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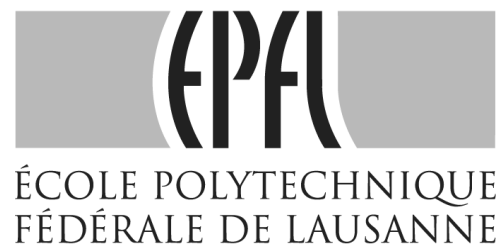
Accounting for response behavior heterogeneity in the measurement of attitudes: an application to demand for electric vehicles

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Abstract

Hybrid choice models have proved to be a powerful framework that integrates attitudinal and perceptual data into discrete choice models. However the measurement component of such a framework often fails to exploit individual-specific information that might affect the way subjects answer to indicators of opinion. In this paper we propose an HCM with a measurement model that takes into account heterogeneity in the response behavior. Precisely, we capture effects of exaggeration in answers to psychometrics. We moreover provide an application of this model to the evaluation of the future demand for electric vehicles.

Keywords

Hybrid choice models, attitudes, perceptions, psychometrics, response behavior, measurement model, demand model, electric vehicles

1 Introduction

In the last decades, research on demand models applied to transportation has been characterized by an emphasis on the importance of taking into account psychological constructs as explanatory factors of transportation decisions (McFadden, 1999). Attitudes or perceptions can indeed influence mobility decisions, such as the daily transportation mode choice or the purchase choice of a new car, in a non-negligible way. Classical economic variables such as the duration of a trip or the price of a car are alone not sufficient to completely explain and predict choices.

Since attitudes or perceptions cannot be directly observed from collected data, a couple of issues are raised regarding (1) the measurement of attitudes and (2) their integration into a choice model.

Attitudes are usually measured by means of indicators of individuals' opinions. The measurement of attitudes is a critical aspect since it provides a quantitative evidence of their existence. It is often performed by means of *psychometrics* (Bearden and Netemeyer, 1999). Recent studies in demand for transportation modes have made an wide use of such survey techniques. For example, Vredin Johansson *et al.* (2006) use psychometrics to collect information about individuals' perception about comfort, convenience and flexibility of transportation modes. Schüssler and Axhausen (2011) collect extensive psychometric data to measure risk propensity, environmentalism and variety seeking.

Once measurement of attitudes or perceptions have been collected, it is essential to define a framework that allows for an adequate characterization of them. Structural equation modeling (SEM) has provided a powerful solution to this issue (Bollen, 1989). Such models have had important applications in social sciences (Bielby and Hauser, 1977) and in transportation (Golob, 2003). In order to assess the impact of psychological constructs on choice, a comprehensive framework, namely the *hybrid choice modeling (HCM)* framework (Ben-Akiva *et al.*, 2002), was developed. This framework integrates SEM and discrete choice models. The importance of including attitudes as explanatory variables of choice has been demonstrated in numerous studies on transportation mode choice and vehicle choice (Espino *et al.*, 2006, Abou-Zeid *et al.*, 2010, Van Acker *et al.*, 2011, Daziano and Bolduc, 2011, Atasoy *et al.*, forthcoming).

The measurement model is a fundamental component of the HCM framework. Therefore the complexity of the relationship between a latent variable and its indicators deserves a greater attention than it is currently given. In particular, individuals' response behaviors are usually considered as homogeneous in the literature. However, this might not always be the case. Experiments on survey design in social sciences have shown that some respondents tend to exaggerate their answers, while others might provide more moderate answers to express the same opinion (Schuman and Presser, 1996).

This paper proposes an advanced specification of the measurement component of the HCM framework, where heterogeneity of response behavior is handled. Precisely we take into account exaggeration or moderation effects.

This research is based on a case study which aims at evaluating the future demand for electric vehicles. In the framework of a joint projet between Renault Suisse S.A. and EPFL's Transportation Center (TraCe), a *stated preferences (SP)* survey was conducted in Switzerland. Its purpose is to understand and predict individuals' preferences among gasoline or diesel cars and a hypothetical electric car, in the context of the release of several electric car models by Renault. In this case study, we capture the dispersion effects occuring in the answers to opinion indicators relative to a *pro-convenience attitude*, which characterizes individuals who favor the practical aspects of a car to its design.

The paper is structured as follows. Section 2 presents the HCM framework that takes into account for heterogeneity in response behavior. Section 3 presents an application of the HCM to the vehicle choice case study. Finally Section 4 concludes and discusses some further improvements to the present model.

