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Artti Juutinen (Finland), Rauli Svento (Finland), Yohei Mitani (Norway), Erkki Mäntymaa (Finland), Yasushi Shojie (Japan), Pirkko Siikamäki (Finland)

Modeling observed and unobserved heterogeneity in choice experiments

Abstract

Fast progress has recently been made in heterogeneity modeling in the choice experiment models. Especially scale heterogeneity has been given new explicit role and interpretation. This paper estimates scale heterogeneity extended stated preference models with special emphasis on including both observed and unobserved heterogeneity. The results show that the scale heterogeneity augmented models are not generally enough to consider both preference and scale heterogeneity. Instead the preference heterogeneity needs to be explicitly modeled also in the Generalized Multinomial Logit model.

Keywords: choice experiments, stated preferences, scale heterogeneity, observed heterogeneity, unobserved heterogeneity.
JEL Classification: C25, Q51, Q57.

Introduction

Heterogeneity modeling in choice experiment settings has proceeded fast recently. Especially the role of scale heterogeneity modeling has reached new levels. Papers by Fiebig et al. (2010) and Greene and Hensher (2010) have shown how scale heterogeneity can be modeled and how different versions of multinomial logit models can be derived from their models as special cases. In this paper we use the Generalized Mixed Logit (GMXL) model and investigate the role of scale heterogeneity by modeling the respondent heterogeneity explicitly in this GMXL model. We include both observed and unobserved heterogeneity in the model. Our data is a stated preference data related to the managerial development of the Oulanka National Park in Finland (see Juutinen et al., 2011).

The research concerning the roles played by preference and scale heterogeneity in stated preference models is still in its beginnings. Some robust results can, however, already be stated. The differences between the studied commodities show clearly in earlier results, the more complicated the choice situation is (e.g. the particular commodity is unfamiliar for respondents) the stronger the role scale heterogeneity seems to play, see e.g. Fiebig et al. (2010). We have only one commodity in our study so that we do not open this comparison but since our case is related to environmental valuation we can expect the scale heterogeneity to have a role in our data. Valuation of environmental commodities, especially in the context of national park management, can be expected to be a heterogeneity creating and heterogeneity sensitive task.

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It seems to be the case that the Generalized Mixed Logit model (GMXL) turns out to capture the data generating processes in a more accurate manner than the usual random parameter versions of the conditional logit model. More research, especially empirical evidence, is still needed in clarifying and identifying the roles of preference related and scale related heterogeneities in the generalized logit model setting. Our hypothesis is that it is too bold an assumption to assume that both of these can be captured by a single scale factor in the model (see also Hess et al., 2009).

The paper is organized as follows. Section 1 presents the specification and estimation details of the generalized multinomial logit model. Section 2 explains our choice experiment setting and section 3 gives the results. The final section concludes.

1. Heterogeneity in stated preferences

The usual starting point in choice experiment (CE) modeling is the conditional logit model (CLM) of McFadden (1974) which assumes that the error terms have a heteroscedastic extreme value (HEV) distribution

$$U_{ij} = \beta' x_{ij} + \varepsilon_{ij}, i = 1,\dots,N; j = 1,\dots,J,$$

$$Prob(y_i = j \mid x_{i1},\dots,x_{iJ}) = \frac{e^{\beta' x_{ij}}}{\sum_{j=1}^{J} e^{\beta' x_{ij}}}, \qquad (1)$$

$$F(\epsilon_{ij}) = \exp(-\exp(-\varepsilon_{ij})),$$

where U_{ij} denotes utility of individual i from alternative (or commodity) j, x_{ij} is a vector of the attributes related to alternative j, β is a vector of parameters to be estimated and ε denotes the Gumbel distributed error terms.

The basic approach to model unobserved heterogeneity of preferences is by using random parameter versions of the conditional logit model by Train (2009) also named mixed logit (MIXL). Then the model has the following form:

$$U_{ij} = \beta_i' x_{ij} + \varepsilon_{ij},$$

$$Prob(y_i = j \mid x_{i1}, \ldots, x_{iJ}) = \frac{e^{\beta_i' x_{ij}}}{\sum_{j=1}^{J} e^{\beta_i' x_{ij}}}, \quad (2)$$

$$\beta_i = \beta + \vartheta v_i,$$

where the individual specific parameter vector β_i is identified with β being the vector of population means of the random parameters and v_i is a vector of random variables which capture the individual unobserved heterogeneity with mean zero and standard deviation of one. The standard deviation of individual specific parameters around the population mean are captured by the nonzero elements of the lower triangular Cholesky matrix ϑ.

