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## The role of respondents' comfort for variance in stated choice surveys: evidence from a SCUBA diving case

Diana Emang <sup>a,b,\*</sup>, Thomas Hedemark Lundhede <sup>a,c</sup> and Bo Jellesmark Thorsen<sup>a,c</sup>

<sup>a</sup>*Department of Food and Resource Economics, Faculty of Science, University of Copenhagen, Frederiksberg C, Denmark;* <sup>b</sup>*Faculty of Forestry, Universiti Putra Malaysia, Selangor, Malaysia;* <sup>c</sup>*Centre for Macroecology, Evolution and Climate, University of Copenhagen, Frederiksberg C, Denmark*

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Preference elicitation among outdoor recreational users is subject to measurement errors that depend, in part, on survey planning. This study uses data from a choice experiment survey on recreational SCUBA diving to investigate whether self-reported information on respondents' comfort when they complete surveys correlates with the error variance in stated choice models of their responses. Comfort-related variables are included in the scale functions of the scaled multinomial logit models. The hypothesis was that higher comfort reduces error variance in answers, as revealed by a higher scale parameter and vice versa. Information on, e.g., sleep and time since eating (higher comfort) correlated with scale heterogeneity, and produced lower error variance when controlled for in the model. That respondents' comfort may influence choice behavior suggests that knowledge of the respondents' activity patterns could be used to plan the timing of interviews to decrease error variance in choices and, hence, generate better information.

**Keywords:** choice heterogeneity; interview timing; survey implementation; scale parameter models

### 1. Introduction

The stated preference survey method known as choice experiment (CE) is a well-established research instrument in studies addressing the value that various qualities of recreational sites have for users (e.g., Beharry-Borg and Scarpa 2010; Rolfe, Bennett, and Louviere 2000; Schuhmann *et al.* 2013). In CE, respondents make trade-offs between two or more alternatives described by a number of attributes. This allows researchers to estimate respondents' preferences for the specific levels of attributes, producing results relevant to policy development and management of recreational sites (Rolfe, Bennett, and Louviere 2000). As CE applications have grown rapidly, the focus has turned to various ways to improve the performance of the method, e.g., in relation to methods for reducing unexplained variance in the models and, hence, increase the accuracy with which preferences are estimated or inferences made.

Heterogeneity is inherent in choice data and consists of scale (variance) and preference heterogeneity. This study addresses the issue of scale heterogeneity in observed choices made by the users surveyed. Scale heterogeneity refers to the unexplained variance of utility over different choice alternatives, whereas preference

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\*Corresponding author. Email: [diem@ifro.ku.dk](mailto:diem@ifro.ku.dk)

heterogeneity is the variation in preferences over the sampled population (Greene and Hensher 2010). A succession of studies has systematically evaluated approaches to identify and handle differences in scale across data subsets, including the association between scale parameters and survey design aspects. These include studies on the effects of complexity in choices (Sælensminde, 2001) and the numbers of choice sets (Hensher, Stopher, and Louviere 2001). Unfamiliar commodities and complex choice situations may increase scale heterogeneity (Fiebig *et al.* 2009). Decision fatigue, which reduces respondents' cognitive functions, has been shown to result in a higher variance of errors in CE estimates (Hess, Hensher, and Daly 2012).

From a theoretical point of view, it is important to control the factors that influence scale and, thus, unexplained variance in models, as it should enhance estimation accuracy and, notably, inference validity. In the study of the preferences of recreational users, surveys are often administered in the field with interviewers approaching users for interviews. Therefore, from a practical point of view, knowledge of which factors in the implementation of the survey affect unexplained variance could be used in the planning and execution of interviews.

This study specifically asks how comfort factors reported by respondents at the time of the interview may correlate with unexplained variance in choice heterogeneity. We applied a CE to elicit preferences among SCUBA divers at Sipadan, Malaysia. Sipadan is a marine area used for diving activity, and it is administered by a local institution called Sabah Parks. It is a part of the Coral Triangle Network, an area that provides habitat and ecological niches for various marine species (WWF 2012). Sipadan receives more than 40,000 visitors annually (Sabah Parks 2010).

When SCUBA divers are interviewed, they may be under more or less stress or they may be more or less tired or well-rested. This may affect their attention during the interview and the accuracy of their statements in any survey-based leisure science study (including revealed preference studies that rely on stated site visit behaviors, e.g., Hynes, Hanley, and Scarpa 2008 or Scarpa and Thiene 2005). Responding to interviews and relating to potentially complex questions of preferences caused priorities to be cognitively demanding, and the main hypothesis evaluated in this study is that the accuracy and, hence, the unexplained variance of individuals' choice behavior may be correlated with self-reported measures related to their well-being and general comfort.

In selecting which self-reported measures related to comfort to use under our field conditions, we build on two additional strands of literature. First, we draw upon medical and related literature documenting how cognitive abilities are affected by the respondent's sleep patterns (Harrison and Horne 2000; Horne 1988), the time since the respondent's last meal and the respondent's general nourishment status (Masicampo and Baumeister 2008; Gailliot *et al.* 2007) and alcohol intake (Houston *et al.* 2014). As we undertake a field experiment, we rely on self-reported measures and indicators at the time of the survey interview that are relevant according to the literature cited above. The second strand is leisure research studies discussing the challenges of gathering quality information on outdoor recreation activities using field-based surveys. There is little research on the role of respondents' comfort during the interview in this literature. Instead, comfort is discussed mainly as a quality of the outdoor recreational experience itself (Morgan and Lok 2000; Powell 2001; Dimmock 2009) or as a description of the degree to which individuals feel competent in exercising specific forms of leisure activities (Ryan and Trauer 2004; Trauer 2006; Jackson and Csikszentmihalyi 1999). While our CE task elicits respondents' preferences about SCUBA diving site qualities that relate to several of these aspects in the leisure sciences literature, we expand on this

literature by examining the role of respondent comfort during interviews in the unexplained variance in the choice data obtained and, hence, in the reliability of the preferences elicited.

