity trains, and interurban coaches). The experiment was carried out in three waves (January 2014, March 2014 and April/May 2014), contacting students and employees of two universities in Berlin (the Technische Universität Berlin and the Humboldt-Universität zu Berlin), as well as employees of member institutions of the Leibniz-Gemeinschaft (for further details see Bahamonde-Birke *et al.*, 2016). Respondents were required to choose between a first pivotal alternative, representing a trip previously described, and a new one. Alternatives were described in terms of their travel time, fare, number of transfers, mode of transport - regional trains (RE), intercity trains (FVZ) and coaches (LB) - and a safety level.

The original study considered several indicators, associated with different and complex latent variables. For the purposes of this work we only considered one latent variable (TrainFan), which is associated with the following two indicators: "*Investing on the development of high-speed trains should be encouraged*" (HSTrains) and "*New high-speed rail lines should be built*" (RailLines). Originally the indicators were stated in a 10-points Likert scale. For computational issues in this application (opposite to the original study), we reduced it to only five, aggregating consecutive levels. As in the previous case, Figure 4.3 and Table 4.6 present the distribution of the indicators and an overview of the variables considered, respectively.

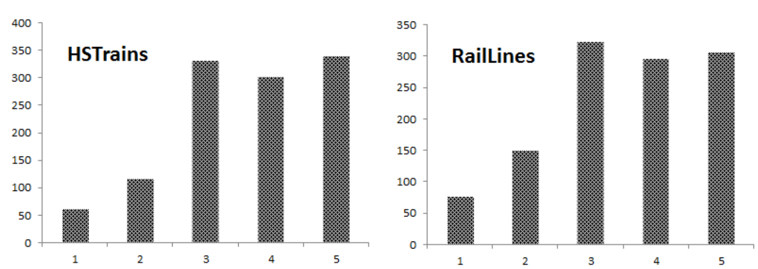

Figure 4.3 – Distributions for the indicators. Case study 4.2.

Table 4.6 – Definition of the variables considered in the model. Case study 4.2.

Variable	***Definition***
Old	Dummy variable indicating individuals older than 50 years.
Bahncard	Dummy variable indicating ownership of a Deutsche Bahn yearly discount card.
Woman	Dummy variable indicating feminine gender.
VeryLowIncome	Dummy variable indicating a net income under 700€ p.m.
LowIncome	Dummy variable indicating a net income between 700€ and 1,500€ p.m.
MiddleIncome	Dummy variable indicating a net income between 1,500€ and 2,500€ p.m.
HighIncome	Dummy variable indicating a net income over 2,500€ p.m.
Price	Travel fare in €.
TravelTime	Travel time in minutes.
Transfers	Number of transfers.
SafetyLevel	Number of severely injured passengers and the number of fatalities in the overall network over a year.
LV TrainFan	Latent variable TrainFan.
HSTrains	Attitudinal Indicator for "Investing on the development of high-speed trains should be encouraged".
RailLines	Attitudinal Indicator for "New high-speed rail lines should be built".

As in Case study 4.1, the distribution of the indicators exhibits an overrepresentation of the upper values, but in this case both distributions are rather similar and the upper levels appear to be uniformly distributed. They can be considered to be a mixture between cases B and D of the simulation exercise.

Table 4.7 presents the results for models assuming continuous (MCT2) and ordinal indicators (OLM2). Again the log-likelihood was computed using numerical integration. The structure of the table is the same as in previous section.

Table 4.7 – Parameter estimates. Case study 4.2.

Variable	***Equation***	***MCT2***		***OLM2***	
Inertia	***Utility Alternative 1***	**0.337**	*(13.48)*	**0.337**	*(13.48)*
FVZ	***Utility Alternative 1 and***	**0**	*(fixed)*	**0**	*(fixed)*
LB	***Utility Alternative 1 and***	**-1.41**	*(-12.65)*	**-1.41**	*(-12.62)*
RE	***Utility Alternative 1 and***	**-0.415**	*(-9.59)*	**-0.413**	*(-9.52)*
Travel Time	***Utility Alternative 1 and***	**-0.0149**	*(-26.57)*	**-0.0149**	*(-26.57)*
Ln(Price) * Very Low Income	***Utility Alternative 1 and***	**-5.27**	*(-31.91)*	**-5.27**	*(-31.9)*
Ln(Price) * Low Income	***Utility Alternative 1 and***	**-4.69**	*(-26.28)*	**-4.69**	*(-26.26)*
Ln(Price) * Middle Income	***Utility Alternative 1 and***	**-3.62**	*(-14.98)*	**-3.62**	*(-15)*
Ln(Price) * High Income	***Utility Alternative 1 and***	**-2.52**	*(-7.81)*	**-2.54**	*(-7.84)*
Safety Level	***Utility Alternative 1 and***	**-0.00374**	*(-4.59)*	**-0.00375**	*(-4.59)*
Transfers	***Utility Alternative 1 and***	**-0.443**	*(-18.25)*	**-0.443**	*(-18.25)*
FVZ * LV TrainFan	***Utility Alternative 1 and***	**0.293**	*(4.81)*	**0.298**	*(4.86)*
Log-likelihood Overall Model		**-10,802.674**		**-10,548.544**	
Log-likelihood DC Component		**-7,460.603**		**-7,460.161**	

Along the line of the previous case study, the differences among the parameters calibrated following the two different specifications are not statistically significant and the major disparities are related to the structural equations models. Again, the overall goodness-of-fit of the model considering the discontinuity of the indicators is superior, but this time, in line with our expectations, the simulation exercise and the results by Daly *et al.* (2012), the proper treatment of the attitudinal indicators is also associated with a better adjustment in the DC-component. However, the difference between the goodness-of-fit for the DC-component is rather small and no conclusive result regarding the predictability of the HDC model, can be derived from the experiment.

4.6 Conclusions

Despite the fact that attitudinal and perceptual indicators normally exhibit a discrete nature (even if the modeler would allow for stating continuous values), based on tradition and on computational reasons they are still predominantly treated as continuous outcomes. Even though the number of studies treating indicators as they are (i.e. discrete) has risen in the last years, the importance of the bias imposed by treating them continuously has not been yet extensively analyzed.

We conducted a study based on simulated and real data, to examine the effects of the usual assumptions concerning attitudinal and perceptual indicators. Along this line, we examined the effect of the relative variability of the latent variables, the distribution of the indicators and the number of observations.

Based on simulated data we were able to show that discrete distributions (for indicators) associated with non-uniformly spaced thresholds are associated with a clear deterioration of the overall goodness-of-fit, and that this phenomenon considerably increases when the estimators are treated as continuous outcomes. A higher relative variability of the latent variables appears, however, to reduce the gap between both approaches.

When focusing exclusively on the predictive capacity of the DC-component (which is the part, modelers usually center their efforts on), we discovered a clear worsening of the adjustment when treating the indicators continuously, as the relative variability of the latent variables increased. This deterioration applies to all distributions considered and is negligible when this variability is small. Concerning the number of observations, it was not possible to observe a clear tendency regarding the differences between both approaches and the amount of available information.

Finally, we tested these findings with real data. In both case studies analyzed, the distribution of the indicators departed from the traditional assumptions underpinning the hypothesis of continuity and, as expected, treating the indicators as ordinal outcomes offers a considerably better goodness-of-fit for the overall model. Unexpectedly, this improvement does not translate into a better predictive capacity of the discrete choices, as in the case associated with small relative variability of the latent variables in the simulation exercise.

Although we were not able to establish that treating the indicators as ordinal variables when dealing with HDC models improves the model´s predictive capacity (when dealing with real data), it must be stressed that considering them as continuous neglects their nature and yields worse overall model goodness-of-fit. Therefore, we recommend considering indicators as ordinal outcomes. However, this treatment is associated with higher computational costs and, given the fact that there is no evidence of significant deterioration in forecasting abilities, a trade-off may be considered.

CHAPTER 5[27]

ABOUT THE CATEGORIZATION OF LATENT VARIABLES

[27] This chapter is based on the article: Bahamonde-Birke, F.J. and Ortúzar, J. de D. (2015). About the categorization of latent variables in hybrid choice models. *4th hEART Symposium of the European Association for Research in Transportation*, København, Denmark, 9-11, September, 2015.

5.1 Introduction

Although firstly suggested during the 80s (McFadden, 1986; Train *et al.*, 1987), hybrid discrete choice models (HCM) did not become a hot topic in travel behavior research until revitalized by Ben-Akiva *et al.* (2002). Then, it was possible to solve a series of computational issues that had prevented this approach becoming a standard tool in discrete choice (DC) modeling.

Starting from the usual hypotheses of discrete choice modeling (McFadden, 1974), HCM aim to enrich the model, taking into account unobserved characteristics of the individuals and of the alternatives. This way, indicators (usually stated on a Likert-scale; Likert, 1932) related with attitudes toward life and perceptions about the alternatives on offer, are gathered from a sample of individuals. As these indicators are not considered attributes on their own, but rather an expression of underlying attitudes and perceptions, the modeler usually relies on a Multiple Indicators Multiple Causes (MIMiC) model (Zellner, 1970; Bollen, 1989), allowing for the identification of unobserved latent variables explaining the indicators. It is assumed that these variables also affect the typical utility function of the DC-model, enriching it with exogenous information captured through the indicators.

Although this approach has become popular (v. Acker *et al.*, 2011; Ashok *et al.*, 2002; Daziano and Bolduc, 2013; Bahamonde-Birke and Ortúzar, 2014a; among many others), the way in which different types of latent variables are considered into the utility function has not been extensively analyzed; in fact, they are generally introduced in a simplistic additive fashion, while being explained only by characteristics of the individuals (Vredin-Johansson *et al.*, 2006; Yañez *et al.*, 2010; di Ciommo *et al*, 2013). That being the case, Chorus and Kroesen (2014) argue (rightly) that these types of models do not allow deriving policy implications.

On another hand, Bahamonde-Birke *et al.* (2016) argue that we must distinguished between attitudes (including attitudes toward alternatives and toward perceptions), based on the individual's experience and temperament (Allport, 1935; Pickens, 2005) and real perceptions, related to the way in which individuals perceive their environment (Lindsay and Norman, 1972), as the latter are influenced by the characteristics of the alternatives and not only by those of the individuals (Pickens, 2005). They state that attitudinal latent variables (in contrast with real perceptions) resemble the socioeconomic characteristics of the individuals and hence they should be treated in the same fashion. That being the case, systematic taste variations and categorizations of the latent variables should be considered, rather than just including variables accounting for attitudes in an additive fashion. For example, it may be preferable to identify environmentally aware or wealthy individuals, rather than attempting to associate them with a value in a continuous scale; moreover, it is highly disputable that this characteristics should have a linear impact on decisions.

