

## COMPARISON OF DISCRETE CHOICE MODELS FOR ECONOMIC ENVIRONMENTAL RESEARCH

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### Abstract:

In the paper the discrete choice models are discussed and applied based on empirical data. The main goal of the paper is to find out whether the various discrete choice models provide the analyst with the robust and reliable estimates of values of natural goods or values of changed quality of such goods. Our results indicate that the yielded value estimates using the choice experiment method and discrete choice models are applicable in expert support of decision-making on allocation of public resources to such goods, because they are stable and robust. These issues are investigated for the marginal willingness of Czech visitors to the Mácha Lake beaches to pay for the water quality and beach characteristics.

**Keywords:** discrete choice models, choice experiment, welfare measure, random utility theory, public goods.

**JEL Classification:** C01, C13, C16, D61, H40

### Introduction

The economic valuation of natural resources is a substantial part of neo-classical environmental economics. This economic valuation is directly related to allocation of public funds. Neo-classical environmental economics assume that the market provides insufficient quantities or quality of public environmental goods (Hampl, 2001). The reason is the insufficient inflow of private funds for the given degree of resource use. The solution offered by neo-classical environmental economics is a governmental intervention, typically in the form of allocating public funds to such goods. The question is, however, what is the optimum rate of resources to be invested from public funds (for deeper discussion see Šauer, 1986). The answer largely derives from the value of the natural goods (or the value of change in their quality).

The so-called stated preference methods are applied in order to establish the value, in spite of the related methodological problems (*e.g.*, Slavík, 2007; Cordato, 2004);

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the choice experiment method is the best developed of those at present. Until recently the attention in the Czech Republic has been paid first of all to contingent valuation method (see *e.g.* Šauer *et al.*, 1998a and Šauer *et al.*, 1998b).

Erroneous – overvalued or undervalued – estimates of the value of a natural resource resulting from application of the above methods may eventually lead to erroneous decisions made by the public administration concerning allocation of public funds: immoderate waste or insufficient protection and renewal of natural goods. It is essential to see the current broad debate on non-market valuation methods. Given the large sums of money allocated world-wide to the conservation and renewal of natural resources, the authors take the liberty to pronounce the opinion that the debate, which contributes to the understanding of the degree of efficiency of allocation of public funds *via* developing non-market valuation methods, is very useful to economics.

The ambition of the present paper is to contribute to that debate by bringing a detailed discussion of models used in analyzing choice experiment data. The main objective of this paper is thus to compare and discuss various types of discrete choice models with respect to their ability to model discrete choice data coming from choice experiments and with respect to the welfare measure values they provide analyst with. The paper notices their limitations and conveniences. At the same time, the discussed aspects of discrete choice models are demonstrated on a practical example of primary data analysis gained from environmental research.

The main hypothesis of this paper is that regardless of the model used, the analyst arrives at similar results in respect of the estimated model parameters and estimated welfare measures. The second hypothesis is that the original model used in modelling discrete choice data (*i.e.*, the multinomial logit model) yields robust estimates of welfare changes even where it fails to meet the fundamental assumption called independence of irrelevant alternatives.

The structure of the article is as follows. The economic background of the discrete choice models is explained in the first section. Section two discusses the advantages and limitations of the most common discrete choice models used for choice experiment data modelling. In the third section of the paper, the discussed models are developed on a practical example of summer waterside recreation - the preference analysis of the summer holiday-makers on the Mácha lake beaches in the summer of 2007. In that chapter, models are discussed with respect to their fitness, estimated values, practical results, and advantages in terms of information they provide the analyst with. Welfare measures based on the model estimates are also presented in the same chapter. The last chapter concludes.

## 1. Economic Grounding for the Discrete Choice Models

The choice experiment method is one of the non-market methods for the economic valuation of natural resources. Discrete choice models are used for modelling of the choice experiment data. The research in this area began in the 1970s. Since then both the multinomial logit and probit models have been widely used in transportation, economics, marketing and many other areas to study both revealed and stated preference data. Recently, the research in this field has paid special attention to the

error term of the models in an effort to solve some of the problems of the discrete choice models and to make them more flexible.

Discrete choice modelling in economic theory complies with Lancaster's new approach to the individual utility maximization problem in consumer theory (Lancaster, 1966) and with the random utility theory (McFadden, 1974). According to Lancaster's approach to consumer theory, consumers derive their utility not from the product as such, but from the characteristics/attributes by which the product can be described.

The random utility theory (Manski, 1977; Phaneuf, 2005) then postulates that utility is a latent construct that exists in the consumer's mind and cannot be observed directly. It further assumes that this latent utility can be partitioned into two components: a systematic or representative utility ( $V$ ) and a random, unexplainable component ( $\varepsilon$ ). This random component arises both because of the randomness in the individuals' preferences and because the attributes do not cover all of the individuals' preferences. If we consider random sampling of the respondents, then  $\varepsilon$  can be interpreted as a random term. Because of this random component, the problem is inherently stochastic and an individual's preferences cannot be understood perfectly. It naturally leads to formulation of expressions for probability of choice. Based on the repeated observations of the choices, one can examine how the levels of various attributes affect the probability of choice. Furthermore, the random utility theory assumes a utility maximization principle, *i.e.*, if an individual chooses one alternative over another, then the utility from the chosen alternative is greater than that from the unselected alternative.

The obvious objective in discrete choice modelling is to analyze the individual's choice in relation to the characteristics (attributes) of the product (*e.g.*, choice of a transportation mode in relation to its price, quality, comfort *etc.*).