Thus, the contribution of this paper is to investigate how self-reported measures related to respondents' comfort may influence the non-systematic part of choice heterogeneity and, hence, unexplained variance. We show how this can be accounted for using an estimation method, allowing for scale variation, and how it may improve inferences in the model. The results of this paper have relevance for the practice of outdoor recreational studies and surveys – especially, for face-to-face interviews in which careful planning as to when to survey respondents about their recreational activities could help improve the quality and accuracy of data and reduce unwanted variance.

## **2. Materials and methods**

### **2.1. Data collection and study design**

The survey interviews were undertaken on Mabul Island during January and February 2014. Mabul is located 15 minutes from Sipadan (by boat), and divers stay there because it is prohibited to use Sipadan for accommodation. The survey interview was administered at randomly selected sites, and interviewers selected their next respondents using random draws to reflect, as far as possible, the sample population in terms of, e.g., gender and age (18 years or older). A total of 507 divers were interviewed in face-to-face, personal interviews undertaken in two designated time slots: in the morning (from 9:30 a.m. to 12:30 p.m.) and in the afternoon (from 2:00 p.m. to 5:00 p.m.). These time slots were selected because they were within the curfew that was in place at the time and fitted the daily rhythm of respondents who were waiting to travel or resting after a dive. The morning interview included respondents who were waiting for a boat to return to mainland Malaysia. The afternoon interview comprised those who were relaxing at the beach and cafes. Both groups of divers, thus, had already dived at Sipadan. In the interview process, the interviewers moved between the selected interview sites at cafes, the beach, jetty, and the general accommodation areas to pursue the desired sample size and avoid selecting only from types who lounged primarily in one place. Out of 512 questionnaires distributed, 507 questionnaires were returned with complete answers, producing a response rate of 99.02%.

A central part of the CE involved a questionnaire with a total of 12 choice tasks, which were divided into two blocks, generated by the experimental D-efficient design of NGENE (D-error of 0.000663). Each respondent received six choice tasks. Each choice set included a status quo alternative and two policy alternatives described by five attributes (Table 1). These attributes are important aspects of diving experience and relevant to park management, as indicated by divers in the pilot survey, members of focus group and stakeholders. In each choice task, respondents were asked to choose their preferred alternatives. An example of a choice task is presented in Figure 1.

The diving fee attribute was selected as a payment vehicle since it enabled us to obtain welfare measures of changes in diving experience. Divers currently pay RM40 (USD12) for a diving permit, and five additional payments were presented, ranging from RM80/USD24 to RM640/USD198. It was explained to divers that an increment in the permit fee could be used to finance the improvement in environmental conditions suggested in the choice alternatives. Using fees as a payment vehicle was believed to lend credibility to respondents, as they already pay a fee for diving, and to enhance the perceived

Table 1. Attributes, attribute levels, and variable names.

Attributes	Levels	Variable names
Daily permit fee <sup>***</sup>	RM40 <sup>*†</sup> , 80, 160, 240, 320, and 640 (USD12, 24, 50, 74, 100, and 198)/ diver/day	Fee
Number of divers/day <sup>***</sup>	90 divers/day 120 divers/day <sup>*†</sup> 150 divers/day	90 divers/day 120 divers/day 150 divers/day
Coral cover <sup>**</sup>	50% coral cover 70% coral cover <sup>*</sup> 90% coral cover	50% coral cover 70% coral cover 90% coral cover
Fish diversity <sup>**</sup>	30% of total fish diversity 50% of total fish diversity <sup>*</sup> 70% of total fish diversity	30% fish diversity 50% fish diversity 70% fish diversity
Litter pollution at diving sites <sup>***</sup>	Litter may become significantly noticeable Litter pollution is noticeable <sup>*</sup> Litter may become unnoticeable	High litter pollution Medium litter pollution Low litter pollution

\*The attribute level indicates the current management option.

\*\*Levels of these attributes are referred from WWF (2012).

\*\*\*Levels of this attribute are designed based on observation during the preliminary trip, findings from the pilot study and input from discussions with focus groups and relevant stakeholders.

†Levels of these attributes are assigned by Sabah Parks. Ringgit Malaysia (RM) 3.18 = 1USD at the time of survey interview.

Suppose the following table represents the only management option available for Sipadan in your future visit. Please cross (x) one option that you prefer in the shaded column.













Attribute	Current management	Alternative I	Alternative II
Litter pollution	 Medium	 Low	 High
Number of diver	 120 divers per day	 90 divers per day	 120 divers per day
Coral cover	 70% of live coral cover	 90% of live coral cover	 70% of live coral cover
Fish diversity	 50% of total fish species diversity Occasionally see sharks	 70% of total fish species diversity Frequently see sharks	 50% of total fish species diversity Occasionally see sharks
Daily Permit Fee	RM 40	RM 640	RM 40
Your Choice	<input type="checkbox"/> SQ	<input type="checkbox"/> 1	<input checked="" type="checkbox"/> 2

Figure 1. Example of a choice set.

Note: Suppose the following table represents the only management option available for Sipadan in your future visit. Please cross (x) one option that you prefer in the shaded column.

consequentiality of the survey, since money collected from park fees is tied to park activities. Finally, the instrument is coercive and, hence, should reduce free riding incentives (Whitehead 2006).