2 Methodology

In this section we first introduce the classical hybrid choice model framework and then present the structure of the measurement model that incorporates dispersion effects.

2.1 Hybrid choice model framework

The HCM framework presented by Ben-Akiva *et al.* (2002) includes three main components: a choice model, a latent class model and a latent variable model. In this research we are focusing on the integration of the choice model and the latent variable model.

In the choice model, each alternative i that an individual n faces is represented by a utility function U_{in} , which is the sum of a deterministic term and a random term:

$$U_{in} = V(X_{in}, X_n^*; \beta) + \varepsilon_{in}, \quad \text{with } \varepsilon_{in} \sim \text{EV}(0, 1)$$

The deterministic term $V(X_{in}, X_n^*; \beta)$ is a function V of attributes X_{in} of the alternative i or the respondent n , latent variables X_n^* and a vector of parameter β . The random term ε_{in} has an extreme value distribution.

The utility function U_{in} of each alternative i is measured by choice indicators which are defined

as follows:

$$y_{in} = \begin{cases} 1 & \text{if } U_{in} = \max_j U_{jn} \\ 0 & \text{otherwise} \end{cases}$$

The latent variable model is made of a structural model and a measurement model. The structural model expresses the latent variable X_n^* as a function h of socio-economic characteristics of individual n and of a vector of parameters λ :

$$X_n^* = h(X_n; \lambda) + \omega_n, \quad \text{with } \omega_n \sim \mathcal{N}(0, \sigma_\omega)$$

Due to the fact that latent variable X_n^* reflects an unobservable construct, e.g. an attitude, indicators such as psychometrics are used to obtain measures of it. They consist of ratings of agreement to statements of opinion. The agreement is frequently expressed on a *five-point Likert scale*, ranging from a ‘total disagreement’ (coded as 1) to a ‘total agreement’ (coded as 5). The measurement model relates the responses I_n individuals give to the opinion questions to latent variable X_n^* . Since the responses I_n are discrete variables, the measurement model is specified as an *ordered logit regression*, where the responses I_n^* are latent variables which represent an underlying continuous distribution of I_n (Agresti, 2002, Abou Zeid, 2009):

$$I_n^* = m(X_n^*; \alpha) + v_n, \quad \text{with } v_n \sim \text{Logistic}(0, 1), \quad (1)$$

Here α is a vector of parameters.

The underlying continuous response I_n^* is related to the observed indicators I_n by the following threshold function:

$$I_n = \begin{cases} 1 & \text{if } -\infty < I_n^* \leq \tau_1 \\ 2 & \text{if } \tau_1 < I_n^* \leq \tau_2 \\ 3 & \text{if } \tau_2 < I_n^* \leq \tau_3 \\ 4 & \text{if } \tau_3 < I_n^* \leq \tau_4 \\ 5 & \text{if } \tau_4 < I_n^* \leq +\infty \end{cases}$$

Here we assume that each indicator has 5 levels. Parameters τ_1, \dots, τ_4 are thresholds which are estimated.

The HCM integrating the choice model and the latent variable model is estimated by maximiz-

ing the following likelihood function:

$$\begin{aligned}\mathcal{L} &= \prod_{n=1}^N f(y_{in}, I_n | X_{in}; \alpha, \beta, \lambda, \sigma_\omega) \\ &= \prod_{n=1}^N \int_{X_n^*} P(y_{in} | X_{in}, X_n^*; \beta, \sigma_\omega) \cdot f(I_n | X_{in}, X_n^*; \alpha, \sigma_\omega) \cdot f(X_n^* | X_n; \lambda, \sigma_\omega) dX_n^*\end{aligned}$$

2.2 Incorporation of dispersion effects in the measurement model

So far the standard way in the literature was to consider an error term v_n with the same variance of 1 for each individual n in the measurement equation of an HCM. However this assumption might not always be justified. A more realistic specification of Equation (1) would include an error term v_n whose standard deviation σ_{v_n} depends on the individual.

$$I_n^* = m(X_n^*; \alpha) + v_n, \quad \text{with } v_n \sim \text{Logistic}(0, \sigma_{v_n}), \quad (2)$$

Experiments on survey design in social sciences have shown that some subjects tend to provide answers which are systematically situated at extremes of the scale of agreement, though their commitment to the opinion statement is not strong (Schuman and Presser, 1996). We hence wish to take these exaggeration effects into account in the measurement of the latent variable. We proceed as follows:

1. We identify the respondents that systematically provide answers situated at extremes and those who provided more moderate responses.
2. We introduce a scale parameter which depends on the response behavior of the subject.