## 2. Discussion of Discrete Choice Models

A decision-maker chooses among a set of  $J$  options. The dependent variable  $Y$ , a discrete variable with a countable number of  $J$  values, represents the outcome of the decision. The goal of the analysis is to understand what variables and to what extent influence this choice. The utility of the alternative  $j$  for some decision-maker can be expressed as a linear combination of the observed (non-random) factors  $[X_{j1}, X_{j2}, \dots, X_{jH}] = \mathbf{x}'_j$  with parameters  $\boldsymbol{\beta}' = [\beta_0, \beta_1, \dots, \beta_H]$ , and the unobserved, random factors  $\varepsilon_j$ ,  $j = 1, 2, \dots, J$ . These factors together represent for the decision-maker  $i$ ,  $i = 1, 2, \dots, n$ , the utility as

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \mathbf{x}'_{ij} \boldsymbol{\beta} + \varepsilon_{ij}, \quad j = 1, 2, \dots, J. \quad (1)$$

If the decision-maker chooses the alternative which brings the greatest utility to him, then the probability of the choice of the alternative  $j$  over  $j'$ ,

$$\pi_{ij} = P(V_{ij} + \varepsilon_{ij} > V_{ij'} + \varepsilon_{ij'}) = P(\varepsilon_{ij'} - \varepsilon_{ij} < V_{ij} - V_{ij'}), \quad (2)$$

is the cumulative distribution function of a random variable  $\varepsilon_{ij'} - \varepsilon_{ij} = \varepsilon_{ijj'}^*$ . Different discrete choice models are obtained from different assumptions about this probability distribution.

### Multinomial logit model

The most widely used discrete choice model, a multinomial logit model (MNL), is derived under the assumption that each  $\varepsilon_{ij}, j = 1, 2, \dots, J$ , has the so-called Gumbel (or type I extreme value) distribution with the cumulative distribution function

$$F(\varepsilon_{ij}) = \exp[-\exp(-\varepsilon_{ij})] \quad (3)$$

and with the variance of  $\lambda^2\pi^2/6$ . If these random variables are distributed identically and independently (IID) and follow the Gumbel (type I extreme value) distribution, then their difference follows the logistic distribution (McFadden, 1974; Agresti, 2002)

$$F(\varepsilon_{ijj'}^*) = [1 + \exp(-\varepsilon_{ijj'}^*)] \quad (4)$$

with a zero mean and with the variance of  $\pi^2/3$  (a scale parameter  $\lambda$  can be arbitrarily set to 1). As can be proven, the probability of choice of the alternative  $j$  by the individual  $i$  is then

$$\pi_{ij} = \frac{\exp(V_{ij})}{\sum_j \exp(V_{ij})} = \frac{\exp(\mathbf{x}_{ij}' \boldsymbol{\beta})}{\sum_j \exp(\mathbf{x}_{ij}' \boldsymbol{\beta})}, \quad (5)$$

where  $\mathbf{x}_{ij}$  denotes the values of the  $H$  explanatory variables for subject  $i$  and response choice  $j$ . The problem with the MNL model arises from the IID assumption. The odds of choosing an alternative  $j$  over an alternative  $j'$  do not depend on the other alternatives in the choice set.

This direct consequence of the IID assumption – independence of irrelevant alternatives (IIA) – is expressed as a proportionate shift: an increase in the probability of one alternative reduces the probabilities for all the other alternatives by the same percentage. If the IIA property holds, it is possible, for example, to reduce a number of choice alternatives without influencing the relations among the remaining ones. It is unrealistic in some applications. The key IID assumption is that the errors are independent of each other. However, unobserved factors related to different alternatives might be similar and hence the random component might be dependent. Then the assumption of independence can be inappropriate.

The IIA condition is usually tested with the Hausman-McFadden test (McFadden *et al.*, 1976; Hensher *et al.*, 2005). Nowadays, the hypothesis of this test is commonly specified as constraints on the parameters of the more general model. For the calculation of the test statistic, each alternative is separately excluded from the model, and the parameters for restricted and unrestricted models are estimated as well as their variance-covariance matrices. The test criterion is chi-square distributed with the degrees of freedom given by the number of estimated parameters.

Although the IID/IIA conditions may be worrying, any unrealistic assumption about the error term is likely to be of small consequence if the amount of information in the unobserved component is minimal. The richness of information in  $V_{ij}$  captured in attributes depends in particular on the proper implementation of the design and pretest stages of the choice experiment.

To measure how well the model fits the data, the goodness-of-fit statistics on the basis of the log-likelihood function are usually used (*e.g.*, Agresti, 2002). There exist

many such statistics (Pecáková, 2007); the one most used in literature on discrete choice modeling is McFadden's statistic:

$$D_{MF} = \frac{\ln L_0 - \ln L_E}{\ln L_0} , \quad (6)$$

where  $L_0$  is the likelihood of the intercept-only model and  $L_E$  is the likelihood of the estimated model. The interpretation of this statistic is not the same as that of the R-squared statistic in the linear regression and usually its values are low; fortunately, an unambiguous relationship between them exists that provides better interpretation (Domencich, McFadden, 1975), where pseudo R-squared values between the range of 0.3 and 0.4 can be translated as an R-square of between 0.6 and 0.8 for the equivalent linear model.

For the comparison of models, the log-likelihood ratio statistic, the so-called deviance, is normally used (Hensher *et al.*, 2005; Agresti, 2002). It is the statistic for testing the null hypothesis that the restricted model (R) holds against the alternative that the more general, unrestricted model (U) holds:

$$D = -2(\ln L_R - \ln L_U) . \quad (7)$$

It has an approximately chi-square distribution with degrees of freedom equal to the difference in the number of parameters between both the compared models.

Wald tests are used most commonly for hypotheses about the significance of the single parameters; however, sometimes likelihood ratio tests are recommended instead (Hosmer and Lemeshow, 2000). The Wald test is known to have low power and it can be biased where there are insufficient data.