It is important to note that categorizing a latent variable would depict *de facto* a latent class model (Kamakura and Russell, 1989; Bhat, 1997) - beyond theoretical issues, related to causality - with every category representing a different latent class. In fact, by starting from a latent class model and attempting to enrich the identification of the classes by using indicators, the modeler could face a similar problem.

This chapter provides a theoretical discussion about the different factors affecting the categorization of latent variables, as well as their consequences. In the same line, we consider previous attempts that have been conducted to deal with this problem. Finally, we propose an alternative way to categorize latent variables and test our hypotheses with the help of two study cases (real data). We compare the results obtained, following the previously described approaches and offer a discussion about the implications and assumptions of the various methods. This discussion offers valuable insights about the way in which attitudes should be treated in hybrid discrete choice models.

5.2 Methodological framework

In a HDC framework (Ben-Akiva *et al.*, 2002), individuals are assumed to exhibit utility functions which take the following shape (under the assumption of additive linearity):

$$U_j = \beta_X \cdot X + \beta_\eta \cdot \eta + \varepsilon \qquad [5.1],$$

where X stands for observed attributes of the alternatives and characteristics of the individuals, while η is a vector representing the unknown latent variables. β_x and β_η are vectors of parameters to be estimated, and ε an error term. If ε is considered to follow an EV1 distribution with the same mean for all alternatives and a diagonal covariance matrix, the choice probabilities will be given by a Logit model. If the covariance matrix is not diagonal, other member of the Generalized Logit family may describe the choice situation; finally, assuming a Normal distribution leads to the Probit model. For identifiability purposes, some components of the covariance matrix must be constrained without loss of generality (Walker *et al.*, 2007). A given alternative j will be selected if $U_j > U_k \ \forall\ k \neq j$; in this case the dummy variable y_j would take a positive value.

The latent variables are constructed in accordance with a MIMiC model and are a function of positively observed explanatory variables and, eventually, of other latent constructs (Kamargianni *et al.*, 2014; Link, 2015). This way, assuming a linear additive specification, these structural equations may be described in the following manner:

$$\eta = \alpha_X \cdot X + \alpha_\eta \cdot \eta * + \upsilon \qquad [5.2],$$

where X, is once more the set of exogenous observed explanatory variables; η and $\eta*$ are vectors of latent constructs and υ an error term following any distribution, but usually assumed to be Normal with mean zero and a given covariance matrix Σ_η. Finally, α_x and α_η are matrices of parameters to be estimated.

In this framework, the structural equations set is unidentified[28], and it is mandatory to consider it jointly with a measurement equations set (for identifiability purposes, the utility function itself may be considered as an extra measurement equation; Bahamonde-Birke and Ortúzar, 2015). Assuming a linear specification the latter may be represented as follows:

$$I = \gamma_X \cdot X + \gamma_\eta \cdot \eta + \varsigma \qquad [5.3],$$

[28] Even when considering both set of equations jointly, it is still necessary to fix certain parameters without loss of generalization (typically the variances of the structural equations) to achieve identification (Vij and Walker, 2014).

where I is a vector of exogenously gathered indicators and ς an error term, the distribution of which depends on the assumptions regarding the indicators; when considering the indicators as a continuous output, ς is usually assumed to be Normal (Vredin-Johansson *et al.*, 2006; Daziano and Barla, 2012); in turn, when the indicators are considered to be of discrete nature, ς may be assumed to follow a Logistic distribution (Daly *et al.*, 2012; Hess *et al.*, 2013); in both cases the distributions have zero mean and a diagonal covariance matrix Σ_I; finally, γ_x and γ_η are matrices of parameters to be estimated.

The estimation of the integrated framework may be performed sequentially (estimating first the MIMiC model and then considering the latent variables into the discrete choice component) or simultaneously. Nevertheless, estimating the model sequentially is not advisable as it may lead to biased results (Bahamonde-Birke and Ortúzar; 2014b). For simultaneous estimation, the likelihood function for the integrated framework would take the following form:

$$L = \int_{\eta} P(y \mid X, \eta; \alpha, \beta, \varepsilon, \upsilon) \cdot P(I \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) \cdot f(\eta \mid X, \eta^*; \alpha, \upsilon) \cdot d\eta \qquad [5.4],$$

where the first part corresponds to the likelihood of the discrete choice component and the second stands for likelihood of observing the gathered indicators. The third component corresponds to the distribution of latent variables over which the likelihood function must be integrated.

5.2.1 Categorizing a latent variable

This is not an easy subject (in contrast with observed socio-economic characteristics such as income or age), as these variables are not observed and consequently exhibit an intrinsic variability. Under these circumstances, it is not possibly to assign an individual to a specific group but only to establish a probability with which an individual should be categorized in given way. Moreover, as latent variables do no exhibit an unequivocal scale, it is not easy to establish thresholds for the categorization, and as such the process appears to be rather arbitrary.

An intuitive approach to deal with the aforementioned problem would be to construct a dummy variable taking a positive value when a given latent variable η_c exceeds a certain threshold ψ. This way, it would be possible to establish a probability with which a certain individual should be categorized in a given way, defining a latent class model indirectly (when the dummy variables are introduced into the utility function). Then, it should be possible to calibrate the threshold and the likelihood function would take the following form (assuming only two categories, but extending the framework for more categories is straightforward):

$$
\begin{aligned}
L = & \int_{\eta} P(y \mid X, \eta, 0; \alpha, \beta, \varepsilon, \upsilon) \cdot P(I \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) \cdot f(\eta \mid X, \eta^*; \alpha, \upsilon) \cdot d\eta \cdot P_c \\
& + \int_{\eta} P(y \mid X, \eta, 1; \alpha, \beta, \varepsilon, \upsilon) \cdot P(I \mid X, \eta; \alpha, \gamma, \varsigma, \upsilon) \cdot f(\eta \mid X, \eta^*; \alpha, \upsilon) \cdot d\eta \cdot (1 - P_c)
\end{aligned} \quad [5.5],
$$

with the probability of an individual being categorized in certain fashion (P_c) given by:

$$
P_c = P(\eta_c < \psi \mid s, \alpha, \upsilon) = P(\alpha_{Xc} \cdot X + \alpha_{\eta c} \cdot \eta^* + \upsilon_c - \psi < 0) \quad [5.6]
$$

Unfortunately HDC models do not exhibit a close form for the probabilities (given their complex error terms structure) and therefore they are estimated using simulation (Ben-Akiva *et al.*, 2002; Bierlaire; 2003). This way we do not observe a continuous distribution for the error term υ of the latent variable η_c, but rather a set of stochastic (or pseudo-stochastic) draws describing a probability function. As a consequence, discontinuity issues arise, the threshold cannot be calibrated and a perfect convergence of the algorithm cannot be theoretically assured[29].

a) Latent variable latent class approach (LVLC)

An alternative to overcome the problem above would be to rely on an auxiliary continuous distribution function, to establish the probability with which a certain individual would be categorized in given manner. This approach will lead to the latent variable/latent class specification (Walker and Ben-Akiva; 2002; Hess *et al.*, 2013). This way the likelihood of

[29] When considering the model sequentially by integrating over the domain of the latent variables, the model achieves perfect convergence, but the threshold remains unidentified and must be fixed a priori (Bahamonde-Birke *et al.*, 2016).

the individual belonging to a certain latent class is given by the probability of the latent variable being smaller (or larger) than a threshold (to be calibrated), making use of the auxiliary function. If we assume this auxiliary function to be a Logistic distribution, equation [5.6], may be depicted as follows (Hess *et al.*, 2013)[30]:

$$P_c = \frac{1}{e^{\lambda(\eta_c - \psi)} + 1} = \frac{1}{e^{\lambda(\alpha_{Xc}\cdot X + \alpha_{\eta c}\cdot \eta^* + \upsilon_c - \psi)} + 1} \quad [5.7],$$

which is indeed a continuous expression. Unfortunately, this approach implies adding (artificially) the variability associated with the auxiliary distribution function (or of the latent class model, if we approach the modeling from this perspective) to the latent variable's own variability υ. Even though it may be argued that the extra variability (which may be calibrated – note that in this specification λ is perfectly identified) represents the error induced in the categorization process, there is no clear statistical justification for that.

To avoid the inclusion of the extra variability, the modeler may exogenously fix λ at a high level, but when doing so mathematical issues arise.

b) Latent class with psychometric indicators approach (LCPI)

This approach (Hurtubia *et al.*, 2014) does not attempt to categorize continuous latent variables *per se*, but rather to include psychometric indicators into a latent class framework. In this structure, it is assumed that the latent variable depends exclusively on positively observed characteristics of the individuals (X)[31], while its error term follows a Logistic distribution with zero mean and scale parameter λ (which has to be fixed without loss of generality). Under this assumption, the probability of an individual belonging to a certain class is given by:

$$P_c = \frac{1}{e^{\lambda(\alpha_{XC}\cdot X - \psi)} + 1} \quad [5.8],$$

[30] In the original specification Hess *et al.* (2013) multiply η_c by a parameter to be estimated and fix λ, but it is straightforward to see that both specifications are equivalent.

[31] Even though the model by Hurtubia *et al.* (2014) only considers characteristics of the individuals as explanatory variables, it is straightforward to extend it for attributes of the alternatives.

As can be observed, this approach overcomes the variability issues of the LVLC, considering only the logistically distributed error term. The main difference between this approach and the HDC framework is that in this case the latent variable does not impact directly on the measurement equations, but rather indirectly. This way the measurement equations are just a function of positively observed characteristics of the individuals (X) and the parameters to be calibrated depend on the latent class the individual is associated with. Thus, under this approach equation [5.3] exhibits the following structure:

$$I = \gamma_{XC} \cdot X + \varsigma \qquad [5.9],$$

where γ_{xc} is a latent class specific matrix of parameters. This leads to the following likelihood function (it is important to note that the original structure does not require integrating over the domain of the categorized latent variable, as the probability functions are given by closed-form expressions; it is straightforward to extend this approach in order to consider non-categorized latent variables):

$$\begin{aligned} L &= P(y \mid X, 0; \alpha, \beta, \varepsilon, \upsilon) \cdot P(I \mid X, 0; \alpha, \gamma, \varsigma, \upsilon) \cdot P_c \\ &+ P(y \mid X, 1; \alpha, \beta, \varepsilon, \upsilon) \cdot P(I \mid X, 1; \alpha, \gamma, \varsigma, \upsilon) \cdot (1 - P_c) \end{aligned} \qquad [5.10],$$

This approach offers computational advantages (as it requires no integration over the domain of the latent variables) as well as statistical consistency. One disadvantage relies on the fact that it does not allow for the latent variable to be considered directly (continuously) into the measurement equations. This may be necessary, for instance, when using a latent variable accounting for wealth (under the presence of unreported information; Sanko *et al.*, 2014) in a categorized fashion (Bahamonde-Birke and Hanappi, 2016), among other specifications.