2.2.1 Identification of respondents with extreme versus moderate answers

In order to segment individuals according to their response behavior, we define an index E_n which is the number of extreme responses a subject provided:

$$E_n = \sum_{r=1}^R J_{rn},$$

where R is the total number of opinion questions in the questionnaire and J_{rn} is an indicator of extreme response which is equal to 1 if respondent n specified a ‘total disagreement’ or a ‘total

agreement' to an opinion question r and 0 otherwise.

$$J_{rn} = \begin{cases} 1 & \text{if } I_{rn} = 1 \text{ or } I_{rn} = 5 \\ 0 & \text{otherwise} \end{cases}$$

Here, I_{rn} denotes the answer of respondent n to the opinion statement r , with $r = 1, \dots, R$.

The definition of this index enables us to obtain a *degree of extremity* of an individual's response behavior. In Section 2.2.2 we explain the use of this index in the specification of the scale of the error term of the measurement model.

2.2.2 Specification of the scale parameter

We construct the scale parameter of Equation (2) according to the two following rules.

Group-specific scale: We define a threshold θ such that an individual n with $E_n \geq \theta$ is assigned to the 'extreme' group and an individual m with $E_m < \theta$ is assigned to the 'moderate' group. A group-specific scale σ_{VExt} is specified for the 'extreme' group only.

Progressive scale: In addition, the scale σ_{VExt} relative to the 'extreme' group varies with E_n . Precisely, we specify an individual-specific scale such that the larger the extremity index E_n is, the larger scale σ_{V_n} is.

The scale parameter of Equation (2) is hence defined as follows:

$$\begin{aligned} \sigma_{V_n} &= I_{E_n < \theta} \cdot 1 + (1 - I_{E_n < \theta}) \cdot \sigma_{\text{VExt}}(E_n) \\ &= I_{E_n < \theta} \cdot 1 + (1 - I_{E_n < \theta}) \cdot E_n \cdot \gamma, \end{aligned}$$

where $I_{E_n < \theta}$ is equal to 1 if we have $E_n < \theta$ for individual n and 0 otherwise, and γ is a parameter which we estimate.

3 Application to demand for electric cars

This section shows an application of the HCM with an enhanced measurement model presented in Section 2. We first introduce the case study. Second, we present the specifications of the measurement model and the whole HCM framework into which it is integrated. Third, we demonstrate the validity of our approach by reporting the estimation results.

3.1 Case study

The HCM we present in this paper was developed and estimated on data from a vehicle choice case study. An SP survey was conducted at the beginning of 2011 and aimed at understanding the preferences of individuals among three car alternatives: their own car, a possible analogous car model from Renault and an electric car from Renault too. The last alternative is hypothetical since electric cars are not widely available on the market yet.

Customized choice situations were presented to a sample of respondents who are representative of car buyers in Switzerland. They included variables which are assumed to be critical in the decision process. These variables are mainly purchase prices, costs of fuel or characteristics related to the purchase of the hypothetical electric alternative, such as the price of the monthly lease of the battery or a potential governmental incentive that could encourage the purchase of an electric car. Respondents of the survey were asked to indicate the car they would choose if they had to change their car at that moment.

In addition to the collection of data on individuals' preferences for the three car alternatives, we asked the respondents to rate their agreement on 25 statements of opinion, using a five-point Likert scale, ranging from a total disagreement to a total agreement. These questions of opinion were related to the following themes: the importance of car design, the perception of leasing, the perception of an electric vehicle as an ecological solution, the attitude towards new technologies, and the reliability, security and use of an electric vehicle.

Examples of the statements of opinion which were displayed are reported below. For the full list of statements of the questionnaire, see Appendix A.

- I give more importance to my vehicle's spaciousness or capacity to transport people and luggages than to its look.
- Leasing is an optimal contract which enables me to change my car frequently.
- I prefer driving a car with a powerful engine than a car that emits little carbon dioxide.
- I never travel without a GPS.
- The low range of the battery is a real disadvantage.

More information on the data collection procedure and on the experimental design used for the generation of the choice situations can be found in Glerum *et al.* (2011).

3.2 Model specification

We developed an HCM for the choice between a gasoline car from a competitor of Renault (CG), a gasoline car of brand Renault (RG) and an electric car from the same brand (RE). Re-

sults from exploratory factor analyses showed us that an important factor affecting the choice of car was a pro-convenience attitude, characterizing individuals who favor the practical aspects of a car over its design. We first present the specification of the latent variable model which takes into account dispersion effects occurring in the measurement of the pro-convenience attitude and then the specification of the whole HCM into which it is integrated.