MIXL has been very popular recently based on the fast progress with simulation based solutions. The normal distribution is frequently used for random parameters while the willingness to pay is naturally positive and thus it is usually assumed log normally distributed. Louviere et al. (2008) have, however, criticized the use of normal distributions in MIXL models. Based on the distributions of utility weights obtained from individual level estimations they have found that distributions do not appear to be normal.

Observed preference heterogeneity can be added to the MIXL model with heterogeneity explaining covariates in the equation of individual specific parameters in the model (2). Then the model has the form:

$$U_{ij} = \beta_i' x_{ij} + \varepsilon_{ij},$$

$$Prob(y_i = j \mid x_{i1}, \ldots, x_{iJ}) = \frac{e^{\beta_i' x_{ij}}}{\sum_{j=1}^{J} e^{\beta_i' x_{ij}}},$$

$$F(\epsilon_{ij}) = \exp(-\exp(-\varepsilon_{ij})), \quad (3)$$

$$\beta_i = \beta + \theta z_i + \vartheta v_i,$$

where z_i is a set of variables which are preference heterogeneity explaining cofactors for person i and θ is the corresponding parameter vector to be estimated.

In writing model (1) it has implicitly been assumed that the error terms have been scaled to have unit variance so that a common scaling factor has been used. When this scale factor is made explicit the utility can be written as:

$$U_{ij} = \beta' x_{ij} + \frac{\varepsilon_{ij}}{\sigma}, \quad i = 1, \ldots, N; j = 1, \ldots, J.$$

This scaling can of course be made on individual basis, i.e. the scaling factor would then be σ_i for i = 1,…, N. Recently Fiebig et al. (2010) and Greene and Hensher (2010) have shown how the scale factor can be estimated in the (GMXL) Generalized Mixed Logit Model. When this scaling is applied to the MIXL model without preference heterogeneity explaining covariates, the scaling factor is multiplied out and an assumption is made that the scaling factor can have a weighted influence on unobserved heterogeneity. The model with the scale factor can be expressed in the following form:

$$U_{ij} = \left[\sigma_i \beta + \gamma \vartheta v_i + (1-\gamma)\sigma_i \vartheta v_i\right] x_{ij} + \varepsilon_{ij}, \quad (4)$$

where γ is the weighing factor to be estimated. When γ approaches zero the model approaches a model where the scale heterogeneity affects both the population means and individual means of the parameters. When γ approaches one the model approaches a model where the scale heterogeneity affects only the population means.

The goal of this paper is to include observed covariates in both the random parameters and in the scale factor as explanatory variables. The scale factor to be estimated has the following form:

$$\sigma_i = \exp(\sigma + \delta' h_i + \tau w_i), \quad (5)$$

where h is a vector of scale explaining covariates for respondent i and $w_i \sim N(0,1)$ is a vector of random variables, and δ and τ are the corresponding parameters. In estimations we use the assumption that the scale variance heterogeneity is normally distributed so that, neglecting the observed heterogeneity, $E\sigma_i = \exp(\sigma + \tau^2/2)$. Since $\sigma_i\beta$ enters the model as a product some normalization is needed in order to identify them both. The natural normalization is to set the mean of σ_i equal to one so that β is the mean vector of utility weights. To accomplish this we set σ equal to $-\tau^2/2$. The model naturally has to be estimated using simulation draws for the random variables v and w.