Additionally, it must be pointed out that the interpretation of results tends to be rather obscure, especially in the case of the measurement equations, as these may be related to the absence of causality assumptions inherent to latent-class models. Opposite to the HDC framework, where it is assumed that the stated indicators are an expression of underlying attitudes and perceptions, in the LCPI approach the indicators are a tool to improve class-identification (individuals would be more or less likely to belong to a certain latent class given the indicators they have stated) and no assumptions regarding their causes are made. Along the same line, the interpretation of the function used to categorize the individuals remains obscure (which is also a deficiency of latent-class models), as it is not easy to establish a clear meaning for it (opposite to the latent variables, for instance) and often it appears to be rather an ad-hoc function to classify the individuals.

Finally, the complex structure of the LCPI framework (which requires the joint consideration of several sets of latent-class specific equations) is very demanding in terms of data variability. Hence, empirical identification issues arise and simpler structures must be favored for the categorizing function (at the expense of a theoretical interpretation).

c) Direct categorization of latent variables approach (DCLV)

Starting from the classical HDC framework (equations [5.1], [5.2] and [5.3]), we propose assuming an independent Logistic distribution with zero mean and given scale parameter (which can be fixed without loss of generality) for the error term υ_{c1} of equation [5.2][32]. Under this assumption equation [5.6] may be represented as a continuous expression.

$$P_c = P(\eta_c < \psi \mid s, \alpha, \upsilon) = P(\alpha_{Xc} \cdot X + \alpha_{\eta c} \cdot \eta^* + \upsilon_{c1} - \psi < 0) = \frac{1}{e^{\lambda(\alpha_{Xc} \cdot X + \alpha_{\eta c} \cdot \eta^* - \psi)} + 1} \qquad [5.11]$$

In order to include the latent variable directly into the measurement equations (as in equation [5.3]), it is still necessary to rely on simulation. For that matter we can construct a second latent variable, which is equivalent to the original one, but includes a simulated error term υ_{c2}, the specification of which is exactly the same as that considered in equation [5.11].[33] This way the likelihood function is not subject to discontinuity issues, while it still may be integrated over the domain of the latent variables relying on simulation techniques.

It is important to note that the DCLV framework would dominate the LCPI approach, as in this case is possible to include class specific parameters into the measurement equations (via the inclusion of a dummy associated with the categorized latent variable).

[32] Just in the case of the latent variable to be categorized. The error of additional latent variables may follow any distribution.

[33] It is important to note that it would be necessary only to fix the scale parameter of one error term (the continuous or the simulated one) and the second could be estimated; but this is not advisable for

Nevertheless, it must be pointed out that the inclusion of latent class specific parameters must be carefully considered and be in accordance with any underlying hypotheses. In other case, the modeling would be subject to the same problems of the latent class structures (LC, LCPI) and, therefore, it may be advisable to omit using latent class specific parameters in the measurement equation.

Thus, the general specification (considering latent class specific parameters in the measurement equations) for the likelihood function following the DCLV approach (considering only two categories) is the following:

$$\begin{aligned} L = & \int_{\eta} P(y \mid X, \eta, 0; \alpha, \beta, \varepsilon, \upsilon) \cdot P(I \mid X, \eta, 0; \alpha, \gamma, \varsigma, \upsilon) \cdot f(\eta \mid X, \eta^*; \alpha, \upsilon) \cdot d\eta \cdot P_c \\ & + \int_{\eta} P(y \mid X, \eta, 1; \alpha, \beta, \varepsilon, \upsilon) \cdot P(I \mid X, \eta, 1; \alpha, \gamma, \varsigma, \upsilon) \cdot f(\eta \mid X, \eta^*; \alpha, \upsilon) \cdot d\eta \cdot (1 - P_c) \end{aligned} \quad [5.12],$$

5.2.2 Limitations

The main limitation associated with all the approaches mentioned above, is the necessity of a continuous closed-form expression (as the Logistic distribution) for the categorizing function. This may appear to be a rather innocuous limitation, but it has major implications when working with panel data (or pseudo-panel data). In this case, integration over the domain of the latent variables should be performed on an individual level (e.g. via random panel effects; Bhat and Gossen, 2004). Although it is possible to include random panel effects, the fact that the error terms associated with the categorizing function are independent, would cause the categorization to be, at least to a certain extent, independent for all choices of the same individual.

Another inconvenient is related with the non-monotonicity of the categorizing function. This leads to the existence of local optima and therefore the categorization's threshold will depend on the starting value. Nevertheless, this problem is common to all latent class approaches.

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statistical and theoretical consistency (we are assuming that both variables represent the same error term).

5.3 Case studies

To analyze the different approaches presented in Section 5.2, we compared them making use of empirical data. Even though in the previous section we allowed for the DCLV framework to consider latent class specific parameters in the measurement equations, it is highly disputable if it would be advisable (given the lack theoretical justification); moreover HDC models usually do not even consider positively observed attributes in the measurement equations. For that reason, in our analysis we will just consider latent variables as explanatory variables in the measurement equations, when following the LVLC and DCLV approaches (the structure of both approaches will only differ in the specification of the error terms). This allows for a direct comparison between both approaches.

LCPI models exhibit a totally different structure and, therefore, a fair comparison is not possible. First, because of the aforementioned empirical identification issues, it would not be possible to consider the same degree of complexity for the categorizing function (structural equations). In fact, when doing so, it was only possible to work with one of five indicators in Case study 4.1 and with none (out of two) in Case study 4.2, and for that reason simpler specifications should be analyzed at the expense of the meaning of the classes being constructed. Second, a comparison of the goodness-of-fit would be spurious, as the LCPI must necessarily be more likely than models estimated according to the LVLC or DCLV specifications. In the LCPI classes are defined exclusively to maximize the goodness-of-fit and are not based on theoretical assumptions (additionally, the measurement equations would have more degrees-of-freedom). As a matter of fact, if we consider the likelihood of the discrete choice component only, it is clear that a simple latent class model (with no indicators) would outperform every competing approach (including the LCPI; Hurtubia *et al.*, 2014), as in this case the latent classes do not have to satisfy, additionally, a distribution of indicators or theoretical assumptions.

As a consequence we do not consider the LCPI in our empirical analysis, and our conclusions in this sense will be based exclusively on the aforementioned theoretical arguments.

5.3.1 Case study 5.1 - Electromobility in Austria

Our first case study comes from the DEFINE project and a web-based survey conducted in Austria during February 2013. The survey considered a SP-experiment and was set in the context of choosing between different options for electromobility (Bahamonde-Birke and Hanappi, 2016). The sample was representative of the Austrian society and consisted of 1,449 respondents, where 787 of them were considered in the discrete choice experiment.

This vehicle purchase experiment used a labelled experimental design, including four alternatives referring to different propulsion technologies: conventional vehicles (CV), plug-in hybrid-electric vehicles (PHEV), hybrid-electric vehicles (HEV) and electric vehicles (EV). Each alternative was described by the following attributes: purchase price (PP), power (PS), fuel costs (FC) and maintenance costs (MC). In addition to these attributes, the EV was further characterized 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 using 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), and a one-year-ticket for public transport (IM4).

Additionally, attitudinal indicators related to the degree of agreement with eight different sentences were collected. Bahamonde-Birke and Hanappi (2016) considered the following five of them to construct a latent variable related to the environmental attitude of the individuals: "*I am an ecologically aware person*" (EcAwareness), "*I pay attention to regional origins when shopping foods and groceries*" (LocalFood), "*I buy ecologically friendly products*" (EcoFriendly), "*Environmental protection measures should be enacted even if they result in job losses*" (Protection) and "*I pay attention to the CO2 footprint of the products I buy*" (CO2Footprint). The level of agreement was stated using a six points Likert scale (Likert, 1932). Table 5.1 presents an overview of the variables that are relevant to our study[34].

[34] Bahamonde-Birke and Hanappi (2016) considered further variables and also estimated more involved models than those considered in this study. For the purposes of this work, this specification was

Table 5.1 – Definition of the variables considered in the model. Case study 5.1.

Variable	*Definition*
MidSkill	Dummy variable indicating a career and technical education.
HighSkill	Dummy variable indicating a college education or higher.
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.
LSMid, LSHigh	Dummy variables indicating medium or high availability of loading stations for EV.
LV Green	Latent variable Green accounting for environmental awareness.
CLV Green	Categorized latent variable Green accounting for individuals with high environmental awareness.
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".

We estimated two models following the approaches presented in the previous section, using PythonBiogeme (Bierlaire, 2003). Taking advantage of having just one latent variable, the log-likelihood was computed using numerical integration. The latent variable (*LV Green*) accounts for environmental awareness and was categorized in two levels. The inclusion of an individual specific dummy variable (accounting for environmentally concerned individuals) associated with the alternatives HEV, PHEV and BEV, was the only difference between both classes. The results for the models are presented in Table 5.2. The results of the t-test for statistical significance are presented in parenthesis and the log-likelihood for the overall model, as well as for the DC component only, are also reported (the results for the measurement equations are presented in the appendix B.1). The indicators were considered discrete outputs following an ordered logit (OLM) approach (Bahamonde-Birke and Ortúzar, 2015).

considered appropriate, as additional complexity would only add noise to our analysis, as well as computational complexity.

Table 5.2 – Parameter estimates. Case study 5.1.