3.2.1 Latent variable model

The structural equation for the latent variable model expresses the pro-convenience attitude X^* as a linear function of socio-economic characteristics of the decision-maker.

It can be represented by a specification table (see Table 1). Latent variable X^* is given by the inner product between columns ‘Coefficient’ and ‘Variable’. The socio-economic attributes characterizing the pro-convenience attitude X^* are described in column ‘Variable description’.

Exploratory factor analyses led to the identification of three following indicators of the pro-convenience attitude X^* :

Opinion convenience 1 (I_{C1}): Design is a secondary element when purchasing a car, which is above all a practical transport mode.

Opinion convenience 2 (I_{C2}): I give more importance to my vehicle’s spaciousness or capacity to transport people and luggages than to its look.

Opinion convenience 3 (I_{C3}): I prefer having a car with a new propulsion technology to a car with a nice look.

A common way to specify a measurement model is to consider function m as a linear expression in Formula (1). Each latent continuous response indicator I_{rn}^* is then specified as follows:

$$I_{rn}^* = \alpha_r \cdot X_n^* + v_n, \quad \text{with } v_n \sim \text{Logistic}(0, \sigma_{v_n}), \quad (3)$$

where $r \in \{C1, C2, C3\}$ is one of the three indicators of the pro-convenience attitude. Let us note that for identification purposes, α_{C1} is normalized to 1.

We consider a scale as defined in Section 2.2.2. In order to identify the threshold θ above which individuals belong to the ‘extreme group’, we specify a measurement model for all possible values of θ . For each of these measurement models, we compute the $\bar{\rho}^2$ indicator of fit and select the threshold θ for which the measurement model has the best fit.

The $\bar{\rho}^2$ indicator of fit is calculated as follows:

$$\bar{\rho}^2 = 1 - \frac{\mathcal{L}(\hat{\mu}) - Q}{\mathcal{L}(0)}, \quad (4)$$

where $\hat{\mu}$ is a vector of the estimated parameters, $\mathcal{L}(\hat{\mu})$ is the corresponding loglikelihood, Q is the number of parameters, and $\mathcal{L}(0)$ is the loglikelihood of the null model. For a latent variable model, we defined the null model by setting all parameters to 0, except thresholds τ_1 , τ_2 , τ_3 and τ_4 , which are estimated.

Figure 1 shows the values of $\bar{\rho}^2$ as a function of θ . The measurement model has the highest fit when θ is set to 7. A measurement model with $\theta = 7$ is therefore selected and integrated to the HCM.

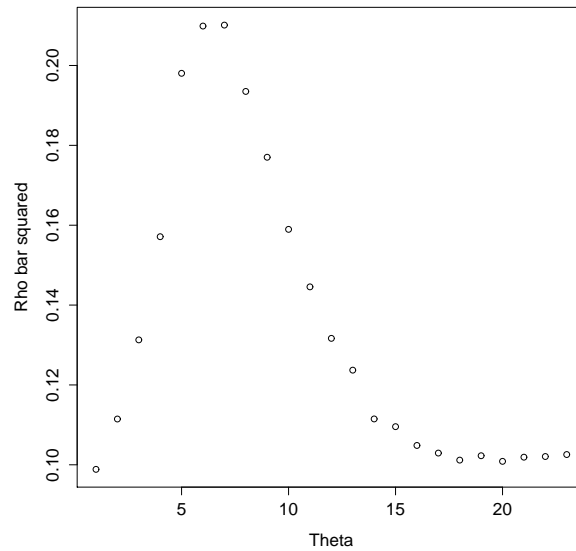


Figure 1: Fit indicator $\bar{\rho}^2$ as a function of threshold θ .

3.2.2 Hybrid choice model

The specification of the HCM is represented in Table 2. The utility function of each alternative i is given by the inner product between column ‘Coefficient’ and the column corresponding to i . For example, this column is ‘CG’ for the car from competitors of Renault.

The choice model includes the following variables:

Characteristics of all car alternatives: They consist of the purchase prices $price_{CG}$, $price_{RG}$ and $price_{RE}$ relative to alternatives CG, RG and RE, in CHF.