2. The choice experiment

2.1. Study area. Our choice experiment relates to Oulanka National Park in Finland[1]. The park is located in north-eastern Finland (66°22'N, 29°17'E), adjacent to the Russian border and close to the Arctic Circle. The park was established in 1956 to protect unique riparian ecosystems with rich flora and fauna. There were two major expansions to the park in 1982 and 1989, so that currently Oulanka NP covers approximately 28 000 hectares (Gilligan et al., 2005). It is managed by the Natural Heritage Services of Metsähallitus, whose public administration duties include the management of protected areas (Heinonen, 2007). Finnish national parks are managed within the Parliamentary legislation, the Ministry of the Environment's

[1] Juutinen et al. (2011) have studied visitor valuations related to this park and thus we do not open those in this paper.

guidelines and Metsähallitus' own principles and management and land use plans for each park. Following the IUCN protected area management categories, Oulanka NP is a category II national park (Dudley, 2008; IUCN and UNEP, 2003).

Following the growth of nature-based tourism, national parks have become important tourist attractions worldwide. In Finland Oulanka NP is one of the most popular national parks. The average annual number of visits tripled since 1992 from 60 000 to 185 500 visits in 2007 (Metsähallitus, 2008). The number of visitors to the park has increased to the point that the park manager, Metsähallitus, now requires information for fulfilling the needs of the visitors and protecting the nature of the park. There are clear tradeoffs between development of the services and facilities and protection of the biodiversity of the park. Therefore, Oulanka NP is a highly suitable case for a choice experiment exercise.

2.2. Survey design. The process started in cooperation with Metsähallitus by preparing a questionnaire for a small scale pilot study conducted as an onsite visitor survey during five days in October 2007. Based on the pilot study, the final questionnaire was developed and tested using focus groups (the questionnaire is available on request from the authors). The questionnaire of the final survey consisted of four parts. The first part contained questions related to visitors' environmental attitudes and their desire for outdoor recreation. This part was an introduction to the survey, including questions related to the importance of nature and the environment for visitors, activity to spend time in nature, and respondents' attitude to nature protection in Finland. The second and the most important part of the questionnaire contained the choice experiment. It gave information about Oulanka NP and choice sets related to management alternatives of the park. It included descriptions of the attributes of the choice experiment, i.e. biodiversity, expected number of visitors, entrance fee, size and number of resting places, and information boards, as well as the levels of the attributes as shown in Table 1. The third part of the survey asked facts about this visit to the park, especially places where respondents visited as well as motives and activities during the visit in the park. The final part included questions regarding respondents' socio-economic status, including year of birth, education, and employment.

Table 1. Attributes and their levels with variable names used in the analysis

Attributes	Levels	Variable name
Biodiversity: number of endangered species of plants and animals in the park	1. Decreases: populations decrease so that 15 species extinct in the park. 2. Stays at the present state: number of endangered species 150*. 3. Increases: a 10 % increase in populations of endangered species.	Biodiv $^{-}$ Biodiv $^{\pm}$ Biodiv $^{+}$
Expected number of visitors: on average on the most visited places	1. Decreases: a visitor encounters 10 people during a 1 km walk. 2. Increases as anticipated: a visitor encounters 40 people during a 1 km walk*. 3. Increases a lot: a visitor encounters 70 people during a 1 km walk.	NumVisitors $^{-}$ NumVisitors $^{\pm}$ NumVisitors $^{+}$
Entrance fee: for adult visitors only	1. No entrance fee*. 2. Entrance fee € 2/ person/ visit. 3. Entrance fee € 5/ person/ visit. 4. Entrance fee € 10/ person/ visit. 5. Entrance fee € 20/ person/ visit.	Payment
Size and number of resting places on the most visited places	1. Stays at the present state: a resting place after every 2 km*. 2. Expansion of present resting places: 2 new camp fire places on the most crowded ones. 3. Construction of new resting places: a resting place after every 1 km.	RestPlace $^{\pm}$ RestPlace $^{+}$ RestPlace $^{++}$
Information boards by the side of hiking routes in English	1. Stays at the present state: no information boards*. 2. Few more boards: a board after every 3 km. 3. Far more boards: a board after every 1 km.	InfoBoard $^{\pm}$ InfoBoard $^{+}$ InfoBoard $^{++}$

Note: *The attribute level describes the basic alternative.