## 2.2. Socio-demographic information

Almost 92% of the diver sample were foreign and originated from 38 different countries. Most of the foreign divers came from China (24%) while the rest came from countries such as Germany (8.5%) and the United States of America (7.7%). Domestic divers accounted for only 8.3%. Divers between 30 and 39 years of age dominated the sample, whereas only 2.7% were older than 50. Male divers constituted 58.19% of the sample. Many of these divers were single and had university-level education. Their employment rate was around 74% and their gross monthly income varied between RM7,000 and RM14,000 (USD2000 and USD4000). From the dataset, 26.23% were active members of a SCUBA diving club while 1.58% and 2.17% belonged to ecotourism and environmental clubs, respectively. Additionally, a large part of the sampled population was planning to visit Sipadan in the future (85.01%).

## 2.3. Self-reported comfort variables

Overall, the comfort of an individual can be described subjectively by a diversity of context-specific measures (Angner 2010) that relate to physical and psychological well-being. The respondents to our survey are involved in physically and mentally exhausting SCUBA diving activities. In this study, we tried to capture divers' comfort by using self-reported measures of their intake of food and beverages, alcohol consumption, sleep duration, and digestion time. We based these choices on a review of relevant literature, which we elaborate in the sub-sections below. The self-reported variables related to comfort that were derived from our sample of divers are summarized in Table 2.

The variable 'Rested' was measured using questions about the stated length of sleep the night before. The variable 'Digestion' was measured using questions about how long it had been since the respondents had their most recent meal. The variable 'Beer' was measured by asking about the type and quantity of their recent beverage consumption. The variable 'Food' was a yes–no question about whether respondents thought their recent meal had been adequate. We incorporated these four measures into our models by recoding them as binary dummy variables as explained in Table 2. We note that there are

Table 2. Descriptions and distributions of the variables specific to divers.

Variable	Description	Number of respondents
Rested	Those who stated they had slept at least 5 hours	479
Digestion	Those who stated they had eaten, etc., more than an hour ago	380
Beer <sup>1</sup>	Those who drank little alcohol (less than two beers)	30 <sup>2</sup>
Food	Those who stated they ate and drank well at their last meal	500

Note: All variables are dummy coded 1 = yes, 0 = no. These variables explained events that occurred before the interview.

<sup>1</sup>We did not distinguish styles of beer, nor did we make any distinction between alcohol levels or the size of 'a beer', drinking patterns and effects from previous beer consumption.

<sup>2</sup>The distribution of the 'beer' variable is not randomly distributed across the sampled population, but tends to correlate with gender and age.

obvious correlations among the variables, since almost all respondents reported their most recent meal to have been adequate, and a large majority also had more than 5 hours sleep. The role of these correlations in the results is discussed below.

The approach of using very concrete self-reported measures rather than, e.g., asking directly for ‘well-being’ has the advantage of being easy to interpret, rich in information and it also has an edge of practicality for a field setting like ours (Lucas and Baird 2006). It also comes with caveats, since the approach could be subject to biases or errors, and efforts were, therefore, made to reduce possible inaccuracies. For example, if divers were unable to recall the exact number of hours they slept the previous night, the interviewers would alternatively ask the sequence of their activities before sleeping to determine when divers went to sleep and when they woke up. Nevertheless, the approach is less controlled compared to, e.g., a controlled, randomized experimental set-up in which randomized treatments of sleeping, eating, and drinking patterns are applied. However, such controlled experiments are inherently infeasible under our field conditions and would risk affecting the distribution of preferences over diving experience. We discuss this in our caveat section.

### 2.3.1. *Digestion time (Digestion)*

According to our observations during the data collection, the diet for divers holidaying in Sipadan consisted of plant-based foods and drinks (e.g., rice, bread, fruit, and tea) supplemented with meat. Food science research shows that the digestion time for rice is around three hours (Koh *et al.* 2009), digestion time for meat protein is reported to be around two and a half hours (Gatellier and Santé-Lhoutellier 2009) while digestion time for fruits ranges from two to four hours (Tarko *et al.* 2009). There is considerable variation, depending on individual characteristics and food properties (Hur *et al.* 2011; Kong and Singh 2008). Divers in the sampled population who had sufficient digestion time were assumed to be more relaxed, better at handling the interview’s cognitive load and, hence, answer choice questions with less ambiguity in choice.

### 2.3.2. *Eating and drinking (Food)*

SCUBA diving activity requires divers to have good dietary habits. Eating and drinking replenishes glucose levels and restores energy to the brain (Beedie and Lane 2012), whereas a low level of blood glucose can affect decision-making processes (Baumeister and Tierney 2011; Masicampo and Baumeister 2008; Gailliot *et al.* 2007). Sufficient water intake is important to maintain thermoregulation (Jéquier and Constant 2010) and avoid dehydration, which could impair cognitive abilities (Popkin, D’Anci, and Rosenberg 2010), even at mild dehydration levels (Riebl and Davy 2013). Although cognitive performance is influenced by environmental and individual factors (Secher and Ritz 2012), cognitive performance significantly decreases when dehydration level increases (Pross *et al.* 2013). Divers inhale compressed dry air while underwater, which increases the risk of dehydration along with the hot climate at Sipadan. Therefore, it is relevant to control for the influence of the quality of the most recent food and drink intake by the divers.