Characteristics of gasoline/diesel cars: They consist of the operating costs for cars, for which the cost of driving 100 km is below 12 CHF:

$$UseCostGasoline_{CG} = \min(Cost100_{CG}, 12)$$

$$\text{UseCostGasoline}_{\text{RG}} = \min(\text{Cost100}_{\text{RG}}, 12)$$

Characteristics of electric cars: These characteristics are discrete variables generated by an experimental design, consisting of operating costs, where *UseCostElecHigh* is an indicator of the highest level (5.40 CHF per 100 km) and *UseCostElecMed* of the medium level (3.55 CHF per 100 km); monthly lease of the battery *Battery*, in CHF; governmental incentive, where *IncentiveHigh* is an indicator of the highest level of incentive (−5'000 CHF), *IncentiveMed* of the medium level (−1'000 CHF) and *IncentiveLow* of the lowest level (−500 CHF).

Socio-economic characteristics of the respondent: These variable include the use of public transportation (*PT*), households with a monthly income higher than 8'000 CHF (*Income*), number of cars in the household (*NbCars*), French-speaking individuals (*French*), respondents' age (*Age*), target groups of customers which have been facing or will be facing soon the purchase choice of a new car (*TG12*, *TG3*, *TG45*).

Attitudinal variable: A pro-convenience attitude X^* is characterized by the latent variable model with threshold $\theta = 7$.

Model constants: Alternative specific constants ASC_{CG} and ASC_{RG} are also specified.

3.3 Model estimation

The choice model and the latent variable model building the HCM specified in Section 3.2 were estimated jointly using the extended version of the software Biogeme (Bierlaire and Fetiaron, 2009).

The estimation results of the measurement model are shown in Table 3. A meaningful characterization of individuals with a pro-convenience attitude is obtained. All parameters are significant except the one relative to gender. It was kept since it nearly reaches the 90% significance level.

Parameter γ is positive and significantly different from 0. The motivation for the introduction of a scale parameter was that the more extreme one individual is in its answers, the larger his scale will be. We hence need to verify that the scale for an individual n with extremity index $E_n \geq 7$ is greater than 1. This result holds since $\sigma_{v_n} = 7 \cdot \gamma = 1.42$.

We remark that instead of estimating τ_1 , τ_2 , τ_3 and τ_4 , we estimate parameters τ_1 , δ_1 , δ_2 and δ_3 , such that

$$\tau_2 = \tau_1 + \delta_1$$

$$\tau_3 = \tau_2 + \delta_2$$

$$\tau_4 = \tau_3 + \delta_3,$$

for convenience reasons.

The estimation results of the choice model are displayed in Table 4. The signs of the estimates which are significantly different from 0 at least at a 90% level are consistent with expectations. Unsignificant parameters were kept in the model to allow comparisons with other parameters¹

The pro-convenience attitude X^* affects significantly the choice of the electric alternative. Moreover, its interaction with the price variables enables us to conclude that the higher the pro-convenience of an individual is, the less affected he will be by changes in the purchase price of a vehicle (see Glerum *et al.*, 2012 for a more detailed analysis).

Finally, in order to obtain a quantitative assessment of the improvement of the above HCM compared to a standard HCM with scale σ_{v_n} equal to 1 for each individual n , we report indicators of fits for both models (see Table 5). The $\bar{\rho}^2$ indicator of fit is computed using Equation (4), where the null loglikelihood is the loglikelihood of an HCM with all parameters set to 0 except parameters τ_1 , τ_2 , τ_3 and τ_4 .

It can be concluded that an improvement of the fit of the HCM can be observed by taking into account dispersion effects. The $\bar{\rho}^2$ statistic improves from 0.16 to 0.24.

4 Conclusion

This paper demonstrates that heterogeneity in response behavior exists and that it can be captured through a parametric scale. Two groups of respondents could indeed be identified: individuals with recurrent extreme responses and individuals with moderate responses. In addition, the scale increases as the degree of extremity in the subject's response behavior increases.

This research highlights the fact that a higher attention should be given to the measurement of latent variables. The collection of psychometric data and their integration into the HCM framework need to be handled in a careful way. In particular, responses to psychometrics vary a lot across subjects and measurement models should reflect a greater deal of individual-specific information.

Future works include the investigation of indicator-specific scales. At present, the scale of each measurement equation was identical across indicators. The specification of a different scale could hence measure the strength of the exaggeration effect in each indicator of opinion. We also plan to model the respondents' degree of extremity using a latent class model. A characterization of the individuals showing extreme versus moderate answers can thus be obtained.

¹For example, β_{FrenchRG} is insignificant, but it was kept in the model to compare the effect of variable *French* on all three alternatives.