The number of attributes and levels gave rise to 405 possible profiles (3*3*5*3*3 = 405). To develop the profiles presented to respondents in the questionnaire, we applied an orthogonal main effect design (by SPSS orthogonal design procedure), which is frequently used in empirical studies although effective designs are coming more popular (Louviere et al., 2000). This procedure reduced the number of profiles to a level of 25 alternatives. This number was considered too large a task for a respondent to complete (Louviere et al., 2000). To reach a more manageable level of alternatives, we generated three random numbers for each alternative. Then using one set of random numbers at a time we sorted the alternatives in a descending order and signed the alternatives to 12 choice sets in this order. The total number of choice sets is 36 as the procedure was repeated three times. Each choice set included two signed alternatives and a status quo alternative in which the levels of attributes refers to present situation except the expected number of visitors which was assumed to increase as anticipated (the basic alternative in Table 1). Thus 24 alternatives were used at a time in generating the 12 choice sets, but all the 25 alternatives were used in generating the 36 choice sets. The first four choice sets were then used in the first version of questionnaire and so on resulting in nine versions of the questionnaire. This procedure was used to achieve trustworthy results in estimation due to variation among the choice sets. Dominating alternatives were checked and eliminated from the choice sets. Thus, the respondents faced four choice sets and in each set they selected between three alternatives. An illustration of a choice set is presented in Figure 1. We constructed all versions of the questionnaire in two languages, English and Finnish. In order to help the choice tasks, respondents were given the possibility to look at separate answering instructions.

Table 2. Choice situation example

Choice task 1			
	Alternative 1	Alternative 2	Alternative 3 (basic alternative)
Biodiversity: number of endangered species of plants and animals in the park.	Decreases: populations decrease so that 15 species extinct in the park.	Decreases: populations decrease so that 15 species extinct in the park.	Stays at the present state: number of endangered species 150.
Expected number of visitors: on average on the most visited places.	Increases as anticipated: a visitor encounters 40 people during a 1 km walk.	Increases as anticipated: a visitor encounters 40 people during a 1 km walk.	Increases as anticipated: a visitor encounters 40 people during a 1 km walk.
Entrance fee: for adult visitors only.	Entrance fee € 2/ person/ visit.	Entrance fee € 10/ person/ visit.	No entrance fee.
Size and number of resting places on the most visited places.	Construction of new resting places: a resting place after every 1 km.	Stays at the present state: a resting places after every 2 km.	Stays at the present state: a resting places after every 2 km.
Information boards by the side of hiking routes in English.	Few more boards: a board after every 3 km.	Far more boards: a board after every 1 km.	Stays at the present state: no information boards.

Note: Please choose one of these three alternatives.

2.3. Data. We targeted the survey to the typical park visitors in order to obtain applicable results for efficient park management. The onsite guided survey was conducted during the summer season 2009, between beginning of June and end of September in the two most visited sites of Oulanka NP: the Kiutaköngäs Rapids including Oulanka visitor center and the Oulanka Camping place, and the Juuma district, the area of the "Small Bear Ring" hiking trail. These areas face high environmental stress due to a large number of visitors and are also very species-rich locations, so-called biodiversity hot-spots, within Oulanka NP, and thus have a great need for careful planning and development of recreational use. For the sampling we applied the same survey methodology used in the traditional visitor monitoring surveys of national parks in Finland (Kajala et al., 2007). We used random sampling so that all individuals (over 18 years) who come past the survey point were asked for their willingness to take part to the survey as they arrive. The total number of respondents was 589.

We removed 116 respondents from the database because they always selected the basic alternative (status quo), but according to a specific control question did not truly consider that as the best alternative in the choice set. Instead, they revealed some other reasons for their choices which can be interpreted as having lexicographic preferences or protest responses. For example, as clarifications in the follow-up question, the two most common reasons for always selecting the basic alternative were "I don't accept an entrance fee of national parks; also in the future management of the parks should be covered by tax revenues" or "I don't accept an entrance fee and if it would be started to use I would go to some other place to recreate". Thus, we rejected protest responses, but left the true zero-bidders in the sample (see Jacobsen and Thorsen, 2010)[1].