Variable	Equation	LVLC		DCLV	
Vienna	S.E. LV Green	-0.333	(-2.56)	-0.182	(-1.71)
Male	S.E. LV Green	-0.597	(-5.58)	-0.587	(-5.74)
HighSkill	S.E. LV Green	1.05	(6.16)	0.879	(5.89)
MidSkill	S.E. LV Green	0.536	(3.85)	0.477	(3.72)
Old	S.E. LV Green	1.09	(7.18)	0.955	(6.67)
MidAge	S.E. LV Green	0.657	(5.15)	0.615	(5.14)
Carsharing	S.E. LV Green	1.33	(4.9)	0.988	(4.99)
CarUser	S.E. LV Green	-0.567	(-5.53)	-0.474	(-5.7)
Threshold	C.F	3.76	(5.27)	2.23	(7.18)
Scale	C.F	0.538	(5.06)	1	(fixed)
ASC_CV	Utility CV	0	(fixed)	0	(fixed)
ASC_HEV	Utility HEV	-0.0165	(-0.07)	0.0945	(0.41)
ASC_PHEV	Utility PHEV	-0.235	(-0.94)	-0.207	(-0.88)
ASC_EV	Utility EV	-1.09	(-2.65)	-0.982	(-2.36)
PP	Utility CV	-1.21	(-7.92)	-1.27	(-9.07)
PP	Utility HEV	-1.8	(-22.39)	-1.79	(-22.85)
PP	Utility PHEV	-1.76	(-19.94)	-1.77	(-20.48)
PP	Utility EV	-1.66	(-9.79)	-1.73	(-10.69)
MC	Utility CV, HEV, PHEV, EV	-21.1	(-9.32)	-20.6	(-9.6)
FC	Utility CV, HEV, PHEV, EV	-21.4	(-14.96)	-20.7	(-15.87)
PS	Utility CV	0.0327	(5.22)	0.0341	(5.74)
PS	Utility HEV	0.0353	(7.18)	0.0348	(7.37)
PS	Utility PHEV	0.0354	(7.2)	0.0367	(7.5)
PS	Utility EV	-0.000269	(-0.05)	-0.000232	(-0.05)
PS * Male	Utility CV	-0.019	(-4.14)	-0.0195	(-4.21)
PS * Male	Utility HEV	-0.0164	(-3.38)	-0.0164	(-3.38)
PS * Male	Utility PHEV	-0.0155	(-3.16)	-0.0162	(-3.26)
PS * Male	Utility EV	-0.00302	(-0.55)	0.000491	(0.09)
MidAge	Utility HEV	-0.266	(-2.5)	-0.287	(-2.65)
MidAge	Utility PHEV	-0.383	(-3.46)	-0.374	(-3.48)
MidAge	Utility EV	-0.784	(-4.55)	-0.946	(-4.91)
Old	Utility HEV	-1.18	(-5.82)	-1.19	(-5.63)
Old	Utility PHEV	-1.44	(-6.24)	-1.35	(-6.07)
Old	Utility EV	-2.55	(-9.02)	-2.88	(-8.77)
CLV Green	Utility HEV	3.48	(6.86)	3.19	(6.56)
CLV Green	Utility PHEV	3.25	(6.08)	2.71	(4.84)
CLV Green	Utility EV	5.77	(8.5)	5.89	(9.83)
RA	Utility EV	0.00444	(6.25)	0.00459	(6.81)
LSMid	Utility EV	0.0121	(0.07)	0.0426	(0.25)
LSHigh	Utility EV	0.661	(4.22)	0.71	(4.43)
IM3	Utility EV	0.306	(2.19)	0.305	(2.14)
Log-likelihood Overall Model		-16,177.759		-16,169.571	
Log-likelihood DC Component		-6,612.876		-6,605.847	

As can be observed, the differences between the parameters obtained following both approaches are not large and many are not statistically different. This is valid for all parameters of the structural and measurement equations as well as for the utility functions, with the exception of the threshold parameter of the categorizing function. This parameter evidently exhibits a different value, as the LVLC approach is associated with a greater error and a wider distribution, implying that the threshold must be located further away from the expected value, in order to capture the same individuals.

Regarding goodness-of-fit, the DCLV approach exhibits a better performance than the LVLC. This superior adjustment is mostly explained by the discrete choice component. This result is in accordance with our expectations, as the LVLC considers an additional error component, which is indeed unnecessary for the estimation of the model. Along this line, the fact that the improvement in goodness-of-fit is mostly explained by the discrete choice component, is based on the fact that the categorization (and its additional error term) affects only the utility functions.

5.3.2 Case study 5.2 - Modal choice in Germany

In this SP experiment respondents were asked to choose between different interurban public transport alternatives in Germany (regional and intercity trains, and interurban coaches). The experiment was carried out in three waves (January 2014, March 2014 and April/May 2014), contacting students and employees of two universities in Berlin (the Technische Universität Berlin and the Humboldt-Universität zu Berlin), as well as employees of member institutions of the Leibniz-Gemeinschaft (for further details refer to Bahamonde-Birke *et al.*, 2014). Respondents were required to choose between a first pivotal alternative, representing a trip previously described, and a new one. Alternatives were described in terms of their travel time, fare, number of transfers, mode of transport - regional trains (RE), intercity trains (FVZ) and coaches (LB) - and a safety level.

The original study considered several indicators, associated with different and complex latent variables. For the purposes of this work we only considered one latent variable (TrainFan) again, which is associated with the following two indicators: "*Investing on the development of high-speed trains should be encouraged*" (HSTrains) and "*New high-speed rail lines should be built*" (RailLines). Originally the indicators were stated in a 10-points Likert scale. For computational issues in this application (opposite to the original study), we reduced it to only five, aggregating consecutive levels. Table 5.3 presents an overview of the variables considered.

Again, models were estimated following the LVLC and DCLV approaches. Estimation was performed using PythonBiogeme and considering numerical integration for the computation of the likelihood function. Indicators were considered discrete outcomes

(OLM). Table 5.4 presents the results for both models. The structure of the table is the same as in the previous case (results for the measurement equations are presented, again, in the appendix B.2).

Table 5.3 – Definition of the variables considered in the model. Case study 5.2.

Variable	*Definition*
Old	Dummy variable indicating individuals older than 50 years.
Bahncard	Dummy variable indicating ownership of a Deutsche Bahn yearly discount card.
Woman	Dummy variable indicating feminine gender.
VeryLowIncome	Dummy variable indicating a net income under 700€ p.m.
LowIncome	Dummy variable indicating a net income between 700€ and 1,500€ p.m.
MiddleIncome	Dummy variable indicating a net income between 1,500€ and 2,500€ p.m.
HighIncome	Dummy variable indicating a net income over 2,500€ p.m.
Price	Travel fare in €.
TravelTime	Travel time in minutes.
Transfers	Number of transfers.
SafetyLevel	Number of severely injured passengers and the number of fatalities in the overall network over a year.
LV TrainFan	Latent variable TrainFan.
HSTrains	Attitudinal Indicator for "Investing on the development of high-speed trains should be encouraged".
RailLines	Attitudinal Indicator for "New high-speed rail lines should be built".

Table 5.4 – Parameter estimates. Case study 5.2.

Variable	*Equation*	*MCT2*		*OLM2*	
Old	*S.E. LV TrainFan*	**0.207**	*-0.36*	**-0.093**	*-0.41*
Bahncard	*S.E. LV TrainFan*	**0.684**	*-5.41*	**0.673**	*-5.46*
Woman	*S.E. LV TrainFan*	**-0.686**	*(-5.64)*	**-0.663**	*(-5.75)*
MiddleIncome	*S.E. LV TrainFan*	**0.368**	*-3.19*	**0.426**	*-3.24*
HighIncome	*S.E. LV TrainFan*	**0.515**	*-2.53*	**0.606**	*-2.82*
Threshold	*C.F*	**0.622**	*(1.44)*	**-0.346**	*(-0.59)*
Scale Parameter	*C.F*	**10**	*(fixed)*	**1**	*(fixed)*
Inertia	*Utility Alternative 1*	**0.336**	*-13.48*	**0.345**	*-13.48*
FVZ	*Utility Alternative 1 and*	**0**	*(fixed)*	**0**	*(fixed)*
LB	*Utility Alternative 1 and*	**-1.17**	*(-12.65)*	**-0.559**	*(-12.62)*
RE	*Utility Alternative 1 and*	**-0.167**	*(-9.59)*	**0.448**	*(-9.52)*
Travel Time	*Utility Alternative 1 and*	**-1.49**	*(-26.57)*	**-1.56**	*(-26.57)*
*Ln(Price) * Very Low*	*Utility Alternative 1 and*	**-5.29**	*(-31.91)*	**-5.41**	*(-31.9)*
*Ln(Price) * Low Income*	*Utility Alternative 1 and*	**-4.7**	*(-26.28)*	**-4.85**	*(-26.26)*
*Ln(Price) * Middle Income*	*Utility Alternative 1 and*	**-3.63**	*(-14.98)*	**-3.8**	*(-15)*
*Ln(Price) * High Income*	*Utility Alternative 1 and*	**-2.54**	*(-7.81)*	**-2.67**	*(-7.84)*
Safety Level	*Utility Alternative 1 and*	**-0.00374**	*(-4.59)*	**-0.00408**	*(-4.59)*
Transfers	*Utility Alternative 1 and*	**-0.446**	*(-18.25)*	**-0.46**	*(-18.25)*
*FVZ * CLV TrainFan*	*Utility Alternative 1 and*	**0.716**	*(4.93)*	**1.42**	*(5.27)*
Log-likelihood Overall Model		**-10,543.642**		**-10,535.416**	
Log-likelihood DC Component		**-7,461.029**		**-7,453.871**	

While in Case 1 all estimators (aside from the threshold) were not statistically different in both models, in Case 2 the parameters associated with the categorized latent variable are statistically different. As the categorized latent variable is considered in conjunction with the modal parameter of the intercity trains, it also affects the remaining modal parameters. This difference may be attributed to the fact that changing the distribution (the variability) of the categorizing function may allow for identifying different groups of people. In fact, taking a look at the threshold parameters, it seems (accounting for the wider variability of the LVLC) that the thresholds have been set at a different level.

Notoriously in this case, when following the LVLC approach, the parameter associated with the scale parameter λ of the categorizing function diverged (at least in computational terms). For that reason it was necessary to fix it as 10 (greater values would lead to computational issues, when computing the Fisher information matrix, but neither the estimates nor the final value of the log-likelihood would be majorly affected).

Again, the DCLV approach offers a better adjustment than the LVLC model, which may be mainly related to a better explanation of the discrete choices. Interestingly in this case, the scale parameter of the LVLC model suggests that the categorizing function should be as similar to a Dirac delta function as possible. In this limit, the LVLC model would collapse to the DCLV. Nevertheless, achieving this limit (or getting close to it) is not possible due to computational limitations; therefore, it is impossible to get rid of the error induced through the LVLC approach.

5.4 Conclusions

Categorizing a latent variable or in general terms, defining the conditions to categorize individuals based on their latent characteristics should offer significant advantages in discrete choice modeling. Nowadays, the dominant approach for categorizing individuals is the latent class approach, but this method may be subject to criticism given its inherent lack of causality assumptions and the obscure interpretation of the functions used to define class-membership. Additionally, the approach does not take advantage of additional information, such as the perceptual and attitudinal indicators. This criticism may be overruled when latent-classes are used for identifying objective properties (such as missing information, lexicographic respondents, etc.); however, when attempting to model attitudes, perceptions, values and other latent characteristics of the individuals, alternative approaches may be favored.

In this work we explore different ways to improve the categorization of individuals, focusing on the categorization of latent variables. This approach exhibits, as main advantage, a clear interpretation of the function used in the categorization process (the latent variable), as well as taking exogenous information (perceptual and attitudinal indicators) into account. Unfortunately, technical issues (associated with the estimation technique via simulation) arise when attempting a direct categorization. Therefore, alternative strategies have been proposed.

First, we considered the LVLC approach, which effectively overcomes these technical issues, but is associated with an artificial increase in the error. A second method is the LCPI approach, but it is guilty of the same deficiencies of latent class models: lack of causality assumptions, obscure interpretation of the class-membership function and additionally in this case, obscure interpretation of the measurement equations for the indicators and major issues related to empirical identifiability. It is important to mention that, by definition, this approach should offer superior goodness-of-fit than alternatives approaches, as the class-membership function is constructed to maximize the adjustment and not in order to satisfy *a priori* theoretical hypotheses; we consider this one of its major disadvantages. Finally, we propose an alternative way to attempt a direct categorization of latent variables (DCLV). This approach overcomes the error issues of the LVLC.

