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Using online self-assessment tool to improve conjoint analysis

Application in choices of wildlife excursions

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Abstract

Purpose – Dolphin excursions have become increasingly popular worldwide. Many past studies assessing the value of dolphin excursions use choice-based methods such as the conjoint analysis. However, this method is often criticized as being hypothetical. The purpose of this paper is to describe a relatively low cost but effective approach to enhance understanding of consumer preference obtained by conjoint analysis. The method relies heavily on using internet-based survey tools.
Design/methodology/approach – Enabled by an online tool, individuals are asked to self-explicate their preferred alternatives using the same attributes as are found in the conjoint design. The difference between the self-constructed, preferred alternatives and those offered in conjoint experiment are incorporated into choice models. Unlike previous research where only rough estimates can be provided, the proposed method allows precise capture of respondents' preferred alternative through the automated online survey design.
Findings – Results show that although the extra effort involved in data collection is small, the gain in model fit, choice interpretation, and the value (welfare) estimation is sizeable. Evidence indicates that consumers would be willing to pay up to $50 more for adventurous excursions and guarantees that they will interact with dolphins could worth up to $70 per trip. The approach presented in this paper can also serve as a method to test for preference consistency.
Originality/value – This study is the first using an online survey to assess values associated with dolphin excursion. It describes the benefit of involving online tools to enhance modeling and interpretation of consumer behavior. Applications of internet-based surveys on household consumer products are abundant (such as food and electronics) but this study offers a much less discussed application in environmental service.
Keywords Dolphin excursion, Choice model, Conjoint experiment
Paper type Research paper

1. Introduction

Since Luce and Tukey (1964) published the first paper in 1964 on conjoint analysis in the first volume of the *Journal of Mathematical Psychology*, the technique has become increasingly popular among researchers studying human choice and decision making.

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First applications of conjoint analysis include studies on transportation (McFadden, 1974) and marketing (Green and Rao, 1971). Since conjoint analysis reveals how individuals may trade-off among various characteristics of the item under study, economists have found it useful in demand analysis. Early works using conjoint analysis focussed on marketing new products, while the use of this method in environmental and resource economics often related to non-market goods, such as public goods (Adamowicz *et al.*, 1994). Thus, conjoint analysis may be described differently, depending on its use. A common descriptor, choice experiment, ties conjoint analysis to the literature on discrete choice or stated preference. In recent years, a wider application of conjoint analysis in fields including food, medicine, information system management, and finance has occurred and this trend is expected to continue, particularly given the convenience of computer-aided internet surveys (Hu *et al.*, 2006; Netzer *et al.*, 2008; Bateman *et al.*, 2010; Batte *et al.*, 2010; Murray *et al.*, 2010; Farley *et al.*, 2013; Yoo and Doiron, 2013; Richards *et al.*, 2014).

This study uses conjoint analysis to examine individuals' stated choices of spinner dolphin excursions in Hawaii, USA, based on data collected using an in-person survey. A typical application of conjoint analysis presents respondents with various profiles of excursions, described by their attributes. Then respondents are asked to indicate their preferred alternatives among those offered. By recording the preferred choices, researchers can model the implicit trade-offs respondents make among the different attributes, which are likely to include a price factor. A discrete choice model can often be applied to such an analysis. In addition to advances in econometrics and other relevant modeling techniques, a variety of approaches have been developed in the literature to improve conventional conjoint analysis by incorporating additional information on the decision-making process into the analysis. Improvement in the predictive power of conjoint analysis will, in turn, improve the assessment of social and economic consequences of choices. This study contributes to this effort by including a disagreement measure in a standard conjoint analysis.

In addition to conjoint choice questions, each respondent in this study was asked to construct their own preferred excursion using the same trip attributes found in the experiment. By specifying a particular level for each attribute, for example choosing "small boat" under the attribute "size of boat," a complete profile of the respondent's preferred excursion was established. A straightforward method that combines information from the self-constructed preference with the information from the conjoint experiment is used to enhance the conjoint analysis. Results indicate that this small increase in data collection effort reaps relatively large benefits in the attempt to better understand of respondents' choices. The enhanced approach is also shown to successfully differentiate welfare implications for individuals based on their choices made in both the conjoint evaluation stage and in the self-evaluation stage. The proposed approach may also offer a test for preference consistency.