### 2.3.3. *Sleep duration (Rested)*

Sleeping is an important natural activity in daily life. When individuals are sleep-deprived, thinking performance deteriorates, and cognitive errors increase

(Durmer and Dinges 2005). Divers were asked how long they slept the night before the interview to investigate whether being well-rested influenced divers' cognitive abilities. Although sleep duration varies according to individual lifestyle factors (Tamakoshi and Ohno 2004), and sleeping patterns are affected by physical, mental, or social conditions (Ito *et al.* 2000; Tamakoshi and Ohno 2004), epidemiology studies have shown that maintaining the cognitive performance needed for decision-making requires sleep (Harrison and Horne 2000; Horne 1988). The type of sleep that supports recovery is slow-wave sleep obtained during the first four hours of sleep (Rechtschaffen and Kales 1968). We, therefore, assume that those respondents who had slept a minimum of five hours can be described as well-rested and design our variables accordingly.

#### 2.3.4. Alcohol consumption (Beer)

Significant intake of alcoholic drinks (more than three to four drinks per day) may reduce cognitive functions, including reduced attention span and reduced ability to engage in abstract reasoning and hypothesis generation (Houston *et al.* 2014). Individuals with high alcohol intakes may also have lower cognitive flexibility and poorer memory and planning abilities (Blume, Marlatt, and Schmalzing 2000), and it is associated with greater neurocognitive difficulties in problem-solving and decision-making (Glass *et al.* 2009). However, adults who only have moderate intake (less than or equal to two drinks per day for men and less than or equal to one drink per day for women) have a lower risk of cognitive impairment (Neafsey and Collins 2011). This information is the fundament for our hypothesis that divers who drank fewer than two beers before the interview are sufficiently clear-headed, and we test whether the consumption of beer influenced unexplained variance in their choices.

#### 2.4. The econometric framework and models

The multinomial logit (MNL) model applied in the choice literature relies on McFadden's (1974) random utility model (RUM). Building on Lancaster's consumption theory (1966), the RUM assumes that the utility of a good is a function of its attributes and that individuals choose a particular good among all goods by evaluating all attributes. This provides a basis for discrete choice statistical estimation techniques to estimate the utility function, which predicts the choices made by an observed sample (Bradley and Daly 1994). Given a set ( $J$ ) of  $n$  alternatives, an individual ( $i$ ) links a utility ( $U_{ji}$ ) with each alternative ( $j$ ) and chooses the alternative that maximizes utility. Hence, the utility is expressed as:

$$U_{ji} = V_{ji} + \varepsilon_{ji} = \beta' x_{ji} + \varepsilon_{ji} \quad (1)$$

where  $V_{ji}$  is the deterministic and observable part of the representative utility function conditional on ( $j$ ) and attributes measured in the study, as well as possibly individual characteristics; thus,  $\beta$  is a vector of the parameter to be estimated, and  $x_{ji}$  is the vector of observed variables for alternative  $j$  and individual  $i$ . Meanwhile  $\varepsilon_{ji}$  is the unexplained and, hence, random component of utility. When an individual chooses alternative  $k$  over alternative  $j$ , it implies that the utility of choosing alternative  $k$  is greater than the utility of alternative  $j$ .



Under the assumption that the stochastic part ( $\varepsilon_{ji}$ ) is independently and identically distributed (i.i.d.) across the utility and follows a Gumbel distribution with variance  $\sigma^2$ , this leads to the closed form of logit choice probability as in the specification for the MNL:

$$P_{ki} = \frac{\exp(s\beta' x_{ki})}{\sum_j \exp(s\beta' x_{ji})} \quad (2)$$

Embedded in the i.i.d. Gumbel assumption on the error term is the scale parameter of the Gumbel distribution,  $s$ , which enters the model in Equation (2). For convenience,  $s$  is often assumed to unity (Ben-Akiva and Lerman 1985; Swait and Louviere 1993), implying that scale is assumed to be uniform across respondents and responses. The estimation of mean willingness-to-pay (WTP) for attributes is insensitive to this assumption, since  $s$  cancels out in the computation of WTP. However, scale not only interacts with the deterministic part of the model but also the unobserved heterogeneity captured in  $\varepsilon_{ji}$ , and the variance is given by  $(\pi^2/6s^2)$ .

#### 2.4.1. The scale MNL model (S-MNL)

Bradley and Daly (1994) pioneered the use of the scaling approach in modeling by allowing for differences in the unexplained variance across different subsets of data and found that, without accounting for scale variation, inaccurate estimation of preferences and choice probabilities could arise. Progress in heterogeneity modeling has put emphasis on the treatment of scale heterogeneity, and more flexible logit models that account for respondents' scale heterogeneity have been developed (Juutinen *et al.* 2012). Fiebig *et al.* (2009) demonstrated the extended application of scale heterogeneity in logit family models in which heterogeneity is accounted for by a pure scale effect. Breffle and Morey (2000) investigated parametric methods to incorporate heterogeneity in the context of a repeated discrete-choice model, and Hess, Rose, and Bain (2009) developed a modeling framework that allows for random scale heterogeneity and heterogeneity in relative sensitivities. The use of scale heterogeneity in decision heuristics has also been studied in the form of respondents' non-attendance to the different choice attributes (Campbell, Hensher, and Scarpa 2011; Hensher, Rose, and Greene 2005) and in assessing the impacts of the opt-out options, including its relation to choice behavior (Kontoleon and Yabe 2003), but these are less related to our study.

As explained above, the scale parameter in its simplest form may just be assumed to be a constant. It is a potential challenge that unexplained variation may vary systematically between groups in any sample of interest, possibly biasing preference parameter estimates and inference, and such variation could be captured through explicit modeling of the scale function's parameters (Hensher 2007). The scale parameter,  $s$ , is inversely proportional to the standard deviation of the estimated  $\beta$  coefficient up to a constant of  $\pi^2/6 \approx 1.3$  (Ben-Akiva and Lerman 1985). This shows that, for fixed values of  $\beta$ , a low value of  $s$  implies a large variance in the unobserved component of utility – thus, a low strength of preference across alternatives. A larger  $s$  implies a decreasing role for the unobserved component of choice utilities, enabling a better prediction of choices across alternatives. Furthermore, if  $s$  varies systematically across subgroups of respondents, both inference and estimations can be biased (Swait and Louviere 1993).