We tested the aforementioned approaches with the help of two case studies. The LCPI approach was not considered (based on the just described theoretical concerns, as well as its empirical identifiability issues). Hence, we just considered the LVLC and DCLV approaches.

In the first case study, it was not possible to establish the existence of major differences in the estimated parameters (aside from the threshold parameter), but in the second case study, the differences in the variability of the class-membership function led to a different categorization. In line with our expectations, the DCLV approach offered a superior goodness-of-fit, as the LVLC introduced an additional error term. The improvements in goodness-of-fit were mainly explained by a better adjustment of the discrete choice component.

Based on our empirical results and theoretical analysis, the DCLV appears to be the superior approach. On the one side, it offers a consistent treatment of the error term, which is in accordance with the underlying theory. Along this line, it offers a better performance than the LVLC approach, in terms of the goodness-of-fit. Finally, the approach performed stably (no identification issues) for the considered case studies (opposite to the LCPI).

To end, it must be remarked that all approaches are based on non-monotonic categorizing functions leading to the existence of local optima. Therefore, different starting values must be evaluated. Additionally, is must be mentioned that the approaches do not allow considering the correlation among the responses provided by the same individual, when working with panel-data (at least to a certain extent). Further research must be conducted in this regard.

CHAPTER 6[35]

ABOUT ELECTROMOBILITY IN AUSTRIA AND MODELING WITH MISSING INFORMATION

[35] This chapter is based on the article: Bahamonde-Birke, F.J. and Hanappi, T. (2015). The potential of electromobility in Austria. An analysis based on hybrid choice models. *Transportation Research Part A: Policy and Practice* **83**, 30-41.
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6.1 Introduction

Both the coming scarcity and the negative environmental impact of fossil fuel resources as well as governmental guidelines are driving the automobile industry to focus on alternative, more efficient and cleaner, propulsion technologies. In addition, an increasing number of restrictive CO_2 emission regulations (Fontaras and Dilara, 2012) accompanied with rising fuel prices (Macharis *et al.*, 2010) have led to a significant change in the way that some characteristics of the automobiles are perceived. Consumers – and the public in general – are pushing for lower emission, more fuel efficient, and smaller engines (Fontaras and Samaras, 2010; Thiel *et al.*, 2014).

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

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

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

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

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

This chapter aims to analyze the acceptance of electric vehicles by the Austrian population as well as the perspectives of electromobility in the country, which, as previously mentioned, have only been cursorily studied in the past. This way, we provide functional models to analyze how different features of alternative powered vehicles may impact their adoption in Austria. Along this line, we analyze the impact that different incentive policies may have on the acceptance of electric vehicles, considering not only classical subsidies (as reported in the literature by Jenn *et al.*, 2013; Zhang *et al.*, 2014; among many others) but also policies encouraging the joint use of electrical vehicles and public transportation. Additionally, as we are forced to deal with unreported income under the presence of endogeneity and correlation with socio-economical characteristics of the individuals (making unsuitable the classic imputation techniques reported in the literature; Kim *et al.*, 2007; Fosgerau and Bierlaire, 2009), we develop an alternative approach to address this problem, extending the method proposed by Sanko *et al.* (2014). The rest of the chapter is organized as follows; Section 6.2 presents a brief description of our dataset as well as of the variables we are considering, while Section 6.3 offers a theoretical overview of the modeling background and enunciates our approach the deal with unreported income. Our results are discussed in section 6.4 and section 6.5 summarizes our conclusions.

6.2 Description of the dataset

Data was collected through a web-based survey conducted by a German commercial subcontractor (GfK) in February 2013. The sample of 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.[36] Individuals in the second subgroup did not receive the same DCE.

Each respondent received nine independent choice scenarios, which took about 20-30 minutes to complete; including the standard demographic questions. Although comparable studies sometimes restrict the number of choice scenarios to avoid a potential drop in attention, pre-testing of the questionnaire showed that respondents were generally comfortable with the load of information and the total duration. An important issue that emerged from this test was the relevance of the descriptions of (a) the propulsion technologies and (b) the availability of charging stations. While the choice scenarios were described within a simple table to facilitate comparison, additional pop-up boxes were used to convey more detailed information. This approach proved to be especially important to communicate e.g. the differences between hybrid-electric and conventional vehicles or improvements in the charging station network.

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

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

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

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

Although this type of preference-statement data cannot be directly used as explanatory variables in a discrete choice model, it provides further information on the underlying preferences of the individuals. Therefore it is argued, for instance, by Breffle *et al.* (2011) that this type of data is crucial for improving the modeling of heterogeneous preferences within standard discrete choice models. Our approach to this issue is outlined in section 6.3. In the context of this work, we only consider the information associated with the DCE on vehicle purchase. Nevertheless for estimating the models associated with attitudes toward life and income (see next section), we consider the information provided by all individuals.

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

The vehicle purchase DCE was based on a labeled experimental design including four choice alternatives referring to one propulsion technology each: conventional vehicles (CV), plug-in hybrid-electric vehicles (PHEV), hybrid-electric vehicles (HEV) and battery electric vehicles (BEV). Each alternative is described in terms of the purchase price (PP), power (PS), fuel costs (FC), and maintenance costs (MC). In addition to these attributes, the BEV is further characterized 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).

6.3 Methodological approach

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

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

$$P_{iq} = \frac{e^{\lambda \cdot V_{iq}}}{\sum_{j \in A(q)} e^{\lambda \cdot V_{jq}}} \qquad [6.1]$$

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

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

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

$$\eta_{liq} = \sum_r \alpha_{lri} \cdot s_{riq} + \upsilon_{liq} \qquad [6.2]$$

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

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

$$y_{ziq} = \sum_l \gamma_{lzi} \cdot \eta_{liq} + \varsigma_{ziq} \qquad [6.3],$$

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

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

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

$$L = \int_{\eta} P_{ij}(X,\eta)\cdot P(y\,|\,\eta;\gamma,\varsigma)\cdot f(\eta\,|\,s,\alpha,\upsilon)\cdot d\eta \qquad [6.4],$$

where the first term refers to the probability of the chosen alternative, as depicted in equation [6.1] (which, in turn, depends on observable characteristics of the individuals and of the alternatives of the alternatives X_{iq} and on the latent variables η_{liq}). The second term stands for the probability of observing a given indicator for a given individual and the last component represents the probability distribution of the latent variables.

6.3.1 Treatment of unreported information and other income related issues

The survey included questions regarding personal and household net income. Given the reluctance of individuals to reveal this information, respondents were not required to answer this question and 30.02% of the sample skipped these questions. A potential alternative addressing this problem is to construct a variable for all individuals skipping this question (Hall *et al.*, 2006; Fosgerau and Bierlaire, 2009; among many others), but it is highly debatable if it can be assumed that individuals skipping the income questions behave in a similar way, since the underlying factors affecting the decision to skip the question vary widely. Another approach would be to impute these variables (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 simultaneously include both in the utility function and the decision as to which variable is ultimately included should rely on theoretical arguments.

To address this problem we construct a latent variable measuring wealth in a broader sense, defined by a structural equation considering the socio-economic characteristics of the individuals. The personal and household net incomes are considered to be measured indicators of the individual's wealth, therefore explained by the latent variable through measurement equations. We use a discrete choice framework to model the decision whether to reveal information on personal and/or household income within the survey, as proposed by Sanko *et al.* (2014). To do this, we introduce a utility function associated with the likelihood of revealing income, which depends on the characteristics of the individuals as well as on the latent variable wealth, yielding as outcome the probability with which a certain individual would reveal their income. Figure 6.1 summarizes the way in which income is included in the model.

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

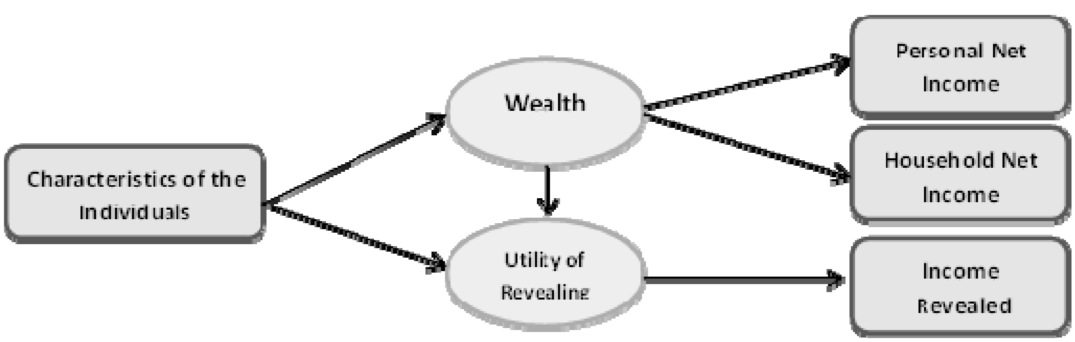

Figure 6.1 – Modeling framework for treating income information.

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

Finally, as a linear effect of the wealth on the decision making process is unrealistic, it is convenient to segment individuals into different categories. Therefore, the latent variable is categorized as proposed by Bahamonde-Birke *et al.* (2016). That being the case, equation [6.4] takes the following shape (when considering a categorization in two levels; straightforward for more levels):

$$L = \int_{\eta} P_{ij}\,(X,\eta,\eta_{WC}=0)\cdot P(y\,|\,\eta;\gamma,\varsigma)\cdot f(\eta\,|\,s,\alpha,\upsilon)\cdot d\eta\cdot P(d\eta_{W}<\psi\,|\,s,\alpha,\upsilon)$$
$$+\int_{\eta} P_{ij}\,(X,\eta,\eta_{WC}=1)\cdot P(y\,|\,\eta;\gamma,\varsigma)\cdot f(\eta\,|\,s,\alpha,\upsilon)\cdot d\eta\cdot P(d\eta_{W}\geq\psi\,|\,s,\alpha,\upsilon) \qquad [6.5],$$

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

6.3.2 Treatment of the environmental concern

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

The analysis reveals that not all of the indicators collected can be linked beyond doubt with greener attitudes. In fact, a factor analysis reveals that it is only possible to identify a high correlation for five of the statements (i, iv, v, vi and viii; see Appendix C.1).

Notwithstanding, an evaluation of the remaining indicators reveals that those are not actually related to their own attitudes but rather to an evaluation of either society (b and c) or the economy (g). Under these circumstances, the latent variable was constructed omitting these latter indicators.