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References

- Abou Zeid, M. (2009) Measuring and modeling activity and travel well-being, Ph.D. Thesis, Massachusetts Institute of Technology.
- Abou-Zeid, M., M. Ben-Akiva, M. Bierlaire, C. Choudhury and S. Hess (2010) Attitudes and value of time heterogeneity, paper presented at *Applied Transport Economics: A Management and Policy Perspective*, 523–545.
- Agresti, A. (2002) *Categorical Data Analysis*, Wiley Series in Probability and Statistics, Wiley-Interscience.
- Atasoy, B., A. Glerum and M. Bierlaire (forthcoming) Attitudes towards mode choice in switzerland, *disP - The Planning Review*. Accepted for publication.
- Bearden, W. and R. Netemeyer (1999) *Handbook of marketing scales: multi-item measures for marketing and consumer behavior research*, Association for Consumer Research, Sage Publications.
- Ben-Akiva, M., D. McFadden, K. Train, J. Walker, C. Bhat, M. Bierlaire, D. Bolduc, A. Boersch-Supan, D. Brownstone, D. Bunch, A. Daly, A. de Palma, D. Gopinath, A. Karlstrom and M. A. Munizaga (2002) Hybrid choice models: Progress and challenges, *Marketing Letters*, **13** (3) 163–175.
- Bielby, W. T. and R. M. Hauser (1977) Structural equation models, *Annual Review of Sociology*, **3**, pp. 137–161.

- Bierlaire, M. and M. Fethiarison (2009) Estimation of discrete choice models: extending BIO-GEME., paper presented at *Proceedings of the 9th Swiss Transport Research Conference (STRC)*, September 2009.
- Bollen, K. A. (1989) *Structural equations with latent variables*, Wiley.
- Daziano, R. A. and D. Bolduc (2011) Incorporating pro-environmental preferences towards green automobile technologies through a bayesian hybrid choice model, *Transportmetrica*, 1–33.
- Espino, R., C. Roman and J. Ortuzar (2006) Analyzing demand for suburban trips: A mixed RP/SP model with latent variables and interaction effects, *Transportation*, **33** (3) 241–261.
- Glerum, A., L. Stankovikj, M. Thémans and M. Bierlaire (2012) Forecasting the demand for electric vehicles: accounting for attitudes and perceptions, *Technical Report, TRANSP-OR 120217*, Transport and Mobility Laboratory, Ecole Polytechnique Fédérale de Lausanne.
- Glerum, A., M. Thémans and M. Bierlaire (2011) Modeling demand for electric vehicles: the effect of car users' attitudes and perceptions, paper presented at *Proceedings of the Second International Choice Modeling Conference*, Leeds, UK.
- Golob, T. F. (2003) Structural equation modeling for travel behavior research, *Transportation Research Part B: Methodological*, **37** (1) 1–25, January 2003.
- McFadden, D. (1999) Rationality for economists?, *Journal of Risk and Uncertainty*, **19** (1-3) 73–105.
- Schuman, H. and S. Presser (1996) *Questions and answers in attitude surveys: experiments on question form, wording, and context*, Quantitative Studies in Social Relations, Sage Publications.
- Schüssler, N. and K. Axhausen (2011) Psychometric scales for risk propensity, environmentalism and variety seeking, paper presented at *Proceedings of the 9th International Conference on Survey Methods in Transport*, November 2011.
- Van Acker, V., P. L. Mokhtarian and F. Witlox (2011) Going soft: on how subjective variables explain modal choices for leisure travel, *European Journal of Transport and Infrastructure Research*, **11**, 115–146.
- Vredin Johansson, M., T. Heldt and P. Johansson (2006) The effects of attitudes and personality traits on mode choice, *Transportation Research Part A: Policy and Practice*, **40** (6) 507–525.

Coefficient	Variable	Variable description
λ_{Mean}	1	-
λ_{Male}	X_{Male}	1 if the respondent is male and 0 if the respondent is female
$\lambda_{\text{NbPeople}}$	NbPeople	Number of members in the respondent's household
λ_{Age}	$X_{\text{Age}>45} \cdot \text{Age}$	1 if the respondent is older than 45 and 0 otherwise; age of the respondent
λ_{Retired}	X_{Retired}	1 if the respondent is retired and 0 otherwise
$\lambda_{\text{Homeowner}}$	$X_{\text{Homeowner}}$	1 if the respondent is a homeowner and 0 otherwise
σ_{ω}	ω	Random variable $\mathcal{N}(0, 1)$

Table 1: Specification table of the latent variable model.