### ***Nested logit model***

If the IIA does not hold, it is necessary to consider a choice model that is less restrictive. Recently, much research effort has been concentrated on relaxing the strong IID and IIA assumptions associated with error terms. The generalized extreme value (GEV) model allows correlation in unobserved factors over alternatives; the unobserved portions of utility ( $\varepsilon_{ij}$ ) for all alternatives jointly have a generalized extreme value distribution. The nested logit model (NL model) is the most widely used member of the GEV family of models.

The choice alternatives are structured into several ( $K$ ) groups (the so-called nests)  $B_1, B_2, \dots, B_K$ . IIA holds within each nest, but it does not hold for alternatives among different nests. The vector of unobserved utility  $\varepsilon_i' = [\varepsilon_{i1}, \varepsilon_{i2}, \dots, \varepsilon_{iJ}]$  has a generalized extreme value distribution with the cumulative distribution function

$$F(\varepsilon_i) = \exp \left[ - \sum_{k=1}^K \left( \sum_{j \in B_k} \exp(-\varepsilon_{ij} / \lambda_k) \right)^{\lambda_k} \right] . \quad (8)$$

The parameter  $\lambda_k$  is a measure of the degree of independence in unobserved utility among the alternatives in a nest  $k$ ; full independence among all the alternatives in all nests ( $\lambda_k = 1$ ) reduces the nested logit model to a multinomial logit model.

If the observed utility ( $V_{ij}$ ) is decomposed into an invariable part for all alternatives within a nest ( $W_k$ ) and a part that varies across alternatives within a nest ( $Y_{ij}$ ),

$$U_{ij} = W_{ik} + Y_{ij} + \varepsilon_{ij}, \quad j \in B_k, k = 1, 2, \dots, K, \quad (9)$$

then the probability of choice can be written as a product of two standard logit probabilities: the probability resulting from the choice among nests – the *upper model* (it depends on both the mentioned parts of utility) and the conditional probability resulting from the choice among the alternatives within the nest – the *lower model* (it depends on  $Y_{ij}$  only). Thus,

$$\pi_{ij} = \frac{\exp(W_{ik} + \lambda_k I_{ik})}{\sum_{c=1}^K \exp(W_{ic} + \lambda_c I_{ic})} \cdot \frac{\exp(Y_{ij} / \lambda_k)}{\sum_{c \in B_k} \exp(Y_{ic} / \lambda_c)}. \quad (10)$$

The quantity  $I_k$  (the so-called inclusive value – IV – or inclusive utility of nest  $B_k$ ) that enters as an explanatory variable into the upper model,

$$I_k = \ln \sum_{c \in B_k} \exp(Y_{ic} / \lambda_c), \quad (11)$$

brings in the information from the lower model: it is the log of the denominator of the lower model. The term  $\lambda_k I_{ik}$  expresses the utility expected from the choice among the alternatives in nest  $B_k$ . Its parameter  $\lambda_k$  can be used to test whether the correlation structure of the nested model differs from the multinomial logit model.

The principle of the test is that if the IV parameter does not differ statistically from 1, then a nested logit collapses into a multinomial logit model. The significant values of the test statistic (with an approximately standard normal distribution) justify nested structures (Louviere *et al.*, 2000). A number of researchers have independently shown that the IV parameter for the lower model is the ratio of the scale parameter of the upper model to the scale parameter of the lower model; in the NL model the scale parameter is introduced in the variance of the unobserved effects for each alternative (the variance is an inverse function to the scale). This is real progress; nevertheless, the NL model cannot be identified without imposing an additional restriction. One possibility is that the researcher constrains the IV parameter to be the same for all (or some) nests, indicating that the correlation is the same in each of these nests (Train, 2003). That is also the approach applied in the NL model estimation in this paper.

The NL model enables us to model choices in a hierarchical structure. These are sometimes interpreted as a sequential decision-making process, that is, that the respondents decide first on the nest and then on the particular alternative within the nest. However, this decision-making process is not necessary for the nested logit model application. In other words, the “NL tree structures are determined so as to accommodate differences in variance or scale that exist in the unobserved components of the utility expressions (*i.e.*, on econometric and not behavioral grounds)” (Hensher *et al.*, 2005). All the parameters of a nested model can be estimated by standard maximum likelihood techniques.

### Probit model

The probit model (PM) provides an alternative way to fix the problem of the limitations of the multinomial logit model, especially regarding the IID and IIA properties. (Hausman, 1978) As Train suggest, “...the (multinomial) logit model is limited in three important ways. It cannot represent random taste variation, it exhibits restrictive substitution patterns due to the IIA property and it cannot be used with panel data when unobserved factors are correlated over time for each decision-maker... PM deals with all three.” (Train, 2003).

The basic assumption of the PM is that the unobserved utility components are joint normally distributed with the density

$$f(\boldsymbol{\varepsilon}_i) = \frac{1}{(2\pi)^{J/2} |\boldsymbol{\Omega}|^{1/2}} \exp[-0.5 \boldsymbol{\varepsilon}_i' \boldsymbol{\Omega}^{-1} \boldsymbol{\varepsilon}_i], \quad (12)$$

with a mean vector of zero means and a known covariance matrix  $\boldsymbol{\Omega}$ . The choice probability of the alternative  $j$  can be expressed as

$$\pi_{ij} = F(\boldsymbol{\varepsilon}_i) = \int_{\varepsilon_i} f(\boldsymbol{\varepsilon}_i) d\boldsymbol{\varepsilon}_i. \quad (13)$$

With a full covariance matrix, various patterns of correlation and heteroskedasticity can be accommodated according to need, so that the IID and IIA are relaxed. However, the probabilities of choice can be expressed only in the form of integrals and they must be evaluated numerically through simulation. Also, the model interpretation is not as straightforward and intuitive as in the logit models. The linear combination of observed factors – the representative utility – in this model is a probit, *i.e.*, a percentile of the normal distribution.