Following Fiebig *et al.* (2009), we account for scale heterogeneity with the following specification, which we termed the scale-multinomial logit (S-MNL) model:

$$P_{ki} = \int \left\{ \frac{\exp(s_i \beta)' x_{ki}}{\sum_j \exp(s_i \beta)' x_{ji}} \right\} / f(s_i) ds_i \quad (3)$$

The individual-level random scale parameter,  $s_i$  is drawn from a positive normalized distribution  $f(s_i)$ , and this function may contain structural elements explaining systematic sources of variance contributions. In the estimation (and apart from the unknown parameters),  $s_i$  is still not identifiable in absolute terms, but can be estimated at a relative scale in which the model assumes that  $\beta$  is common and, therefore, allows the relative scale to vary between individuals. Identification of  $s$  is achieved by constraining the location of the scale distribution,  $E [f(s)]$ , to unity (Christie and Gibbons 2011) and estimating the size of  $s_i$  relative to this location.

In this CE application, the dive permit fee is included as one of the attributes. If an estimated  $\beta$  coefficient for one of the attributes,  $A$ , is divided by the  $\beta$  coefficient for the attribute of the diving fee,  $\beta_{\text{fee}}$ , and multiplied by  $-1$ , it becomes the WTP value for that attribute  $A$  (Louviere, Hensher, and Swait 2000).

$$\text{WTP}_A = - \frac{\beta_A}{\beta_{\text{fee}}} \quad (4)$$

#### 2.4.2. Hypothesis testing in the scale function

With this basis, the study estimated two models: (i) the MNL model excluding the issue of varying scale across individuals, and (ii) the S-MNL models including the comfort variables in modeling scale variance. Thus, we calculate the  $t$ -statistic as:

$$t_{\hat{s}} = (\hat{s} - s_0) / se(\hat{s})$$

where  $s_0$  is a non-random, known constant: here, the parameter normalized to 1, and  $se(\hat{s})$  is the standard error of the estimator. We test the hypothesis that:

$H_1$ : For all the parameters of high comfort variables in the scale function, we expect  $\hat{s} > 1$ , reflecting the higher comfort among divers, thus producing the smaller variance in their choices.

### 3. Results

We estimated the MNL model and the S-MNL models using the open source freeware BIOGEME 2.0 (<http://biogeme.epfl.ch/>; Bierlaire 2003, 2008). Based on interviews with 507 divers, a total of 3,042 choice observations were used in model estimations. The S-MNL model (Table 4) produced a slightly better fit compared to the MNL model, i.e., adjusted  $\rho^2$  increased from 0.190 to 0.193, and the log-likelihood increased slightly from  $-2697.901$  in the MNL model to  $-2684.166$  in the S-MNL model. Following Rolfe, Bennett, and Louviere (2000), the significance of this improvement is tested using the Swait-Louviere log-likelihood ratio test. The calculated statistic was  $[-2 * (-2697.901) - (-2684.166)] = 27.47$  larger than 9.488, the critical value of the  $\chi^2$

distribution at four degrees of freedom at 5% significant level, implying that the S-MNL model is a better model. Nevertheless, the MNL model is discussed as a point of reference and compared to the S-MNL model. There is, however, a considerable amount of unexplained heterogeneity left in both models, and the  $\rho^2$ s are at the lower end of a good fit (Ben-Akiva and Lehrman 1985; Hensher and Johnson 1981). However, most of the coefficients are statistically significant, and the signs of estimated coefficients are as expected *a priori* in almost all cases.

We deliberately ignore systematic heterogeneity in preferences regarding the attributes of the choice alternatives. We discuss their mean estimates but focus on the parameterized covariates in the scale function and whether modeling scale variation improves model performance and inference (Juutinen *et al.* 2012). We note that it can be argued that separate estimation for scale and preference heterogeneity can be misguided in fully random coefficient models (Hess and Rose 2012); and, as the hypothesis concerns the random part of the model, we analyzed it using the MNL model rather than a random parameter logit model.

### 3.1. MNL model estimations

The MNL model in Table 3 takes no account of respondents' comfort and its effect on their accuracy in determining choices. Most parameter estimates in the utility function are significant except the parameters for attributes of '90 divers per day' and '70% of fish diversity.' The alternative specific constant (ASC) is large, positive and highly significant. Following Adamowicz *et al.* (1998) and given our design, we interpret the positive ASC as a preference for the current status of Sipadan.

Table 3. Estimates of the MNL model.

Attributes	Mean	Std. error	<i>t</i> -Test	<i>p</i> -Value
Utility function parameter				
ASC	1.092	0.171	6.39	0.00***
Fee	-0.000859	0.000393	-2.18	0.03**
Low litter pollution	1.198	0.170	7.05	0.00***
High litter pollution	-0.624	0.200	-3.12	0.00***
90 divers/day	-0.118	0.117	-1.00	0.32
150 divers/day	-0.876	0.0973	-9.01	0.00***
50% coral cover	0.546	0.189	2.88	0.00***
90% coral cover	1.133	0.151	7.52	0.00***
30% fish diversity	-1.425	0.154	-9.27	0.00***
70% fish diversity	-0.293	0.199	-1.47	0.14
Model statistics				
No. of estimated parameters	10			
Null log-likelihood, $\mathcal{L}(0)$	-3,341.979			
Final log-likelihood, $\mathcal{L}(\hat{\beta})$	-2,697.901			
Likelihood ratio test	1,288.156			
Rho-square ( $\rho^2$ )	0.193			
Adjusted rho-square ( $\rho^2$ )	0.190			

\*\*\*, \*\* and \* denote significance at 1%, 5%, and 10% levels, respectively. The likelihood ratio test is calculated as  $-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})]$ .