The used database includes 473 respondents including 370 domestic and 103 foreign visitors. The share of female respondents is 52.5%, and the average age of respondents is 42.3 years. The proportion of female respondents (Pearson Chi-square test, $\chi^2 = 0.015$, d.f. = 1, $p = 0.901$) and average age (independent samples t test, $t = 0.694$, d.f. 1057, $p = 0.488$) as well as the share of Finnish speaking respondents (Pearson Chi-square test, $\chi^2 = 0.005$, d.f. = 1, $p = 0.946$) did not differ between our data set and the one of the most recent visitor survey (Muikku, 2005). The visitor survey was conducted during a longer period than our survey and it covered also more sites of the park than our study, and therefore, it can be considered as a very representative sample of park visitors. Thus, the current sample represents a rather good match to the known characteristics of the visitor population to Oulanka NP.

We used six individual-specific variables to explain taste and scale variation in the analysis. The variables were selected on the basis of previous analysis of the data set (Juutinen et al., 2011). Table 3 describes the characteristics of these variables.

[1] A logit model analysis revealed that the probability of a protest answer increases if the respondent is a domestic visitor or spends free time in nature several times a week. There are only 10 foreign respondents among the protest answers. Regarding domestic visitors the probability of a protest answer increases if the respondent has visited the park before current visit. Protest answers reflect likely the current Finnish practice in which the right of public access to both public and private land (every man's rights, in Finnish "jokamiehenoikeus", similar to "allemensrätten" in Sweden and "allemennstretten" in Norway) is a key convention of property rights.

Table 3. Observed individual specific covariates

Variable name	Description	Number of respondents
Edu	Gets value one if respondent has college or university education and zero otherwise.	312
First	Gets value one if respondent is visiting the park at the first time and zero otherwise.	223
Frg	Gets value one if respondent is a foreign visitor and zero otherwise.	103
Nat	Gets value one if respondent spends free time in nature only monthly or less frequently and zero otherwise.	108
Inc	Gets value one if respondent's household monthly incomes before taxation are larger than 3000 euros and zero otherwise.	304
Time	Gets value one if respondent spends more than 8 hours in the park during his or her visit and zero otherwise.	257

3. Results

Our modeling approach is the following. First we compare basic mixed logit (MIXL) and generalized mixed logit (GMXL) models. The next step is to include heterogeneous preferences explaining covariates into the means of the random variables as in equation (3). The third step is to include explaining covariates into the scale heterogeneity as in equation (5). The final step is to combine preference and scale heterogeneity explaining covariates into the same model.

In estimating[1] the random parameter multinomial logit and the generalized multinomial logit models we have followed Hensher et al. (2011) by assuming that all parameters except the payment parameter are random. We have used various distributional assumptions. The results are quite robust with respect to distributional assumptions and hence we present here only the results based on normal distribution. Our estimations confirm the result by Greene and Hensher (2010) that the models necessitate allowing the correlations between the random parameters. Thus we always allow for these correlations but in order to save space we do not report the Cholesky matrices here. We have used 500 Halton draws and 500 simulations in the estimations. The results of MIXL and GMXL models are presented in Table 4.

Table 4. MIXL and GMXL models

			MIXL[c]			GMXL[c]	
Attributes & lev.[a,b]		Coeff.	S.E.	*p*-value	Coeff.	S.E.	*p*-value
Random parameters in utility functions							
$BioDiv^-$	Mean of C	-2.34684	.35212	.0000	-8.05970	4.24178	.0574
	S.D.	1.45122	.30477	.0000	3.00573	1.87866	.1096
$BioDiv^+$	Mean of C	.92970	.20723	.0000	3.15068	1.65498	.0569
	S.D.	1.33068	.25717	.0000	2.40336	1.65233	.1458
$NumVisit^-$	Mean of C	.91272	.20427	.0000	4.39439	2.36397	.0630
	S.D.	1.52077	.27225	.0000	5.21241	2.56294	.0420
$NumVisit^+$	Mean of C	-2.47081	.45586	.0000	-8.73630	4.68632	.0623
	S.D.	2.40078	.29919	.0000	8.56143	3.08616	.0055
$RestPlace^+$	Mean of C	.35874	.15711	.0224	1.55509	1.00059	.1201
	S.D.	.93715	.19328	.0000	2.98457	1.47833	.0435
$RestPlace^{++}$	Mean of C	-.87798	.23362	.0002	-3.19271	1.92092	.0965
	S.D.	1.34586	.28969	.0000	4.30493	1.94613	.0270
$InfoBoard^+$	Mean of C	.52981	.15387	.0006	2.55628	1.35733	.0597
	S.D.	.81187	.24023	.0007	3.56858	1.92606	.0639
$InfoBoard^{++}$	Mean of C	-.34359	.16896	.0420	-1.66470	1.08747	.1258
	S.D.	.93938	.24279	.0001	4.34526	1.47716	.0033
Constant	Mean of C	-1.70509	.47734	.0004	-4.66388	3.09724	.1321
	S.D.	2.65805	.40082	.0000	9.09696	1.47007	.0000
Nonrandom parameters in utility function							
Payment		-.13124	.01849	.0000	-.14719	.01539	.0000
τ					1.65879	.28507	.0000
γ					.00079	.02741	.9769
σ					.60230	.87375	
N of sets		1551			1551		