### Random parameters logit model

Any random utility model can be approximated by a mixed logit model (random parameters logit model, or RPL model). It is not restricted to normal distributions like the PM; nevertheless, it is more flexible in the treatment of the variances and correlations of the random component. The RPL model used for discrete choice data analysis overcomes the two major limitations of the MNL model, *i.e.*, the IIA property and the limited ability of previous models to explicitly account for heterogeneity in data (Train, 2003). To be able to take into account correlations among the error components of different choice alternatives, the model introduces into the utility function an additional stochastic element that may be heteroskedastic and correlated across alternatives (Train, 2003).

The utility of the decision-maker  $i$  from the alternative  $j$  is specified in the mixed logit model as

$$U_{ij} = \mathbf{x}_{ij}' \boldsymbol{\beta}_i + \varepsilon_{ij} \quad i = 1, 2, \dots, n, j = 1, 2, \dots, J; \quad (14)$$

here  $\mathbf{x}_{ij}$  are observed variables that relate to the alternative  $j$  and the decision-maker  $\boldsymbol{\beta}_i$  is a vector of coefficients of the observed variables for the decision-maker  $i$  representing individuals' tastes;  $\varepsilon_{ij}$  is a random term with an IID extreme value distribution



In contrast to a standard logit model, all the coefficients (of the variables  $\mathbf{x}_{ij}$ ) vary across decision-makers in the population with a density  $f(\boldsymbol{\beta})$ . They are considered to be random and can be decomposed into their means  $\alpha$  and deviations  $\mu_i$ . Then

$$U_{ij} = \mathbf{x}_{ij}'\boldsymbol{\alpha} + \mathbf{z}_{ij}'\boldsymbol{\mu}_i + \varepsilon_{ij} \quad i = 1, 2, \dots, n, j = 1, 2, \dots, J, \quad (15)$$

here  $\mathbf{z}_{ij}'\boldsymbol{\mu}_i$  represents the error component (when  $\mathbf{x}_{ij} = \mathbf{z}_{ij}$ ). The unobserved portion of utility with this error component can be correlated among alternatives and/or heteroskedastic for each individual (in the case of a zero error component we obtain the standard logit model).

The mixed logit choice probabilities are conceived as a mixture of the logit function evaluated at different values of parameters  $\boldsymbol{\beta}$  with  $f(\boldsymbol{\beta})$  as the density of the mixed distribution. The density  $f(\boldsymbol{\beta})$  is specified as continued and in particular normal, lognormal, uniform, triangular or any other distributions are used. The applicable distribution is given by expectations about decision-makers' behavior in the particular application.

Then, the mixed logit choice probabilities can be expressed as integrals of standard logit probabilities over a density of parameters evaluated at different values of  $\boldsymbol{\beta}$  by the density  $f(\boldsymbol{\beta})$ ,

$$\pi_{ij} = \int \frac{\exp(\mathbf{x}_{ij}'\boldsymbol{\beta})}{\sum_j \exp(\mathbf{x}_{ij}'\boldsymbol{\beta})} f(\boldsymbol{\beta}) d(\boldsymbol{\beta}). \quad (16)$$

To specify the distribution of the coefficients, an estimate of its parameters is necessary. Because of that, two sets of parameters are used in the mixed logit model: parameters which enter the logit formula, and parameters which describe the density. The first type of parameters has an interpretable meaning as representing the tastes of individual decision-makers; the second parameters describe their distribution across decision-makers.

Problems with model estimation via convergence problems may and do occur in the RPL model. The estimation problems differ depending on the distribution of the variables used. In the case of a normal distribution being imposed on the parameters, respondents with a reverse sign compared to the anticipated sign occur in the results. The triangular distribution, which is restricted on both sides (compared to the normal distribution), can then be an alternative for the analyst since it is a proxy for the normal distribution. The triangular, normal and uniform distributions can be constrained as well and thus unacceptable signs on the random parameters can be avoided (Hensher, Greene, 2003). The log-normal distribution can be a suitable alternative as well since it does not induce the problem with the unexpected signs; however, it is often problematic for estimation. All the mentioned distributions were tested on the Mácha lake data. In the paper only the best model specification is presented.

The greatest value of the RPL model can occur in using each parameter with other linked parameter estimates. The mean parameter estimate for a variable, an associated heterogeneity in its parameter and the standard deviation of the parameter estimate represent the utility of this variable associated with a specific alternative and individual.



### 3. Discrete Choice Models: Empirical Application

The following pages are devoted to the empirical application, comparison and discussion of the appropriateness of the discrete choice models discussed in the previous sections of the paper. The models are developed in the same order as they were discussed.

The discrete choice data for the case study were gathered using the choice experiment method, which is one of the choice modelling approaches that are consistent with economic theory (Batemann, 2002). The application of the choice experiment method is linked to a sociologic survey. In the survey, several different products (alternatives) described in terms of their attributes are offered to the respondents. One of the attributes is always the price of the product or a similar measure of its value (*e.g.*, travel distance to a certain place, a tax increase); the “opt-out/status quo” alternative is also offered, meaning no change at no costs/preserving the current situation, *etc.* The products (alternatives) are described by the same attributes, but the level of the attributes varies (*e.g.*, water quality can be the attribute of a product called recreation; the levels of the attribute are good or poor water quality). The consumers then make a “trade-off” between the changes in the attribute levels and the prices of the alternatives. An “opt-out” alternative is essential for the demand prediction. Without the “opt-out” alternative in a choice experiment, it might well happen that a respondent would be forced to choose something that he/she does not want. The data for the following case study were collected on the Mácha Lake beaches in the summer of 2007. The Mácha Lake lies in a tourist district and is crucial for the tourism in the district. In recent years, the Mácha Lake<sup>1</sup> has suffered from low water quality caused by high phosphorus content in the water (water eutrophication), which gave rise to a significant cyanobacterium occurrence in 2004.