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

6.4 Estimation and results

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

Variables relevant for the model are presented in Table 6.1. As can be seen from the table, the wealth latent variable is categorized in order to reflect potentially divergent behavior by wealthier individuals. The categorization threshold was calibrated in accordance with equation [6.5]. Appendix C.2 presents the levels for the attributes considered in the DCE.

Three different models are estimated. First, a classical multinomial logit model (MNL-P) considering the correlation among the answers provided by the same individuals (via random panel effects; Bhat and Gossen, 2004) was calibrated. Additionally, we estimate a behavioral mixture model (MBM1) considering the environmental concerns and a third model (MBM2) considering both environmental awareness and differences in income following the approach presented in Section 6.3.[37]

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

Table 6.1 – 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 $€ \cdot 10^5$.
FC	Fuel cost in € / 100 km.
MC	Maintenance cost in € / 100 km.
PS	Power of the engine in hp.
RA	Driving range in km.
IM2, IM3, IM4	Dummy variables indicating the execution of the respective policy incentive.
Wealthy	LV Wealth > *threshold*
LSMid, LSHigh	Dummy variables indicating medium or high availability of charging stations for BEV.
EcAwareness	Attitudinal Indicator for "I am an ecologically aware person".
LocalFood	Attitudinal Indicator for "I pay attention to regional origins when shopping foods and groceries".
EcoFriendly	Attitudinal Indicator for "I buy ecologically friendly products".
Protection	Attitudinal Indicator for "Environmental protection measures should be enacted even if they result in job losses".
CO2Footprint	Attitudinal Indicator for "I pay attention to the CO2 footprint of the products I buy".

The results for the estimated models are presented in Table 6.2. Linear measurement equations results are presented in Appendix C.3. 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 6.2, wealth negatively affects the likelihood of revealing income, which is in accordance with results previously reported in the literature (Turell, 2000). This way, imputing the income directly would have led to spurious results due to endogeneity issues. In a similar way, male and older individuals are more prone to reveal their income.

Table 6.2 – Parameter estimates for the different models.

Variable	Equation	MNL-P		MBM1		MBM2	
Married	S.E. LV Wealth	-		-		0.939	(9.59)
HighSkill	S.E. LV Wealth	-		-		0.647	(4.63)
MidSkill	S.E. LV Wealth	-		-		0.391	(3.59)
FullTime	S.E. LV Wealth	-		-		0.699	(8.22)
Suburban	S.E. LV Wealth	-		-		0.159	(1.67)
Urban	S.E. LV Wealth	-		-		0.382	(3.94)
NCars	S.E. LV Wealth	-		-		0.659	(11.88)
NewCar	S.E. LV Wealth	-		-		0.491	(5.99)
Constant	Utility Reveal Income	-		-		0.616	(3.22)
LV Wealth	Utility Reveal Income	-		-		-0.152	(-2.36)
Male	Utility Reveal Income	-		-		0.567	(4.58)
Old	Utility Reveal Income	-		-		0.656	(3.99)
MidAge	Utility Reveal Income	-		-		0.531	(3.83)
Vienna	S.E. LV Green	-		-0.258	(-3.27)	-0.294	(-3.76)
Male	S.E. LV Green	-		-0.281	(-4.61)	-0.307	(-5.04)
HighSkill	S.E. LV Green	-		0.461	(4.5)	0.376	(3.61)
MidSkill	S.E. LV Green	-		0.253	(3.02)	0.226	(2.72)
Old	S.E. LV Green	-		0.68	(8.05)	0.611	(7.06)
MidAge	S.E. LV Green	-		0.398	(5.45)	0.314	(4.3)
Carsharing	S.E. LV Green	-		0.666	(3.48)	0.657	(3.69)
CarUser	S.E. LV Green	-		-0.229	(-3.55)	-0.243	(-3.84)
Threshold		-		-		1.91	(4.52)
ASC_CV	Utility CV	0	(fixed)	0	(fixed)	0	(fixed)
ASC_HEV	Utility HEV	0.423	(0.64)	0.191	(0.28)	0.859	(1.16)
ASC_PHEV	Utility PHEV	-0.0551	(-0.08)	-0.378	(-0.57)	0.16	(0.22)
ASC_BEV	Utility BEV	-1.73	(-2.14)	-2.26	(-2.85)	-1.09	(-1.16)
PP	Utility CV	-1.89	(-5)	-1.69	(-4.43)	-4.93	(-4.79)
PP	Utility HEV	-2.36	(-24.27)	-2.4	(-	-5.64	(-5.64)
PP	Utility PHEV	-2.38	(-20.37)	-2.3	(-	-5.68	(-5.96)
PP	Utility BEV	-1.62	(-10.44)	-1.52	(-	-7.21	(-3.73)
PP * Wealthy	Utility CV	-	(-)	-	(-)	3.15	(3.38)
PP * Wealthy	Utility HEV	-	(-)	-	(-)	3.65	(3.85)
PP * Wealthy	Utility PHEV	-	(-)	-	(-)	3.73	(4.08)
PP * Wealthy	Utility BEV	-	(-)	-	(-)	5.59	(3.22)
MC	Utility CV, HEV; PHEV, BEV	-31.2	(-12.09)	-30.5	(-	-31.8	(-11.42)
FC	Utility CV, HEV; PHEV, BEV	-31.5	(-20.68)	-31.1	(-	-31.7	(-18.63)
PS	Utility CV	0.0557	(3.98)	0.0527	(3.73)	0.0655	(4.76)
PS	Utility HEV	0.0503	(9.02)	0.0511	(9.09)	0.0503	(8.55)
PS	Utility PHEV	0.0528	(8.92)	0.0522	(8.93)	0.0531	(8.45)
PS	Utility BEV	0.00666	(1.28)	0.00653	(1.27)	0.0133	(2.23)
PS * Male	Utility CV	-0.0191	(-3.51)	-0.0232	(-4.29)	-0.0246	(-4.16)
PS * Male	Utility HEV	-0.0161	(-2.88)	-0.0178	(-3.2)	-0.0198	(-3.26)
PS * Male	Utility PHEV	-0.015	(-2.66)	-0.0162	(-2.91)	-0.0185	(-3.03)
PS * Male	Utility BEV	-0.00575	(-0.98)	-0.00491	(-0.84)	-0.0059	(-0.91)
MidAge	Utility HEV	-0.171	(-0.6)	-0.377	(-1.3)	-0.248	(-0.73)
MidAge	Utility PHEV	-0.276	(-0.97)	-0.469	(-1.7)	-0.31	(-0.96)
MidAge	Utility BEV	-0.768	(-2.1)	-1.13	(-3.1)	-1.27	(-3.03)
Old	Utility HEV	-1.23	(-3.73)	-1.44	(-4.36)	-1.79	(-4.54)
Old	Utility PHEV	-1.59	(-4.77)	-1.95	(-5.94)	-2.2	(-5.65)
Old	Utility BEV	-2.35	(-5.6)	-3.13	(-6.72)	-3.51	(-6.88)
LV Green	Utility HEV	-	(-)	0.794	(5.27)	0.619	(4.85)
LV Green	Utility PHEV	-	(-)	1.03	(7.49)	0.818	(6.84)
LV Green	Utility BEV	-	(-)	1.21	(6.97)	1.1	(6.39)
RA	Utility BEV	0.00529	(10.11)	0.00531	(10.12)	0.00606	(8.66)
LSMid	Utility BEV	0.312	(1.76)	0.296	(1.68)	0.307	(1.55)
LSHigh	Utility BEV	1.02	(6.34)	1.01	(6.36)	1.13	(6.14)
IM3	Utility BEV	0.499	(3.62)	0.486	(3.56)	0.511	(3.2)
Sigma CV	Utility CV	-2.82	(-21.56)	2.6	(21.47)	-2.79	(-19.62)
Sigma HEV	Utility HEV	-1.05	(-7.18)	-1.27	(-9.85)	-1.06	(-7.57)
Sigma PHEV	Utility PHEV	0.965	(6.81)	-0.567	(-2.4)	0.981	(6.67)
Sigma BEV	Utility BEV	-2.45	(-15.81)	2.27	(14.9)	2.73	(12.74)
Log-Lilikelihood		-5,130.4		-15,108.9		-18,671.1	

Regarding the wealth variable itself, it is possible to confirm that highly skilled individuals as well as individuals working full time are more likely to earn higher incomes. Similarly, urban or suburban residency and the number of automobiles are positively correlated with wealth. Finally, married individuals tend to have higher incomes. It is not possible to establish a relationship between wealth and either gender or age.

With respect to environmental concern, our results support the idea that male and younger individuals care less about the environment than their female and older counterparts, respectively. These findings are in line with previous empirical evidence (Vredin-Johansson *et al.*, 2006; Bolduc *et al.*, 2008; Daziano and Bolduc, 2013; Jensen *et al.*, 2013; Bahamonde-Birke *et al.*, 2016). Highly skilled individuals tend to exhibit more ecological attitudes, while individuals living in Vienna are less concerned about the environment than individuals living in smaller cities or in the countryside. As expected, the attitude toward the environment is reflected in the use of automobiles: green-minded individuals tend to rely more on carsharing and drive less often to their main occupational activity.

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

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

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

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

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

With regard to policy incentives, it is only possible to identify an increase in the willingness-to-pay for electrical cars associated with investment subsidies to support private charging stations (IM3). No change of attitude could be identified in association with the incentives polices related to interactions with transit systems, such as a Park and Ride subscription (IM2) or a one-year-ticket for public transportation (IM4). This is an important topic, as Holtsmark and Skonhoft (2014) identify policy incentives as the main reason for the success of electric vehicles in Norway and according to our results subsidies aiming for the joint use of electric vehicles ant public transportation would not have the desired effects. Along this line, other alternatives such as direct subsidies (Potoglou and Kanaroglou, 2007; Holtsmark and Skonhoft, 2014) may have a higher impact.

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

6.5 Conclusions

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

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

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

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

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

CHAPTER 7[38]

ABOUT TRANSPORT BEHAVIOR, ELECTROMOBILITY AND PERSON- AND ALTERNATIVE-SPECIFIC ERROR COMPONENTS

[38] This chapter is based on the article: Bahamonde-Birke, F.J. (2016). Does Transport Behavior Influence Preferences for Electromobility? An Analysis Based on Person- and Alternative-Specific Error Components. To be presented at *14th World Conference on Transport Research*, Shanghai, PR China, 10-15, July, 2016.

7.1 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, 2016). 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 chapter 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 chapter is organized as follows. Section 7.2 presents an overview of the theoretical approach and extends it in order to consider the correlation among different SP-experiments, while Section 7.3 offers a description of the dataset utilized to test the hypothesis. The results are discussed in section 7.4 and finally, section 7.5 summarizes the chapter's conclusions.