[1] In all estimations we have used the pre-release Nlogit5.

Table 4 (cont.). MIXL and GMXL models

			MIXL[c]			GMXL[c]	
Attributes & lev.[a,b]		Coeff.	S.E.	*p*-value	Coeff.	S.E.	*p*-value
Nonrandom parameters in utility function							
Log-L		-1308			-1299		
Pseudo R^2		.2324			.2376		
AIC		2726			2712		
Fin Smlp AIC		2730			2717		
Bayes IC		3020			3017		
Hannan Quinn		2835			2826		

Notes: [a]Effect coded. [b]Superscript – (+) indicates a reduction (increase) compared with the current level. [c]Models allow correlation between random parameters, but these results are not shown.

According to the MIXL model all random assumed parameters are statistically acceptable and also random. GMXL model is more varied in this respect. A modest increase of resting places and a bold increase in information boards do not pass the 10% statistical meaningfulness level. Also both biodiversity parameters seem to be fixed. Based on all information criteria the GMXL model, however, describes the data generating process more accurately. Notice how τ estimates to be nonzero revealing that scale heterogeneity can be identified in our data set. The high scale parameter improves precision of respondents' answers, because the share of deterministic part of utility function is higher and the variance in the utility function is lower, respectively (see equation (4)). Notice also that γ estimates to be close to zero – with high *p*-value though – which implies that the data generating process supports the specification where the variance of residual taste heterogeneity increases with scale. This outcome turned to be the case also in the other following estimations.

In Table 5 we present the results from estimations where preference heterogeneity explaining covariates have been added into both models. We have gone through a very thorough process of trial and error in trying to find the best covariates to use. Here we report only the final results. The covariates that are important in explaining preference heterogeneity are: whether the visitor is a foreigner (FRG), how much he/she spends time in nature during leisure time (NAT), what is his/her income (INC), whether he/she is a first time visitor (FIRST) and how long time (TIME) he/she spends in the park.

As can be expected the role of preference heterogeneity explaining covariates is smaller in the GMXL model but the important result is that they do play a role also when scale heterogeneity is explicitly modeled. Thus it is a bold assumption to give the scale heterogeneity the complete role of taking care of both preference and scale heterogeneity. First time visitors can be identified in the GMXL model to have strong preferences concerning the information boards. Quite understandably they would like to see a modest increase in these but not a bold increase in any case. All information criteria show the GMXL model explains the data generating process more accurately. Notice how τ diminishes but γ still has not been estimated confidentially.

Next we proceed by including heterogeneity explaining covariates into the scale heterogeneity factor. We do this implementation into the final GMXL model in Table 6 and again we have gone through a very thorough process of looking at the right covariates from the data set. It turns out that education and the amount of leisure time the visitor spends in nature have explanatory power in the scale heterogeneity. Time spend in the park during the visit turns out to be a very sensitive variable in the sense that even though it does not seem to play a role in explaining scale heterogeneity it clearly has a stabilizing effect in the whole model.

The preference heterogeneity and scale heterogeneity including model does not perform better than the model with only preference heterogeneity but obviously also scale heterogeneity turns out to be possible to be explained by covariates. Notice how the role of GMXL specific parameters turn here upside down in comparison with the previous model (the scale).