The study population was the population of the visitors to the paid beaches, which amounts approximately to 5/6 of all visitors to the Mácha Lake. The survey on the beaches was carried out between July and August 2007. Prior to the main survey, several in-depth interviews were made in Prague focusing on waterside recreation then a pre-test was carried out in June 2007. Then the pilot version of the questionnaire was prepared and two pilot surveys were carried out in June in order to improve and finalize the questionnaire and to test the sampling strategy in the field.

The questionnaire was administered on-site to visitors on the four paid beaches. Respondents were intercepted randomly throughout the day on each beach separately and interviewed face-to-face by trained interviewers. Respondents were selected randomly. The survey resulted in a total of 333 completed questionnaires. The questionnaire was designed to be completed in 15 minutes in order to avoid respondent fatigue (for details see Vojáček, Melichar, 2007).

The crucial part of the choice experiment application is the appropriate choice of the attributes. The attributes should characterize the product of interest as well as possible, so that as much as possible of the individual's preferences is covered by the attributes; in other words, so that the random component of the utility ( $\varepsilon_{ij}$ ) in

<sup>1</sup> The Mácha Lake is situated in the Liberec Region. It lies almost 100 km north of Prague. Its size is approximately 305 hectares.

the Random utility model (RUM) is minimized. For the combination of the levels of attributes in the choice experiment cards, the orthogonal main-effects plan (Louviere *et al.*, 2000) was used. The attributes and their levels used in the final sampling<sup>2</sup> are plotted in Table 1. For a detailed discussion of the choice of the attributes and the choice experiment design (see Vojáček, Melichar, 2007).

Table 1  
Choice Experiment Attributes and Their Levels

Attribute	Attribute Levels
Beach overcrowded	Yes No
Water quality	Clear water Slightly polluted water Polluted water
Beach equipment	Yes No
Entrance Fee	CZK 40 (EUR 1.6) CZK 80 (EUR 3.2) CZK 150 (EUR 6)

Each respondent was asked to choose one alternative out of the three possible that is among Site 1, Site 2 and the opt-out option. The opt-out option was presented as choosing neither of the offered possibilities. Each respondent made nine decisions in a row. The pilot surveys showed that respondents were able to cope with nine choice triplets each.

### Description of variables

The explanatory variables used in the modelling exercise were as follows; see Table 2.

Table 2  
MNL Model; Explanatory Variables

Variable	Description of variable	Variable values
<i>Crowd</i>	Overcrowded beach	1=yes; 0=no
<i>Clear</i>	Water pollution level – clear	1=yes; 0=no
<i>Dirty</i>	Water pollution level – dirty	1=yes; 0=no
<i>Noteq</i>	No equipment at the beach	1=yes; 0=no
<i>Fee</i>	Entrance fee	40; 80; 150
<i>Opt_out</i>	The dummy for the opt-out alternative	0 = no, 1 = opt-out

In the discrete choice models, it is not the absolute magnitude of the utility that is measured, but rather the changes in the utility in comparison with the basic scenario (basic

<sup>2</sup> The attributes used in the final survey questionnaire were changed twice according to the pre-test and the pilot survey results.

levels of attributes). Thus, for example, the estimated parameter for Clear water (“Clear”) can be interpreted as a indication of the relative change in the people’s preferences in comparison with the attribute level “*Slightly polluted water*” (the basic attribute level). This coefficient can also be expressed as a relative change in the probability of selecting a certain locality when water quality changes from slightly polluted to clear water and all other attribute levels remain unchanged. The formulae for converting the estimated parameter to the mentioned percentage change differ depending on the model used.

### **Multinomial logit model**

For the analysis the Nlogit4 software was used. First the basic multinomial logit model was estimated. For the estimates see Table 5, column MNL (t-statistic in brackets).

The MNL model performed well. All the parameters of the model were significant at the 1% level and had the expected sign, that is, the people showed a positive preference towards less crowded beaches, they preferred clear water to dirty water, and they perceived dirty water as a very negative factor for the utility they get from their recreation. They also had negative preferences towards beaches which are not equipped and preferred lower entrance fees. The Log likelihood function was –2305.512. The model was statistically significant.

However, the multinomial logit model failed to pass the Hausman and McFadden test of the IIA (with a chi-square value of 832.96 and 5 degrees of freedom), which is crucial for its validity. In this case, the hypothesis that the data comply with the IIA assumption (at an alpha equal to 5%) was rejected. As Louviere *et al.* (2000) state, “*when violations (of the IIA assumption) occur, the cross-substitution effects observed between pairs of alternatives are no longer equal given the presence or absence of other alternatives within the complete list of available alternatives within the model*”.

As has been discussed in the theoretical part of the paper, when the MNL model does not comply with the IIA assumption, the nested logit (NL) model provides the analyst with an alternative as it represents a partial relaxation of the IID and IIA assumptions in the MNL model.

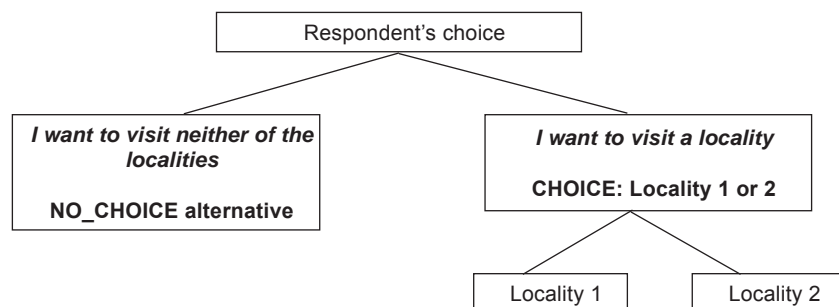
It has to be mentioned that application of the nested logit models in the so called “*unlabelled experiments*” is probably nonintuitive. The nested logit models are usually used in the cases where particular alternatives describe some specific alternative (*e.g.* transportation mode – bus *vs.* car; or particular Lake 1 *vs.* Lake2) which is not our case. In our case *e.g.* Locality 1 and Locality 2 at one particular decision problem are compiled only on the base of orthogonal design and does not represent any particular locality. On the other hand we cannot exclude the possibility that people for some reasons prefer locality named “1” to locality named “2” (for example because they like more number one). From the econometric point of view the nested logit model specification at the case of unlabelled experiment does not pose any problem. If it happens that the nested logit model does not pay any sense it simply collapses to multinomial logit model.