7.2 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):

$$U_i = \beta \cdot X + \varepsilon \qquad [7.1],$$

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:

$$U_i = \beta \cdot X + \upsilon + \varepsilon \qquad [7.2]$$

Here, υ is an error component following a given distribution and whose covariance matrix (Σ_υ) 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:

$$L = \int_\upsilon P(y \mid X, \eta; \beta, \Sigma_\varepsilon, \Sigma_\upsilon) \cdot f(\upsilon \mid \Sigma\upsilon) \cdot d\upsilon \qquad [7.3],$$

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 υ. 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 υ, making use of simulated likelihood techniques (McFadden, 1986).

To deal with panel or pseudo panel data it can be assumed that the error component υ 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.[39] In this case, the integration must be conducted at individuals' level rather than choices.

7.2.1 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):[40]

$$\begin{aligned} U_{11} &= \beta_{11} \cdot X + \upsilon_{11} + \varepsilon_{11} \qquad & U_{21} &= \beta_{21} \cdot X + \upsilon_{21} + \varepsilon_{21} \\ U_{12} &= \beta_{12} \cdot X + \upsilon_{12} + \varepsilon_{12} \qquad & U_{22} &= \beta_{22} \cdot X + \upsilon_{22} + \varepsilon_{22} \\ U_{13} &= \beta_{13} \cdot X + \upsilon_{13} + \varepsilon_{13} \qquad & U_{23} &= \beta_{23} \cdot X + \upsilon_{23} + \varepsilon_{23} \end{aligned} \quad [7.4]$$

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

[39] This approach work well for labelled experiments, but it does not appear to be suitable to address unlabeled data (Daly and Hess, 2010).

[40] Extending this framework for more SP-Experiments and alternatives is straightforward.

$$L = \int_{\upsilon_1}\int_{\upsilon_2} P(y_1 \mid X, \upsilon_1; \beta_1, \Sigma_{\varepsilon_1}, \Sigma_{\upsilon_1}) \cdot P(y_2 \mid X, \upsilon_2; \beta_2, \Sigma_{\varepsilon_2}, \Sigma_{\upsilon_2}) \cdot f(\upsilon_1 \mid \Sigma_{\upsilon_1}) \cdot f(\upsilon_2 \mid \Sigma_{\upsilon_2}) \cdot d\upsilon_1 \cdot d\upsilon_2 \qquad [7.5]$$

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 [7.4] would be given by:

$$\begin{aligned} U_{11} &= \beta_{11} \cdot X + \upsilon_{11} + \varepsilon_{11} + \alpha_{11} \cdot \upsilon_{21} + \alpha_{12} \cdot \upsilon_{22} + \alpha_{13} \cdot \upsilon_{23} \\ U_{12} &= \beta_{12} \cdot X + \upsilon_{12} + \varepsilon_{12} + \alpha_{21} \cdot \upsilon_{21} + \alpha_{22} \cdot \upsilon_{22} + \alpha_{23} \cdot \upsilon_{23} \\ U_{13} &= \beta_{13} \cdot X + \upsilon_{13} + \varepsilon_{13} + \alpha_{31} \cdot \upsilon_{21} + \alpha_{32} \cdot \upsilon_{22} + \alpha_{33} \cdot \upsilon_{23} \end{aligned} \qquad [7.6]$$

Here, $\upsilon_{21}, \upsilon_{22}$ and υ_{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 [7.6] 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.*, 2016). 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:

$$L = \int_{\upsilon_1}\int_{\upsilon_2} P(y_1 \mid X, \upsilon_1, \upsilon_2; \beta_1, \alpha_1, \Sigma_{\varepsilon_1}, \Sigma_{\upsilon_1}, \Sigma_{\upsilon_2}) \cdot P(y_2 \mid X, \upsilon_1, \upsilon_2; \beta_2, \alpha_2, \Sigma_{\varepsilon_2}, \Sigma_{\upsilon_1}, \Sigma_{\upsilon_2}) \cdot \\ f(\upsilon_1 \mid \Sigma_{\upsilon_1}) \cdot f(\upsilon_2 \mid \Sigma_{\upsilon_2}) \cdot d\upsilon_1 \cdot d\upsilon_2 \qquad [7.7]$$

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.

7.3 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, 2016). 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.[41] 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;[42] 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.

[41] The survey duration for the individuals responding DCEs was of approx. 30 minutes (as compared to 20 minutes for the remaining 1,173 individuals).

[42] 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.

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 characterized 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.

7.4 Estimation and results

As equations [7.5] and [7.7] 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 7.1 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 [7.5]). 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 7.1 – Definition of the variables considered in the model.

Variable	Definition
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.
IN	Inertia variable in DCE-MC.
FFT, CT	Free flow time and congestion time for PV in DCE-MC in min., respectively.
PRK, TL, FE	Parking, toll and fuel expenses for PV in DCE-MC in €., respectively.
TT, INT	Travel and interval time for PT-B, PT-T or NMT in DCE-MC in min., respectively.
TCK	Fare for individual ticket for PT-B or PT-C in DCE-MC in €.
NT	Number of transfers for PT-B or PT-T in DCE-MC.
WLK, BCL, EBC	Subdivision of the NMT alternative in DCE-MC: walking, cycling and electric bicycle, respectively.
PP	Purchase Price in DCE-VP in $€ \cdot 10^4$.
FC, MC	Fuel and maintenance cost in DCE-VP in € / 100 km., respectively.
PS	Power of the engine in DCE-VP in hp.
RA	Driving range in DCE-VP in km.
IM2, IM3, IM4	Dummy variables indicating the execution of the respective policy incentive in DCE-VP.
Sigma	Variability of the person- and alternative-specific covariances (υ_{xy} for U_{xy} in eq. [7.6]).
α-PV	Impact of person-specific covariance of alternative PV in DCE-VP (α_{xy} in eq. [7.6]).
α-PT-B	Impact of person-specific covariance of alternative PT-B in DCE-VP.
α-PT-T	Impact of person-specific covariance of alternative PT-T in DCE-VP.
α-NMT	Impact of person-specific covariance of alternative NMT in DCE-VP.

The results for the estimated models are presented in Table 7.2 (DCE-MC) and Table 7.3 (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 [7.5], while the model on the left (Correlated Experiments) was estimated in accordance with equation [7.7]. 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 7.2 – Parameter estimates for the DCE-MC.

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

As can be observed from Table 7.2 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 7.3 – Parameter estimates for the DCE-VP.

Variable	**Equation**	**Independent Model**		**Correlated Experiments**	
ASC_CV	*Utility CV*	0	*(fixed)*	0	*(fixed)*
ASC_HEV	*Utility HEV*	1.28	*(1.35)*	0.807	*(1.01)*
ASC_PHEV	*Utility PHEV*	0.595	*(0.63)*	-0.13	*(-0.14)*
ASC_BEV	*Utility BEV*	-0.744	*(-0.61)*	-1.75	*(-1.48)*
PP	*Utility CV*	-2.36	*(-3.53)*	-2.17	*(-3.05)*
PP	*Utility HEV*	-2.71	*(-15.35)*	-2.56	*(-14.57)*
PP	*Utility PHEV*	-2.3	*(-11.88)*	-2.37	*(-11.79)*
PP	*Utility BEV*	-1.81	*(-6.86)*	-1.98	*(-6.81)*
MC	*Utility CV, HEV;*	-32.8	*(-7.82)*	-32.9	*(-7.83)*
FC	*Utility CV, HEV;*	-33.5	*(-13.38)*	-32.9	*(-13.11)*
PS	*Utility CV*	0.0675	*(3.02)*	0.0525	*(2.27)*
PS	*Utility HEV*	0.0504	*(5.38)*	0.0434	*(4.57)*
PS	*Utility PHEV*	0.0466	*(4.67)*	0.0445	*(4.42)*
PS	*Utility BEV*	0.00488	*(0.52)*	0.00463	*(0.49)*
*PS * Male*	*Utility CV*	-0.0227	*(-2.5)*	-0.0134	*(-1.44)*
*PS * Male*	*Utility HEV*	-0.0147	*(-1.53)*	-0.0105	*(-1.07)*
*PS * Male*	*Utility PHEV*	-0.0184	*(-1.9)*	-0.0141	*(-1.44)*
*PS * Male*	*Utility BEV*	-	*(-0.17)*	-0.00267	*(-0.26)*
MidAge	*Utility HEV*	-0.513	*(-0.97)*	-0.191	*(-0.46)*
MidAge	*Utility PHEV*	-0.49	*(-0.96)*	-0.298	*(-0.52)*
MidAge	*Utility BEV*	-1.48	*(-2.19)*	-1.07	*(-1.21)*
Old	*Utility HEV*	-1.09	*(-1.98)*	-1.15	*(-2.71)*
Old	*Utility PHEV*	-1.14	*(-2.13)*	-1.51	*(-2.72)*
Old	*Utility BEV*	-3.13	*(-4.25)*	-3.45	*(-3.84)*
RA	*Utility BEV*	0.00514	*(5.8)*	0.00538	*(5.87)*
LSMid	*Utility BEV*	0.154	*(0.52)*	0.184	*(0.6)*
LSHigh	*Utility BEV*	0.807	*(2.97)*	0.843	*(2.98)*
IM3	*Utility BEV*	0.424	*(1.86)*	0.416	*(1.77)*
Sigma CV	*Utility CV*	-2.34	*(-12.56)*	-0.585	*(-1.23)*
Sigma HEV	*Utility HEV*	-0.773	*(-4.04)*	-0.775	*(-4.15)*
Sigma PHEV	*Utility PHEV*	0.535	*(2.31)*	0.533	*(2.51)*
Sigma BEV	*Utility BEV*	-2.39	*(-9.78)*	-2.14	*(-9.72)*
a-PV	*Utility CV*	-	*(-)*	0.2	*(3.41)*
a-PV	*Utility HEV*	-	*(-)*	0	*(fixed)*
a-PV	*Utility PHEV*	-	*(-)*	-0.0268	*(-0.44)*
a-PV	*Utility BEV*	-	*(-)*	-0.23	*(-2.08)*
a-PT-B	*Utility CV*	-	*(-)*	-1.06	*(-3.74)*
a-PT-B	*Utility HEV*	-	*(-)*	0	*(fixed)*
a-PT-B	*Utility PHEV*	-	*(-)*	0.613	*(2.78)*
a-PT-B	*Utility BEV*	-	*(-)*	0.833	*(2.77)*
a-PT-T	*Utility CV*	-	*(-)*	-1.43	*(-3.86)*
a-PT-T	*Utility HEV*	-	*(-)*	0	*(fixed)*
a-PT-T	*Utility PHEV*	-	*(-)*	0.46	*(1.79)*
a-PT-T	*Utility BEV*	-	*(-)*	1.06	*(2.7)*
a-NMT	*Utility CV*	-	*(-)*	-0.333	*(-4.23)*
a-NMT	*Utility HEV*	-	*(-)*	0	*(fixed)*
a-NMT	*Utility PHEV*	-	*(-)*	0.0752	*(1.29)*
a-NMT	*Utility BEV*	-	*(-)*	0.325	*(3.42)*
Log-likelihood	*Overall*	-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 that 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 7.3) are in line with the results reported by Bahamonde-Birke and Hanappi (2016) 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 (2016), 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 electrics 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 (2016), 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 significand 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 form 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 7.4 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 7.4 – Impact of the PASECs of the DCE-MC on the DCE-VP.