Coefficient	CG	RG	RE
<i>Linear terms</i>			
ASC_{CG}	1	-	-
ASC_{RG}	-	1	-
$\beta_{\text{UseCostGasoline}}$	$\text{UseCostGasoline}_{CG}$	$\text{UseCostGasoline}_{RG}$	-
$\beta_{\text{UseCostElecHighFluence}}$	-	-	$\text{UseCostElecHigh} \cdot \text{Fluence}$
$\beta_{\text{UseCostElecHighZoé}}$	-	-	$\text{UseCostElecHigh} \cdot \text{Zoé}$
$\beta_{\text{UseCostElecMedZoé}}$	-	-	$\text{UseCostElecMed} \cdot \text{Zoé}$
$\beta_{\text{IncentiveHigh}}$	-	-	IncentiveHigh
$\beta_{\text{IncentiveMed}}$	-	-	IncentiveMed
$\beta_{\text{IncentiveLow}}$	-	-	IncentiveLow
β_{Battery}	-	-	Battery
$\beta_{PT_{CG, TG1245}}$	$PT \cdot TG1245$	-	-
$\beta_{PT_{RG, TG1245}}$	-	$PT \cdot TG1245$	-
$\beta_{PT_{CG, TG3}}$	$PT \cdot TG3$	-	-
$\beta_{PT_{RG, TG3}}$	-	$PT \cdot TG3$	-
$\beta_{\text{Income}_{CG}}$	Income	-	-
$\beta_{\text{Income}_{RG}}$	-	Income	-
$\beta_{\text{NbCars}_{CG}}$	NbCars	-	-
$\beta_{\text{NbCars}_{RG}}$	-	NbCars	-
$\beta_{\text{French}_{CG}}$	French	-	-
$\beta_{\text{French}_{RG}}$	-	French	-
$\beta_{\text{Age}_{CG}}$	Age	-	-
$\beta_{\text{Age}_{RG}}$	-	Age	-
$\beta_{TG12_{CG}}$	TG12	-	-
$\beta_{TG12_{RG}}$	-	TG12	-
$\beta_{TG3_{CG}}$	TG3	-	-
$\beta_{TG3_{RG}}$	-	TG3	-
<i>Non-linear terms</i>			
$-\exp(\beta_{\text{price}_{CG}} + \beta_{X^*} \cdot X^*)$	price_{CG}	-	-
$-\exp(\beta_{\text{price}_{RG, TG1245}} \cdot TG1245 + \beta_{\text{price}_{RG, TG3}} \cdot TG3 + \beta_{X^*} \cdot X^*)$	-	price_{RG}	-
$-\exp(\beta_{\text{price}_{RE, TG12}} \cdot TG12 + \beta_{\text{price}_{RE, TG3}} \cdot TG3 + \beta_{\text{price}_{RE, TG45}} \cdot TG45 + \beta_{X^*} \cdot X^*)$	-	-	price_{RE}

Table 2: Specification table of the choice model.

Structural equation			Measurement equation		
Name	Value	<i>t</i> -test	Name	Value	<i>t</i> -test
β_{Mean}	-6.03	-17.32	τ_1	-9.23	-33.72
β_{Male}	-0.256	-1.54**	γ	0.203	29.62
β_{NbPeople}	0.362	5.46	δ_1	4.76	32.36
β_{Age}	0.0166	5.55	δ_2	2.15	40.76
β_{Retired}	1.40	5.31	δ_3	3.45	41.46
$\beta_{\text{Homeowner}}$	0.673	4.31	α_2	0.552	31.53
σ_ω	3.21	28.04	α_3	0.574	22.61

Table 3: Estimates of the parameters of the latent variable model, with values of *t*-test. (** Statistical significance < 90%, * Statistical significance < 95%).