### **Nested logit model**

In order to apply the NL model framework to the Mácha Lake data, the choice problem needs to be reformulated as a hierarchical nested structure. In the Mácha Lake data,

this seems to be possible, in the way that the respondents could be organizing the choice problem in two stages: first whether they are willing to visit any of the localities offered by the interviewer, and then which of the two localities to visit. This leads to the following nested tree structure (Figure 1):

Figure 1:

**The Tree Structure for the Nested Logit Model**

The estimated nested logit model, according to the depicted hierarchical tree structure is shown in Table 3 below.

Table 3

**Nested Logit Model Estimates**

Variable	Coefficient	Standard Error	b/St.Er.	P[ Z >z]
<b>CROWD</b>	-0.419***	0.680	-6.159	0.000
<b>CLEAR</b>	0.686***	0.079	8.639	0.000
<b>DIRTY</b>	-2.438***	0.095	-25.703	0.000
<b>NOTEQ</b>	-1.991***	0.090	-22.115	0.000
<b>FEE</b>	-0.011***	0.001	-14.335	0.000
<b>OPT_OUT</b>	-2.750***	0.122	-22.463	0.000
	<b>IV parameters</b>	<b>tau(b I,r)</b>	<b>sigma(I r)</b>	<b>phi(r)</b>
<b>CHOICE</b>	0.895***	0.656	13.645	0.000
<b>NO_CHOICE</b>	0.895***	0.656	13.645	0.000

Note: \*\*\*, \*\*, \* = significance at 1%, 5%, 10% levels.

This model again performed well. All the parameters of the model were significant at the 0.1% level and they had the same signs and sizes as in the MNL. In specifying the NL model, the correlation between the “*choice*” and “*opt\_out*” variables needs to be restricted, so that the correlation problem between the nest and the explanatory variable is avoided. The log-likelihood of the model was -2304.386. Comparing our models with the log-likelihood ratio test (the test criterion value 2.252 and critical chi value of 5.99), we cannot reject the null hypothesis that the two models are identical. As the log-likelihood ratio test indicates, the NL model does not significantly improve the model estimation and does not contribute to the explanation of the data variability.

This is also confirmed by a test of the IV parameters of the NL model. This test is used to determine whether the nests help to explain people's choices. The analysis of the IV parameters runs in two steps (Hensher *et al.*, 2005). The first is to find out whether the parameter is not equal to zero (*i.e.*, dividing the estimated IV parameter by its standard error and comparing the resulting value to the critical value of the normal distribution), which is evidently not our case (see in Table 3 the p-value for the CHOICE and NO\_CHOICE attributes). The second step is to determine whether the variable is statistically different from one and thus the nests help explain people's choices. If this is not the case, the NL model collapses into a single branch which is equivalent to a MNL model; in other words, the nested logit model is reduced to the multinomial logit model (see Subsection 2). This occurs in the case of the Mácha Lake data and this fact also explains why the estimated parameters for the MNL model and the NL model do not differ. The value of the Wald test is -1.601 and thus we cannot reject the null hypothesis that the IV parameter is statistically different from 1 (at the 5% significance level of the normal distribution; compare the test statistic to the critical value of  $\pm 1.96$ ). Both the log-likelihood ratio test and the test of the IV parameters indicate that the NL model is no better than the MNL model in explaining individuals' choices.

### **Probit model**

Another possibility which provides the analyst with more flexibility compared to the MNL model is the probit model (PM), where it is assumed that the random component is normally distributed. This model does not rely on the IIA assumption as the MNL model does (see Subsection 3). Despite it is not used in discrete choice data analysis as frequently as the NL or MNL models (for reasons see Subsection 2), PM performed well at the Mácha Lake data. The estimated results depicts Table 5.

The log likelihood of the model is -2302.676. The parameters estimated using the PM do not differ much from those in the MNL model. Also, the log-likelihood ratio test with a test value of 5.672 and a critical value of 5.99 indicates that the PM does not significantly improve the model fit and thus is no better in explaining data variability than the MNL or NL models.

### **Random parameters logit model**

As was discussed recent research in discrete choice data modelling pays special attention to the random parameters logit (RPL) models (Train, 2003). These models relax the IID assumption in terms of the covariances; however, *“all are of open-form solution and as such require complex analytical calculations to identify changes in the choice probabilities through varying levels of attributes and socio-demographic characteristics”* (Louviere *et al.*, 2000; Train, 2003). Compared to the developed previous models, the application of the RPL model brings the analyst extra benefits in data analysis. The RPL model enables to determine whether heterogeneity in the data exists and also to identify possible sources of this heterogeneity. In this regard, they provide the analyst with similar possibilities as the latent class models.

The best RPL model specification out of the many possible specifications for the Mácha Lake data is shown in Table 4 below.