Table 5. MIXL and GMXL models with heterogeneity in means

			MIXL[c]			GMXL[c]	
Attributes & lev.[a,b]		Coeff.	S.E.	*p*-value	Coeff.	S.E.	*p*-value
Random parameters in utility functions							
BioDiv$^-$	Mean of C	-2.06237	.28409	.0000	-8.66762	4.14177	.0364
	S.D.	1.08252	.27259	.0001	5.49692	2.67135	.0396
BioDiv$^+$	Mean of C	.92031	.28409	.0000	4.47688	2.05441	.0293
	S.D.	1.03170	.27259	.0001	3.51836	.92649	.0001
NumVisit$^-$	Mean of C	.36058	.25635	.1595	2.62189	1.40795	.0626
	S.D.	1.19537	.23178	.0000	5.82146	2.59221	.0247
NumVisit$^+$	Mean of C	-1.53245	.42059	.0003	-7.98949	3.83681	.0373
	S.D.	1.98671	.34843	.0000	8.26373	2.05933	.0001
RestPlace$^+$	Mean of C	.15433	.18811	.4120	1.45747	.89314	.1027
	S.D.	.73348	.20434	.0003	2.41433	.71131	.0007
RestPlace^{++}	Mean of C	-1.12250	.26323	.0000	-4.88982	2.42432	.0437
	S.D.	1.01213	.26471	.0001	6.23388	2.65889	.0191
InfoBoard$^+$	Mean of C	.48670	.13438	.0003	1.86465	1.07503	.0828
	S.D.	.70990	.25137	.0047	2.95870	.83002	.0004
InfoBoard^{++}	Mean of C	-.23530	.17085	.1684	-.59350	1.09744	.5886
	S.D.	.74787	.19334	.0001	4.72018	.90488	.0000
Constant	Mean of C	-1.50405	.41772	.0003	-6.00478	3.07989	.0512
	S.D.	1.92147	.37541	.0000	6.21736	2.40429	.0097
Nonrandom parameters in utility function							
Payment		-.12425	.01698	.0000	-.20419	.02524	.0000
Heterogeneity in means							
BioDiv$^-$: Frg		.35409	.21594	.1011			
BioDiv$^+$: Nat		-.35731	.20724	.0847			
NumVisit$^-$: Frg		.67882	.32251	.0353			
NumVisit$^-$: Inc		.53702	.26798	.0451			
NumVisit$^+$: Frg		-.76007	.42484	.0736			
NumVisit$^+$: Time		.37911	.23062	.1002			
NumVisit$^+$: Inc		-1.03938	.36798	.0047			
RestPlace$^+$: First		-.16305	.14193	.2506			
RestPlace$^+$: Inc		.36154	.16281	.0264			
RestPlace^{++}: Time		.39322	.19327	.0419			
RestPlace^{++}: Nat		.71647	.23149	.0020			
Info$^+$: First					3.06818	1.79547	.0875
Info^{++}: Nat		-.50773	.24011	.0345			
Info^{++}: First					-4.74480	2.74366	.0837
τ					1.45094	.25617	.0000
γ					.02675	.02594	.3023
σ					.68658	.87041	
N:o of sets		1551			1551		
Log-L		-1291			-1288		
Pseudo R^2		.2426			.2441		
AIC		2715			2694		
Fin Smlp AIC		2721			2699		
Bayes IC		3073			3009		
Hannan Quinn		2848			2811		

Notes: [a]Effect coded. [b]Superscript – (+) indicates a reduction (increase) compared with the current level. [c]Models allow correlation between random parameters, but these results are not shown.