The next section of the paper discusses the previous research that has improved the behavior modeling that underlies conjoint analysis, primarily in the fields of economics and marketing. A description of the data, particularly the information from the respondents' self-constructed alternatives, and the discrete choice model used in this paper follows. Then, in the results section, a comparison of the proposed model and the conventional choice model based on their parameter estimates and welfare implications is presented. Finally, conclusions are drawn and future extensions are discussed.

2. Previous research

Baseline conjoint analysis involves analyzing how individuals make trade-offs among attributes associated with a marketable or non-marketable product using some type of choice model (Srinivasan, 1988). A major research effort to improve the analysis therefore is to create models that potentially can best capture or approximate the unknown factors in the process. The individuals who made the choices may know the unknown factors, or the researchers examining the choices may not know them (Ben Akiva *et al.*, 1999). The basic choice models such as the logit model can reflect the discrete nature of choices and have been widely applied in the literature.

Over the years, several promising methods have been proposed to ease the restrictions of the logit model while maintaining its simplicity. The first widely adopted alternative, the nested logit model, generalizes the correlation between unknown factors and provides a much richer interpretation of behavior. More recently, a plethora of approaches emerge to model the unknown factors in decision making. Among them, the latent class, random parameter, error component, as well as the most recent generalized multinomial logit models are the most commonly applied. All these models often offer drastic improvement in model fit compared to the conventional logit model. They usually do not require additional information from the decision makers. In other words, model fit improvement can be achieved from further decomposing and parameterizing the unknown choice factors. Thus, these models may be viewed as a kernel to be superimposed over any other approaches described in the rest of this section as well as to the methods proposed in this paper.

Regardless of how sophisticated the empirical models and estimation methods are, knowing and incorporating additional information on how choices are made will improve the result of conjoint analyses. As with any other studies on human, information about their characteristics such as their demographic and social economic status will help researchers to establish linkage between their personal profiles and choices they make (e.g. Hu, 2006; Hu *et al.*, 2011). Thus, a straightforward method to improve a conjoint analysis is to include individuals' personal characteristics. In the past several decades, studies in many disciplines have specified various approaches to incorporate these variables (e.g. Green and Carmone, 1977; Boxall and Adamowicz, 2002; Bhat and Gossen, 2004). The magnitude of the benefits that these additional variables bring to conjoint analysis depends on the application (Vriens *et al.*, 1996; Fennell *et al.*, 2003).

Other researchers include other type of information in the analysis. A large body of relevant literature in this area exists, and therefore, a review of several representative approaches is provided here. Adamowicz *et al.* (1994) used a survey of the respondents' actual choice behavior known as revealed preference to supplement their choices or stated preference as indicated in a conjoint survey. Swait and Adamowicz (2001) introduced the degree of complexity suggested by choice tasks into the analysis. Gilbride and Allenby (2004) differentiated consumers by their distinctive choice formulation process and incorporated latent choice sets into the models. Von Haefen *et al.* (2005) observed whether survey respondents tend to consistently select the same option over different choice situations and included this information in their conjoint analysis. Hu (2007) used consumers' belief/perception prior to the conjoint survey to reveal further insight in their choices. All of these studies are motivated by the practical need to model choice data and each offers a compelling theoretical justification for their approach. Judgment and decision-making literature in economics, sociology, and psychology provides a large range of theory and hypotheses on human decision making to support these applications. Table I summarizes the work described and lists the primary behavioral theory each article suggested or tested.

An additional method that incorporates information into conjoint analysis is proposed here. This method is based on the self-explication framework described and tested in Srinivasan (1988). In its original form, self-explication involves respondents rate and then rank each product attribute separately and utility parameters are then derived from these rankings. This method has been criticized as being non-realistic and may trigger strategic bias and measurement errors (Sattler and Hensel-Börner, 2000). Conjoint analysis has often been seen as a replacement for the self-explication method. It is believed to be able to resemble real choice situation and reduce strategic behavior. However, researchers now begin to question the superiority of conjoint analysis and call for effort to develop improved methods for preference measurement including revisiting the previously discarded self-explication methods (Sattler and Hensel-Börner, 2000; Green *et al.*, 2001; Netzer *et al.*, 2008).