Table 4  
Random Parameters Logit Model Estimates

Variable	Coefficient	Standard Error	b/St.Er.	P[ Z >z]
<b>CROWD</b>	-0.60271***	0.0897785	-6.713	0
<b>CLEAR</b>	0.82837***	0.0957429	8.652	0
<b>DIRTY</b>	-2.64859***	0.1310909	-20.204	0
<b>NOTEQ</b>	-2.16329***	0.1124826	-19.232	0
<b>FEE</b>	-0.01320***	0.0010580	-12.474	0
<b>Nonrandom parameters in utility functions</b>				
<b>OPT_OUT</b>	-3.02757	0.1473119	-20.552	0
<b>Derived standard deviations of parameter distribution</b>				
<b>NsCROWD</b>	0.00115	0.26337231	0.004	0.997
<b>NsDIRTY</b>	0.79486***	0.20579656	3.862	0.000
<b>NsCLEAR</b>	0.00768	0.220668	0.035	0.972
<b>NsEQUIP</b>	0.35964**	0.15766598	2.281	0.225
<b>NsFEE</b>	0.00338***	0.00099496	3.394	0.007

Note: \*\*\*, \*\*, \* = Significance at 1%, 5%, 10% levels.

The model is significant at the 1% level. All the parameters of the model are significant at the 1% level and have the expected signs. The estimated parameters slightly differ from the MNL model estimates. In comparison with the MNL model, people had more negative preferences towards crowded beaches, unequipped beaches and polluted water. They also had more positive preferences towards clear water. The log likelihood function is -2290.49. The log likelihood test with a test value of 30.044 and a critical value of 11.07 indicates that the model is statistically better than the MNL model (and also the NL and PM).

In the output of the RPL model shown in Table 4, all variables except the opt-out variable are specified as random, drawn from a normal distribution. The interpretation of the random parameters is much the same as in the MNL model; however, the mean of the random parameter is the average of the parameters drawn over the number of replications from the chosen distribution (the normal distribution in our case). In comparison with the MNL model, there are five additional variables in the output window. These are derived standard deviations of parameter distribution calculated over each of the number draws and as such relate to the extent of the dispersion around the mean of the parameter.

Insignificant parameter estimates for the clear water and crowdedness of the beaches indicate that the dispersion around the mean is statistically equal to zero. That suggests that all information about the people's preference towards these variables is captured in the estimated mean. However, this is not the case for dirty water, entrance fees, and beach equipment, where the estimated standard deviations of the parameters are statistically significant. This suggests that there exists heterogeneity in the parameter estimates across the sample population (around the mean parameter estimate). It can be interpreted that different individuals have different preferences that differ from the mean estimate for the sample population.

In the data analysis, several characteristics of the sample population were analyzed as possible sources of the heterogeneity in the preferences. These were the respondents' income, repetitiveness of their visits to the Lake, a dummy variable indicating whether the people swim in the water during their stays on the beach, the respondents' sex, the beach where the people met the interviewer.

The data suggest that the source of the heterogeneity in the case of the dirty water variable may be partly explained by the respondents' income (people with a higher income perceive dirty water more negatively) and also by the different preferences of visitors to different beaches (visitors to the main beach in Doksy were less sensitive to water quality). These results indicate a statistically significant interaction of the Dirty x Income variables and the Dirty x Doksy variables, both at the 5% level. The source of the heterogeneity for the equipment variable was the respondents' sex (men had more negative preferences towards unequipped beaches) and the respondents' income (people with a higher income were less sensitive to unequipped beaches); these findings indicate statistically significant interactions of the Equipment x Sex variables and the Equipment x Income variables, both at the 5% level. Finally, the sources of the heterogeneity for the fee variable were the repetitiveness of visits to the Mácha Lake (significant at the 1% level), that is, people who visit the Lake repeatedly are more sensitive to the beach entrance fee levels; swimming in the Lake (significant at the 5% level), that is, people who swim in the lake during their visit are more sensitive to the fee level; and the income (significant at the 1% level), *i.e.* people with a higher income are more sensitive to the entrance fee level.

Another possible way how to analyze the influence of the other socioeconomic and other variables on the respondent's WTP in more simple way is to make the interactions between the choice experiment variable and the other variable in question and to include new variable into the MNL model specification. This was also done by the authors of the paper. The obtained results of such a analysis differ in some aspects and the discussion of these differences goes behind the ambition of this paper.

### ***Model comparison***

The model comparison is shown in Table 5 below. This parameter estimate overview confirms the previous finding that the MNL, NL and Probit models yield principally the same values of the estimated parameters despite the fact that they differ in terms of their assumptions (see the Subsection 2). All the models exhibit a decent fit as they reach approximately an R-squared of 0.3, which represents an equivalent of 0.6 – 0.8 for the linear regression model. The parameters estimated with the RPL model do not differ in terms of their signs, but they differ slightly in terms of their sizes. The difference is the greatest for the dirty water and unequipped beach variables; however, one has to keep in mind that both these variables were estimated as random and their standard deviations are significant at the 1% level (5% for the equipment variable); thus, the values shown in Table 5 for the RPL model present only the mean values of the parameter estimates.



Table 5  
Model Comparison (t-statistic in brackets)

	MNL	NL	PM	RPL
CROWD	-0.419***	-0.419***	-0.419***	-0.603***
	(-6.159)	(-6.159)	(-6.357)	(-6.713)
CLEAR	0.686***	0.686***	0.686***	0.82837***
	-8.639	-8.639	-8.921	-8.652
DIRTY	-2.438***	-2.438***	-2.438***	-2.64859***
	(-25.703)	(-25.703)	(-20.152)	(-20.204)
NOTEQ	-1.991***	-1.991***	-1.991***	-2.16329***
	(-22.115)	(-22.115)	(-17.659)	(-19.232)
FEE	0.011***	0.011***	0.011***	0.0132***
	(-14.335)	(-14.335)	(-14.449)	(-12.474)
OPT_OUT	-2.75***	-2.75***	-1.979***	-3.02757***
	(-22.463)	(-22.463)	(-20.007)	(-20.552)
Log likelihood	-2305.512	-2304.386	-2302.676	-2290.49
Adjusted R2	0.287	0.316	0.300	0.304
Observations	2997	2997	2997	2997

Note: \*\*\*, \*\*, \* = significance at 1%, 5%, 10% levels.