All parameters have the expected signs – with improvements being positive, and decreases in the quality of the diving experience being negative – which also includes the parameter for the fee being negative and significant. The most important attribute to divers is litter pollution, followed by coral covers. Finally, the negative preference parameter for an increased number of divers per dive day and for decreases in fish diversity also conforms to the expected signs. A slightly surprising finding is the significant, positive sign of the parameter estimate for the 50% coral cover. In a companion paper exploring the role of diver experiences for diver preference, we find that this seems mainly related to less experienced divers with few dives behind them (Emang, Lundhede, and Thorsen [unpublished]).

### 3.2. S-MNL model estimations including all comfort variables

The first part of the S-MNL model estimation results in Table 4 refers to the mean parameters of the utility function. The second part includes the parameter estimates for the scale function. Concerning the main attributes, the results reflect that the overall

Table 4. Estimation for the scale variation.

Attributes	Mean	Std. error	t-Test	p-Value
Utility function parameter				
ASC	0.00560	0.00268	2.09	0.04**
Fee	-0.00000524	0.00000316	-1.66	0.10*
Low litter pollution	0.00625	0.00293	2.13	0.03**
High litter pollution	-0.00391	0.00203	-1.93	0.05**
90 divers/day	-0.000509	0.000670	-0.76	0.45
150 divers/day	-0.00468	0.00217	-2.16	0.03**
50% coral cover	0.00255	0.00157	1.62	0.10*
90% coral cover	0.00592	0.00279	2.12	0.03**
30% fish diversity	-0.00771	0.00353	-2.18	0.03**
70% fish diversity	-0.00129	0.00125	-1.03	0.30
Scale function parameter <sup>††</sup>				
Beer	1.12	0.144		
Digestion	1.28	0.0868		
Food	1.47	0.396		
Rested	1.55	0.201		
Model statistics				
No. of estimated parameters	14			
Null log-likelihood, $\mathcal{L}(0)$	-3,341.979			
Final log-likelihood, $\mathcal{L}(\hat{\beta})$	-2,684.166			
Likelihood ratio test	1,315.626			
Rho-square ( $\rho^2$ )	0.197			
Adjusted rho-square ( $\rho^2$ )	0.193			

<sup>††</sup>The scale function parameters are dummy variables estimated relative to the base levels, which are normalized to 1. The normalized level is the 'lack of comfort' responses.

\*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10% levels, respectively. The likelihood ratio test is calculated as  $-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})]$ .

Table 5. Hypothesis testing on all comfort variables affecting scale.

Attributes	Scale parameters	Std. error	<i>p</i> -Value	<i>t</i> -Value	Significance levels at 5%, critical values of 1.960
Beer	1.12	0.144	0.41	0.833	Fail to reject H <sub>0</sub>
Digestion	1.28	0.0868	0.00	3.226	Reject H <sub>0</sub>
Food	1.47	0.396	0.24	1.187	Fail to reject H <sub>0</sub>
Rested	1.55	0.201	0.00	2.736	Reject H <sub>0</sub>

Notes: The hypothesis test is based on a two-tailed test with a large (>120) degree of freedom. Reject H<sub>0</sub> if *t*-value > critical value, or fail to reject H<sub>0</sub> if *t*-value < critical value at 5% significance level. The parameter is different from the base scale parameter and normalized to 1.

pattern of preferences remains the same. Apart from that, results show that increasing the number of variables in the model when modeling the scale function reduces the significance levels of some of the main attributes, e.g., the estimate of the fee parameter is only significant at the 10% level, which may also reflect heterogeneity in sensitivity to price (which we do not model here since we focus on the scale function). In another companion paper, we show that divers from abroad (e.g., Europe, Australia, etc.) have a significantly lower sensitivity to the fee increases (Emang, Lundhede, and Thorsen 2016). Similarly, the negative preference for high litter levels and the positive preference for low coral levels are now only significant at the 10% level and not the 5% level.

As described in Table 2, ‘Beer’ is coded as 1 if the respondent drank alcoholic beverages recently, ‘Digestion’ as 1 if sufficient time since the last meal has passed (more than an hour), ‘Food’ as 1 if the respondent reported that they ate and drank well and, finally, ‘Rested’ as 1 if the respondent reported having slept at least 5 hours. Thus, we would expect respondents for which these statements are true to be able to concentrate better; and, hence, the hypothesis is that each of these would have a scale function contribution factor larger than 1.

Based on hypothesis testing presented in Table 5, ‘Beer’ and ‘Food’ did not contribute significantly to the scale function. Although the sign of the parameters for these variables is as expected, neither is significantly different from 1. We note that, for ‘Food’, this is likely because this group included almost all respondents and, thus, had a strong correlation with, e.g., ‘Rested’, where most people were well-rested. The parameters for respondents reported having rested properly and had sufficient digestion time reveal a fairly strong and significant contribution to the scale function since both of the parameters are larger than 1. Thus, being rested and having proper time to digest recent meals are aspects of the respondents’ comfort that reduce the unexplained variance in their choices.