	PV	***PT-B***	***PT-T***	***NMV***
Sigma	**2.8**	**0.943**	**0.941**	**3.27**
CV	**0.56**	**-1.0**	**-1.35**	**-1.09**
HEV	**0***	**0***	**0***	**0***
PHEV	**-0.08****	**0.58**	**0.43****	**0.25****
BEV	**-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 finding are line with the assumption that individuals concerned about the environment may favor both public or non-motorized transportation and electric vehicles.

7.5 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 modeled.

This chapter 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 modeled 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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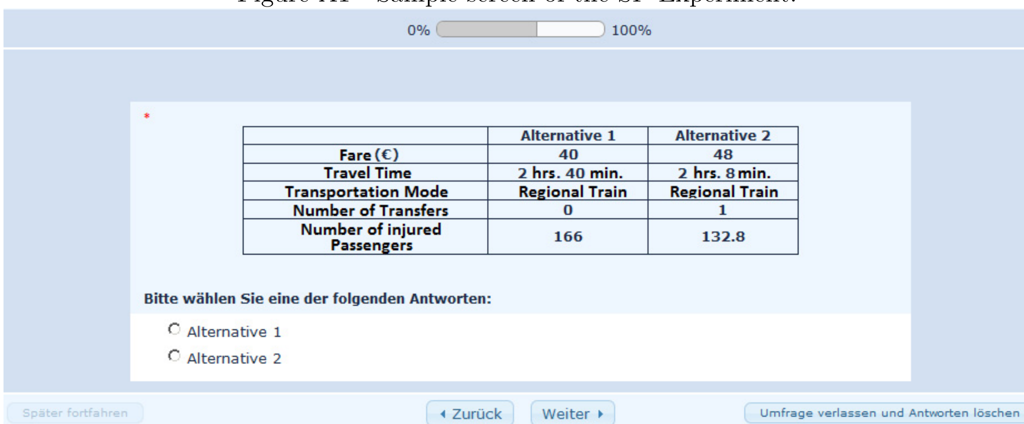
APPENDIX A

Figure A1 - Sample screen of the SP-Experiment.



0% 100%

*

	Alternative 1	Alternative 2
Fare (€)	40	48
Travel Time	2 hrs. 40 min.	2 hrs. 8 min.
Transportation Mode	Regional Train	Regional Train
Number of Transfers	0	1
Number of injured Passengers	166	132.8

Bitte wählen Sie eine der folgenden Antworten:

Alternative 1

Alternative 2

Später fortfahren ◂ Zurück Weiter ▸ Umfrage verlassen und Antworten löschen

* The main characteristics of the experiment were translated to increase readability.

APPENDIX B

Appendix B.1

Table B1 - Parameter estimates for the measurement equations. Case study 5.1.

Variable	*Equation*	*LVLC*		*DCLV*	
Scale	***M.E. EcAwareness***	**0.959**	*(16.14)*	**0.954**	*(16.1)*
Threshold 1	***M.E. EcAwareness***	**-3.25**	*(-15.18)*	**-3.18**	*(-15.29)*
Threshold 2	***M.E. EcAwareness***	**0.0152**	*(0.09)*	**0.0719**	*(0.42)*
Threshold 3	***M.E. EcAwareness***	**3.05**	*(12.85)*	**3.1**	*(13.22)*
Threshold 4	***M.E. EcAwareness***	**5.06**	*(14.74)*	**5.1**	*(14.9)*
Threshold 5	***M.E. EcAwareness***	**7.01**	*(12.11)*	**7.05**	*(12.16)*
Scale	***M.E. LocalFood***	**1.18**	*(14.89)*	**1.22**	*(14.89)*
Threshold 1	***M.E. LocalFood***	**-1.76**	*(-9.58)*	**-1.68**	*(-9.51)*
Threshold 2	***M.E. LocalFood***	**0.655**	*(3.74)*	**0.692**	*(4.11)*
Threshold 3	***M.E. LocalFood***	**2.59**	*(12.3)*	**2.59**	*(12.79)*
Threshold 4	***M.E. LocalFood***	**4.23**	*(15.2)*	**4.2**	*(15.63)*
Threshold 5	***M.E. LocalFood***	**7.17**	*(10.56)*	**7.09**	*(10.7)*
Scale	***M.E. EcoFriendly***	**0.988**	*(15.94)*	**1.02**	*(16.06)*
Threshold 1	***M.E. EcoFriendly***	**-2.68**	*(-12.98)*	**-2.58**	*(-13.01)*
Threshold 2	***M.E. EcoFriendly***	**-0.727**	*(-4.12)*	**-0.664**	*(-3.92)*
Threshold 3	***M.E. EcoFriendly***	**1.28**	*(6.9)*	**1.3**	*(7.32)*
Threshold 4	***M.E. EcoFriendly***	**2.88**	*(12.85)*	**2.88**	*(13.32)*
Threshold 5	***M.E. EcoFriendly***	**6.77**	*(12.65)*	**6.69**	*(12.87)*
Scale	***M.E. Protection***	**0.442**	*(13.06)*	**0.446**	*(13.05)*
Threshold 1	***M.E. Protection***	**-7.7**	*(-13.42)*	**-7.59**	*(-13.39)*
Threshold 2	***M.E. Protection***	**-3.33**	*(-11.57)*	**-3.25**	*(-11.54)*
Threshold 3	***M.E. Protection***	**1.3**	*(5.53)*	**1.34**	*(5.83)*
Threshold 4	***M.E. Protection***	**4.12**	*(10.97)*	**4.14**	*(11.15)*
Threshold 5	***M.E. Protection***	**8.04**	*(11.84)*	**8.03**	*(11.91)*
Scale	***M.E. CO2Footprint***	**0.951**	*(16.84)*	**0.95**	*(16.77)*
Threshold 1	***M.E. CO2Footprint***	**-4.39**	*(-17.52)*	**-4.32**	*(-17.61)*
Threshold 2	***M.E. CO2Footprint***	**-1.92**	*(-10.27)*	**-1.86**	*(-10.29)*
Threshold 3	***M.E. CO2Footprint***	**0.276**	*(1.56)*	**0.329**	*(1.92)*
Threshold 4	***M.E. CO2Footprint***	**1.89**	*(9.4)*	**1.93**	*(9.85)*
Threshold 5	***M.E. CO2Footprint***	**5.31**	*(14.73)*	**5.35**	*(14.89)*

Appendix B.2

Table B2 - Parameter estimates for the measurement equations. Case study 5.2.

Variable	*Equation*	*LVLC*		*DCLV*	
Scale	***M.E. HSTrains***	**1.13**	*(8.48)*	**1.09**	*(7.6)*
Threshold 1	***M.E. HSTrains***	**-3.74**	*(-13.3)*	**-3.77**	*(-12.42)*
Threshold 2	***M.E. HSTrains***	**-2.21**	*(-11.8)*	**-2.21**	*(-11.3)*
Threshold 3	***M.E. HSTrains***	**-0.179**	*(-1.47)*	**-0.16**	*(-1.37)*
Threshold 4	***M.E. HSTrains***	**1.43**	*(10.12)*	**1.47**	*(10.56)*
Scale	***M.E. RailLines***	**2.03**	*(3.9)*	**2.23**	*(2.84)*
Threshold 1	***M.E. RailLines***	**-2.83**	*(-12.73)*	**-2.74**	*(-11.66)*
Threshold 2	***M.E. RailLines***	**-1.5**	*(-10.01)*	**-1.44**	*(-9.44)*
Threshold 3	***M.E. RailLines***	**0.0287**	*(0.26)*	**0.0539**	*(0.53)*
Threshold 4	***M.E. RailLines***	**1.4**	*(9.91)*	**1.4**	*(9.81)*

APPENDIX C

APPENDIX C.1

Table C1 - Indicators' principal component matrix.

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

APPENDIX C.2

Table C2 - Levels for the attributes considered in the DCE.

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

APPENDIX C.3

Table C3 - Parameter estimates for the linear measurement equations.

Variable	Equation	MNL-P[43]	MBM1		MBM2	
LV Wealth	*M.E. Household Net*	-	-		**0.778*10³**	*(21.06)*
Constant	*M.E. Household Net*	-	-		**0.79*10³**	*(6.66)*
St.Dev.	*M.E. Household Net*	-	-		**0.626*10³**	*(15.98)*
LV Wealth	*M.E. Personal Net*	-	-		**0.453*10³**	*(17.27)*
Constant	*M.E. Personal Net*	-	-		**0.723*10³**	*(7.6)*
St.Dev.	*M.E. Personal Net*	-	-		**0.847*10³**	*(38.67)*
LV Green	*M.E. EcAwareness*	-	**-0.564**	*(-24.33)*	**-0.556**	*(-24.53)*
Constant	*M.E. EcAwareness*	-	**2.56**	*(44.72)*	**2.49**	*(44.74)*
St.Dev.	*M.E. EcAwareness*	-	**0.681**	*(41.37)*	**0.68**	*(41.12)*
LV Green	*M.E. LocalFood*	-	**-0.687**	*(-26.06)*	**-0.675**	*(-26.33)*
Constant	*M.E. LocalFood*	-	**2.36**	*(34.47)*	**2.27**	*(34.15)*
St.Dev.	*M.E. LocalFood*	-	**0.707**	*(37.44)*	**0.708**	*(37.69)*
LV Green	*M.E. EcoFriendly*	-	**-0.812**	*(-24.82)*	**-0.796**	*(-24.68)*
Constant	*M.E. EcoFriendly*	-	**2.95**	*(36.48)*	**2.85**	*(36.26)*
St.Dev.	*M.E. EcoFriendly*	-	**0.888**	*(38.44)*	**0.892**	*(38.54)*
LV Green	*M.E. Protection*	-	**-0.423**	*(-13.55)*	**-0.418**	*(-13.59)*
Constant	*M.E. Protection*	-	**3.35**	*(67.37)*	**3.29**	*(68.16)*
St.Dev.	*M.E. Protection*	-	**1.04**	*(51.32)*	**1.04**	*(51.26)*
LV Green	*M.E. CO2Footprint*	-	**-0.789**	*(-25.31)*	**-0.78**	*(-25.51)*
Constant	*M.E. CO2Footprint*	-	**3.49**	*(43.86)*	**3.39**	*(43.79)*
St.Dev.	*M.E. CO2Footprint*	-	**0.896**	*(39.61)*	**0.893**	*(39.67)*

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