Name	Value	<i>t</i> -test	Name	Value	<i>t</i> -test
<i>Parameters in linear terms</i>			<i>Parameters in linear terms (ctd)</i>		
ASC_{CG}	-2.54	-4.23	β_{Battery}	-4.73	-1.63**
ASC_{RG}	-1.78	-2.98	$\beta_{\text{French}_{CG}}$	0.347	2.77
$\beta_{\text{UseCostGasoline}}$	-0.0706	-2.10	$\beta_{\text{French}_{RG}}$	0.109	0.91**
$\beta_{\text{UseCostElecHigh}_{\text{Fluence}}}$	-0.282	-2.35	$\beta_{\text{Age}_{CG}}$	0.0206	4.37
$\beta_{\text{UseCostElecHigh}_{\text{Zoé}}}$	-0.818	-5.13	$\beta_{\text{Age}_{RG}}$	0.00487	1.09**
$\beta_{\text{UseCostElecMed}_{\text{Zoé}}}$	-0.483	-3.11	$\beta_{\text{TG12}_{CG}}$	1.66	4.35
$\beta_{\text{IncentiveHigh}}$	0.748	5.80	$\beta_{\text{TG12}_{RG}}$	0.681	1.80*
$\beta_{\text{IncentiveMed}}$	0.0630	0.47**	$\beta_{\text{TG3}_{CG}}$	-0.984	-1.33**
$\beta_{\text{IncentiveLow}}$	-0.0150	-0.11**	$\beta_{\text{TG3}_{RG}}$	1.29	3.10
$\beta_{\text{PT}_{CG,TG1245}}$	-0.251	-1.86*	<i>Parameters in non-linear terms</i>		
$\beta_{\text{PT}_{RG,TG1245}}$	-0.596	-4.03	$\beta_{\text{price}_{CG}}$	-4.15	-6.05
$\beta_{\text{PT}_{CG,TG3}}$	-2.10	-2.88	$\beta_{\text{price}_{RG,TG1245}}$	-1.97	-6.36
$\beta_{\text{PT}_{RG,TG3}}$	-1.01	-4.63	$\beta_{\text{price}_{RG,TG3}}$	-0.843	-3.51
$\beta_{\text{NbCars}_{CG}}$	-0.269	-3.65	$\beta_{\text{price}_{RE,TG12}}$	-1.01	-7.05
$\beta_{\text{NbCars}_{RG}}$	-0.361	-5.48	$\beta_{\text{price}_{RE,TG3}}$	-0.843	-3.51
$\beta_{\text{Income}_{CG}}$	-0.272	-2.33	$\beta_{\text{price}_{RE,TG45}}$	-0.766	-4.62
$\beta_{\text{Income}_{RG}}$	-0.281	-2.64	β_{X^*}	-0.0527	-4.81

Table 4: Estimates of the parameters of the choice model, with values of *t*-test. (** Statistical significance < 90%, * Statistical significance < 95%).

Model	Q	$\mathcal{L}(0)$	$\mathcal{L}(\hat{\mu})$	$\bar{\rho}^2$
Without dispersion	46	-16'746	-14'030	0.16
With dispersion	47	-13'687	-18'083	0.24

Table 5: Number of parameters Q , null loglikelihoods $\mathcal{L}(0)$, final loglikelihoods $\mathcal{L}(\hat{\mu})$ and $\bar{\rho}^2$.

A Indicators of opinion

Indicator	Statement
1	Finding a solution for the second life of batteries is not a major problem.
2	Renewable energies should be promoted, so that the energy used to charge the battery is also clean.
3	An electric car is a 100% ecological solution.
4	I prefer driving a car with a powerful engine than a car that emits little carbon dioxide.
5	Urban traffic noise should be reduced.
6	When I purchase a new car I pay special attention to the new technologies integrated.
7	My car must have a classic look instead of an innovative one.
8	A control screen is essential in my use of a car.
9	I never travel without a GPS.
10	The brand has little importance when buying an electric vehicle.
11	A gasoline car is easier to use than an electric vehicle.
12	Locating the charging stations of batteries of electric vehicles is a constraint.
13	I prefer cars with gearboxes than automatic cars.
14	Electric cars are not as secure as gasoline cars.
15	The low range of an electric vehicle is a real disadvantage.
16	A electric city car is more attractive than an urban gasoline car.
17	Design is a secondary element when purchasing a car, which is above all a practical transport mode.
18	I give more importance to my vehicle's spaciousness or capacity to transport people and luggages than to its look.
19	I prefer having a car with a new propulsion technology to a car with a nice look.
20	I buy my vehicle according to its brand.
21	Leasing is an optimal contract which enables me to change my car frequently.
22	With a leasing contract I feel that the car does not belong to me completely.
23	I prefer to pay the total price of my car at one time to avoid having to allow a leasing budget every month.
24	A leasing contract is more adapted in the case of the purchase of an electric vehicle.
25	As the technology of an electric car's battery will evolve rapidly, its lease is more adapted, implying its replacement by a more efficient battery when it does not work in an optimal way anymore.

Table 6: Psychometric indicators