### 3.3. Final parsimonious S-MNL model estimations

Table 6 presents the estimation results from the final parsimonious S-MNL model, which excludes the variables of beer and food from the scale function. Model statistics show that the model fit of the final S-MNL model is almost identical to the first S-MNL model since the log-likelihood ratio is virtually indistinguishable and the adjusted  $\rho^2$  remains the same. However, most of the main attributes become significant at a higher level as

Table 6. Estimation for the scale variation (without variables beer and food).

Attributes	Mean	Std. error	t-Test	p-Value
Utility function parameter				
ASC	0.0655	0.0180	3.64	0.00***
Fee	-0.0000611	0.0000274	-2.23	0.03**
Low litter pollution	0.0729	0.0191	3.81	0.00***
High litter pollution	-0.0449	0.0151	-2.97	0.00***
90 divers/day	-0.00567	0.00754	-0.75	0.45
150 divers/day	-0.0550	0.0131	-4.21	0.00***
50% coral cover	0.0305	0.0141	2.16	0.03**
90% coral cover	0.0694	0.0178	3.91	0.00***
30% fish diversity	-0.0898	0.0212	-4.24	0.00***
70% fish diversity	-0.0156	0.0133	-1.17	0.24
Scale function parameter <sup>††</sup>				
Digestion	1.30	0.0867		
Rested	1.56	0.200		
Model statistics				
No. of estimated parameters	12			
Null log-likelihood, $\mathcal{L}(0)$	-3,341.979			
Final log-likelihood, $\mathcal{L}(\hat{\beta})$	-2,685.519			
Likelihood ratio test	1,312.918			
Rho-square	0.196			
Adjusted rho-square	0.193			

<sup>††</sup>The scale function parameters are dummy variables estimated relative to the base levels, which are normalized to 1. The normalized level is the 'lack of comfort' responses.

\*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10% levels, respectively. The likelihood ratio test is calculated as  $-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})]$ .

compared to the first S-MNL model – notably, the parameter of the fee variable is estimated with higher efficiency in this model. Thus, parsimonious modeling of the scale function improves inference. The scale function parameters still both illustrate the positive effect of comfort measures that reduce the unexplained variance in CE estimates. The parameters are tested against the null of the normalized value of 1, and the results can be seen in Table 7.

Table 7. Hypothesis testing of only digestion time and rested variables affecting scale variation.

Attributes	Scale parameters	Std. error	p-Value	t-Value	Significance levels at 5%, critical values of 1.960
Digestion	1.30	0.0867	0.00	3.460	Reject H <sub>0</sub>
Rested	1.56	0.200	0.00	2.8	Reject H <sub>0</sub>

Notes: The hypothesis test is based on a two-tailed test with a large (>120) degree of freedom. Reject H<sub>0</sub> if t-value > critical value, or fail to reject H<sub>0</sub> if t-value < critical value at 5% significance level. The parameter is different from the base scale parameter and normalized to 1.

### 3.4. Comparisons of willingness to pay estimates

The mean WTP measures in Table 8 were estimated using the Delta method. An illustration of the lower and upper limits of the confidence intervals for these estimates is presented in Figure 2. The highest WTP is for preventing a decrease in fish diversity, and divers are also willing to pay more than RM1,000 (USD260) to avoid higher crowding at the dive sites. Divers prefer to pay a higher diving fee to reduce the number of divers in the dive sites and are also willing to pay for reductions in the level of litter pollution. Divers are adversely affected by the lowest level of fish diversity and willing to pay more than RM1,400 (USD350) to avoid loss of fish diversity.

To evaluate the effect of accounting for comfort-related scale variation, we compared the WTP estimates across all three models along with their confidence intervals and

Table 8. Willingness-to-pay estimates.

Attributes	MNL model	First S-MNL model	Final S-MNL model
ASC	1,269* (-182; 2,720)	1,069* (-103; 2,240)	1,072* (-67; 2,211)
	-	-19%	-21%
Low level of litter pollution	1397* (-151; 2,945)	1193* (-66; 2,451)	1193* (-27; 2,413)
	-	-19%	-21%
High level of litter pollution	-726*** (-1,187; -266)	-746*** (-1,189; -303)	-735*** (-1,152; -318)
	-	-4%	-9%
90 divers per day	-137 (-505; 230)	-97 (-400; 206)	-93 (-389; 204)
	-	-17%	-19%
150 divers per day	-1020** (-1,941; -98)	-893** (-1,643; -144)	-900** (-1,628; -172)
	-	-19%	-21%
50% coral cover	636 (-290; 1,561)	487 (-245; 1,219)	499 (-227; 1,226)
	-	-21%	-21%
90% coral cover	1315* (-46; 2,677)	1130** (23; 2,236)	1136** (60; 2,212)
	-	-19%	-21%
30% fish diversity	-1,665* (-3,347; 18)	-1,471** (-2,868; -74)	-1,470** (-2,817; -122)
	-	-17%	-20%
70% fish diversity	-341 (-1,061; 379)	-246 (-829; 336)	-255 (-836; 325)
	-	-19%	-19%
No. of estimated parameters	10	14	12
Null log-likelihood, $\mathcal{L}(0)$	-3,341.979	-3,341.979	-3,341.979
Final log-likelihood, $\mathcal{L}(\hat{\beta})$	-2,697.901	-2,684.166	-2,685.519
Log-likelihood ratio test	1,288.156	1,315.626	1,312.918
Rho-square	0.193	0.197	0.196
Adjusted rho-square	0.190	0.193	0.193

\*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10% levels, respectively. WTP is valued in RM/diver at 95% confidence interval (in parentheses) and the exchange rate is RM3.18 = 1 USD. The percentage increase in the width of the confidence interval for the first and final S-MNL models are compared with the MNL model and shown below the parentheses.