Table 6. GMXL models with heterogeneity in means and heteroscedasticity in scale factor

			GMXL[c]			GMXL[c]	
Attributes & lev.[a,b]		Coeff.	S.E.	*p*-value	Coeff.	S.E.	*p*-value
Random parameters in utility functions							
BioDiv⁻	Mean of C	-1.07320	.23582	.0000	-1.05223	.22885	.0000
	S.D.	1.45056	.24088	.0000	2.50336	.21724	.0000
BioDiv⁺	Mean of C	.42166	.16474	.0105	.45374	.15231	.0029
	S.D.	.59813	.28922	.0386	.47278	.24530	.0539
NumVisit⁻	Mean of C	.39614	.15147	.0089	.4011	.14823	.0068
	S.D.	.56276	.23733	.0177	.46657	.43740	.2861
NumVisit⁺	Mean of C	-.86112	.28941	.0029	-.98576	.31499	.0018
	S.D.	.59922	.44507	.1782	.71197	.51354	.1656
RestPlace⁺	Mean of C	.17296	.13623	.2042	.11047	.11749	.3471
	S.D.	.29389	.91494	.7480	.51030	.72766	.4831
RestPlace⁺⁺	Mean of C	-.54520	.22065	.0135	-.47612	.17826	.0076
	S.D.	.60191	1.00730	.5501	.51020	.88550	.5645
InfoBoard⁺	Mean of C	.37380	.13718	.0064	.18032	.14312	.2077
	S.D.	.20450	.83646	.8069	.23692	.94178	.8014
InfoBoard⁺⁺	Mean of C	-.22342	.15772	.1566	-.03870	.18411	.8335
	S.D.	.41016	.95620	.6680	.30187	.72257	.6761
Constant	Mean of C	-.58938	.36986	.1110	-.80060	.34158	.0191
	S.D.	.50443	2.03549	.8043	.76449	1.56033	.6242
Nonrandom parameters in utility function							
Payment		-.07945	.01174	.0000	-.08986	.01223	.0000
Heterogeneity in means							
Info⁺: First					.29749	.16944	.0791
Info⁺⁺: First					-.34068	.20383	.0946
Heteroscedasticity in scale factor							
Edu		.46005	.17640	.0091	.30570	.16124	.0580
Time		-.34730	.15932	.0293	-.00822	.15227	.9570
Nat		-.62979	.19860	.0015	-.61182	.20053	.0023
τ		.11109	.64789	.8639	.10919	.51585	.8324
γ		.10438	.28648	.7156	.10339	.33613	.7584
σ		1.04729	.36373		1.11224	.29958	
N of sets		1551			1551		
Log-L		-1335			-1332		
Pseudo R^2		.2168			.2181		
AIC		2789			2789		
Fin Smlp AIC		2794			2794		
Bayes IC		3110			3120		
Hannan Quinn		2908			2911		

Notes: [a]Effect coded. [b]Superscript – (+) indicates a reduction (increase) compared with the current level. [c]Models allow correlation between random parameters, but these results are not shown.

Conclusions

We have elaborated how observed and unobserved heterogeneity can be modeled in choice experiment models. Our results show that the model performance can be improved by explicit modeling of respondent heterogeneity in our stated preferences data. In addition, the basic random parameter MIXL model can be improved by allowing scale heterogeneity as in the GMXL model. This finding supports the argument (e.g. Louviere and Meyer, 2007) that much of the heterogeneity in attribute weights used in choice contexts is accounted for by a pure scale effect. Accounting for scale heterogeneity enables one to account for "extreme" respondents who exhibit nearly lexicographic preferences, as well respondents who exhibit very "random" behavior (Fiebig et al., 2010). However, our results also show that it is not enough to use only scale heterogeneity in explaining the phenomenon of hetero-geneity in choice experiment models. Preference heterogeneity needs to be explicitly modeled also in the GMXL model. Most importantly, the scale heterogeneity can also be modeled more accurately using visitor specific covariates. Respondents' preferences can be explained by their attitudes, perceptions, past experiences, and sociodemographic characteristics also when scale heterogeneity is allowed for. Thus one important line of future work is to include scale heterogeneity related questions into the surveys. In addition, scale heterogeneity can be used to test how alternative survey designs perform in order to find the most useful design to be applied (see Czajkowski and Giergiczny, 2011). Better survey designs are needed in particular in the field of environmental economics where the studied commodity has many characteristics that are unfamiliar for the respondents, such as biodiversity and carbon sequestration among other things. Our experience also is that the GMXL model is very sensitive to various assumptions and specifications. It is thus very important to approach its modeling humbly and with a hardworking attitude. Much more research is still needed.

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