### ***Willingness to pay analysis***

The estimates of the parameter values derived for the particular models can be used to derive welfare changes (here, a measure of willingness to pay, or WTP) caused by the changes in the levels of particular attributes. WTP for marginal (discrete) changes in the attribute levels express in fact the change in the consumer surplus of the individual or it's utility. The obviously known methodological problems of the consumer surplus and utility concept are not challenged in this paper (for details see Svoboda, 2008; Skořepa, 2008). This chapter compares the WTP results derived from the estimated models. The estimation of the welfare changes caused by changes in the attribute levels can be calculated as follows:

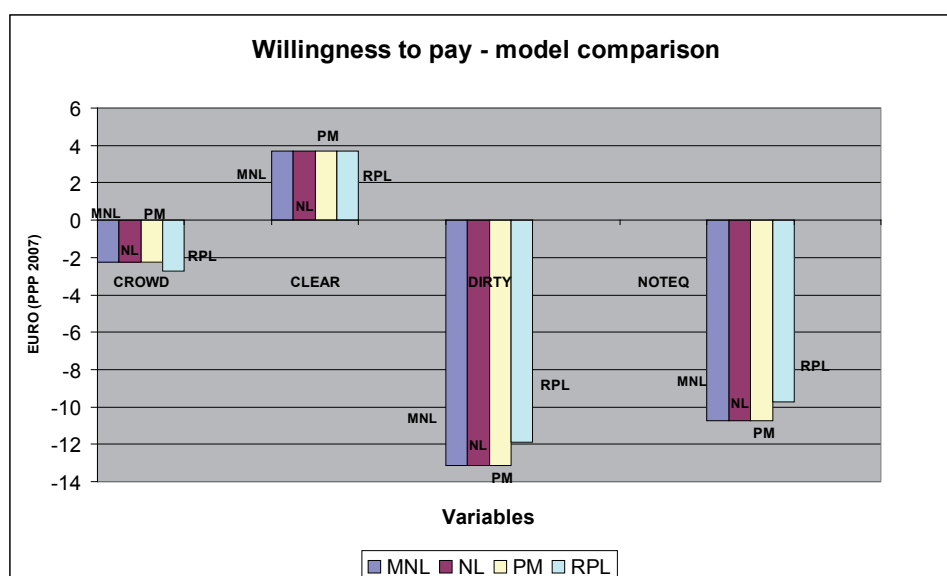
$$WTP_{\Delta x} = \beta / \gamma , \quad (17)$$

where  $\beta$  is the variable coefficient;  $\gamma$  is the marginal utility of income (fee variable coefficient) (Hanemann, 1984). Thus, the point estimates of WTP for a change can be derived by calculating the marginal rates of substitution between the change in a given attribute and the price attribute, that is, by dividing the coefficient of the attribute by the coefficient of the entrance fee attribute. This is the rate at which the respondent is willing to trade off money for improvements to the beach (equipment, crowdedness, water quality) attribute. The following figure presents a comparison of the marginal WTP for the attribute level changes.

As apparent from Figure 2, there are only small differences in the WTP estimates caused by differences in the estimated parameters for the particular models. These minor differences would probably also lead to only minor differences in the aggregated value of water quality and other attributes of the beaches over the population of the Lake visitors.

Figure 2

**Marginal Willingness to Pay for a Change in the Attribute Level (Euro PPP 2007); Model Comparison**



Note: MNL = Multinomial logit model; NL = Nested logit model; PM = Probit model; RPL = Random parameters logit model.

#### 4. Discussion and Conclusions

The paper has discussed, developed and compared a few discrete choice models with respect to the states objectives of the paper. The multinomial logit model performed well. All the parameters of the model were significant at the 1% level. However, the multinomial logit model failed to pass the Hausman and McFadden test of the IIA, which is crucial for its validity. One could then expect that the introduction of other, more advanced models would be significantly beneficial for the data analysis. However, this expectation was not nearly confirmed regarding the nested logit and probit models, which relax the discussed IID assumption within the distribution of the random component. These models did not bring any improvement to the data analysis, and also the estimated parameters of both the nested logit model and the probit model were almost identical. This finding complies with the results of the log-likelihood ratio tests and with the test of the IV parameters in the nested logit model.

Thus, the second hypothesis made in the paper and one of the main messages of the paper has been confirmed. The multinomial logit model seems to be quite robust with respect to deviations of the random component distribution from the model.

Thus, the presented analysis seems to prove that the multinomial logit model could be preferred in practice to both the nested logit and the probit models for this type of data even in situations where it does not comply with the basic IID/IIA assumption. Besides, there are three considerable advantages to the multinomial logit model: computational ease, easy-to-obtain probability expression of an individual selecting a given alternative, and straightforward determination and maximization of its likelihood (which reduces possible model estimation difficulties).

The results for the mixed logit model differ slightly from the three other models: its fit to the data was better, which was also confirmed by the log-likelihood ratio test. A considerable value added by this model is its ability to identify the heterogeneity in the data and searching for its sources, which has also been confirmed in our analysis. This model adverts to a significant heterogeneity in three of the five variables used in the choice experiment data analysis.

The analysis also confirmed the first hypothesis and brings thus another message to the reader. Neither the relative importance of the beach and water quality attributes analyzed in the study nor the WTP estimates for the water quality changes and other beach characteristics were substantially influenced by the application of different econometric models.

Our analysis also arrives at the conclusion that the choice experiment using discrete choice models can be a good instrument of the environmental preferences research. It can help to understand the individual preferences in this area and so can be used in support of decision-making regarding allocation of public funds particularly in case of market inference.

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