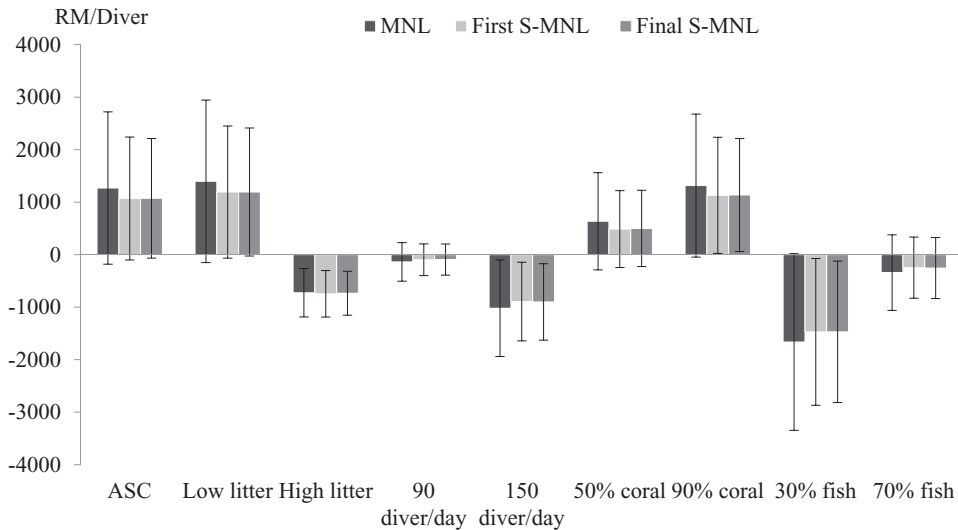


Figure 2. The lower and upper limits of 95% confidence intervals for WTP measures.

related changes. The observed differences in WTP estimates for all diving attributes are minor and clearly have a consistent pattern. Across all models, there is no substantial change in WTP values and the highest and the lowest WTP estimations are consistently assigned to the same attributes. We observe that the relative width of the confidence intervals of WTP estimates in the S-MNL models compared to their width in the MNL model is decreasing in both models that account for scale. This implies more robust estimates when accounting for scale and enhances the ability to make valid inferences based on the data.

### 3.5. Caveats and future work

Ideally, a study like this should identify a truly causal pattern. To do that, our hypothesis would require a fully controlled, randomized experiment exposing SCUBA divers to different sleep deprivation treatments, diets, etc. Such experiments would eliminate any doubt about whether the patterns of comfort variables are correlated with unexplained variance in choices, which could be due to, e.g., other external causal factors. We acknowledge that relying on self-reported measures is sensitive to possible self-selection biases, causing reduced comfort. However, it has the merit of being feasible for the field study we implemented as well as non-intrusive and unlikely to interfere with the divers' experiences and preferences; unlike a controlled experiment. We note that our finding is also corroborated by findings from controlled experiments in the health and psychological literature that documents the effects of such comfort aspects on cognitive abilities.

## 4. Concluding discussion

This paper has contributed to the methodological discussions about the reliable elicitation of preferences of recreation users (Hall and Roggenbuck 2002; Freimund *et al.* 2002; Manning and Freimund 2004). Specifically, we have investigated SCUBA divers'



preferences for a number of environmental attributes closely related to their diving experience. Using respondents' self-reported measures of a number of factors related to comfort levels, we find that respondents' variance in choice depends significantly on some aspects of comfort. Specifically, factors such as sufficient time for digestion and sufficient sleep the night before the interview are variables related to respondent comfort that resulted in lower unexplained variance in models of respondents' choices. We find that the confidence intervals of WTP estimates decrease approximately 20% for most variables when controlling for the role of these factors through the scale function.

Many recreational activities are both physically- and time-demanding activities. This is true for SCUBA diving, but it is also a feature shared with other recreational activities such as mountain biking and rock climbing. Many of these outdoor activities have been studied in the environmental valuation literature (Schuhmann *et al.* 2013; Scarpa and Thiene 2005), and interviewing recreational users about their preferences for variations in site quality and management aspects is a common research practice (Glenn *et al.* 2010; Hynes, Hanley, and Scarpa 2008). For all such studies, the respondents' ability to declare and clearly express their preferences may depend on their comfort when interviewed, and our results suggest that wisely timing the interviews could provide more robust and efficient estimates and models and, hence, improve the ability to make inferences. Practically, for in-field interviews, this implies, e.g., letting the mountain biker rest for a while before an interview is carried out or not to interview a rock climber who is still low on sugar.

Alternatively, we recommend including relevant questions about physical and mental comfort to control for factors that potentially affect the variance in choice. Knowledge of the influence of physical and psychological comfort may also benefit CE studies not related to demanding activities. Sometimes, interviews are extremely costly and time-consuming, which results in relatively lower sample sizes compared to the average online panel-based CE survey. Examples could be remote and dispersed populations in, e.g., Third World countries, where the use of interpreters is involved. In these situations, it seems reasonable to be able to reduce the variance as much as possible without biasing the results.

The concept investigated here is rather simple and based on self-reported indicators of physical and mental comfort. Relying on respondents' perceptions can be biased in many different ways; respondents might not remember how many hours of sleep they had or they might not be willing to reveal the correct intake of alcoholic drinks. This suggests that it would be relevant to explore other ways to measure respondents' comfort in non-invasive ways for future research. Nevertheless, our results show that, even when including these potentially subjective measures in the scale function, the variance in the main effect estimates is reduced, and the models become better at describing our data.

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### ORCID

Diana Emang  <http://orcid.org/0000-0001-7585-5319>

Thomas Hedemark Lundhede  <http://orcid.org/0000-0003-3226-8338>

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