Recognizing that approaches assuming compensatory decision rules (e.g., conjoint analysis) and non-compensatory rules (e.g. self-explication) follow different behavioral assumptions, recent research has examined mixed methods that combine the benefits of both. Kramer (2007) showed that respondents' choice precision and consistency can be improved through personalized recommendations at the product attribute level. Hauser *et al.* (2010) proved that a disjunctions-of-conjunctions decision rule may work better to explain consumer choices. Archak *et al.* (2011) verified the role of textual data and user-generated product attribute evaluation in improving researchers' ability to understand consumer choices. Ready *et al.* (2006), Nunes *et al.* (2004), Netzer and Srinivasan (2007), Liu *et al.* (2007), and Park *et al.* (2008) formally demonstrated ways to combine the self-explication approach and conjoint analysis. These authors showed that the new method could outperform either model when used separately.

This study also proposes a method to combine self-explicated information and the conjoint analysis. After completing the evaluation of the conjoint experiment on the dolphin excursion survey, respondents were asked to construct their preferred alternative using the same attributes and levels, including price. This practice is similar to an online quality and price comparison (Chung, 2013). Then, the characteristics of these alternatives were compared with the alternatives offered in the conjoint experiment choice sets for each individual and the result of this comparison was used to improve model fit and the estimation of the welfare implications. Hailu *et al.* (2000) used a similar approach to construct respondents' preferred alternative in a more aggregated level where various goods were chosen by respondents to form a "bundle" of products. As a result, their approach does not offer attribute-level comparisons. The primary theoretical basis for the approach here is that each individual's choice decisions should be correlated regardless of the question's format (Srinivasan, 1988).

Information included	Representative work	Primary behavioral theory
Actual choice	Adamowicz *et al.* (1994)	Revealed vs stated preference
Choice set complexity	Swait and Adamowicz (2001)	Fatigue and learning
Decision rule	Gilbride and Allenby (2004)	Preference ordering
Choice pattern	Von Haefen *et al.* (2005)	Simplifying heuristics
Reference point	Hu (2007)	Prospect theory

Table I. Methods of including additional information into standard conjoint analysis

Thus, since this study collects respondents' answers to two types of choice questions, internal choice consistency may be tested using a comparison of these answers.

The intention here is not to pinpoint the specific behavioral theory or theories that can be tested empirically with the analysis proposed. Many types of behavior, such as those suggested by the theories detailed in Table I, may lead to similar manifestation in observed choices. At the same time, the behavior or behaviors suggested by various theories are often commingled, making it difficult to identify their unique impacts. Thus, as is consistent with previous research (e.g. Deshazo and Fermo, 2002), the focus of this paper is to show that standard conjoint analysis can be improved by incorporating relevant supplementary information. Further investigation could be conducted to examine the possible sources of such impacts.

3. Research objective and methods

The empirical application presented in this paper is set in an economic evaluation of dolphin excursions in Hawaii. Aggregated data suggest that dolphin and other cetacean excursions have made a significant economic contribution to tourism, the number one industry in Hawaii (Department of Business, Economic Development and Tourism, 2004). Little research, however, on the economic values and parameters associated with dolphin excursions has been done. Past studies have demonstrated the usefulness of conjoint methods in understanding economic issues related to tourism (e.g. Hearne and Salinas, 2002). Dolphin excursions are a unique type of activity that feature various types of services and excursion trips have been offered in Hawaii for a range of prices for more than a decade.

Given this history, the expectation might be that basic demand information could be derived from historical data. This approach has proven difficult. Until recently, most dolphin excursions were offered as part of excursion packages, making it difficult to single out the factors related only to dolphins. Since the existence of stand-alone dolphin excursions has increased significantly in recent years (Stanton, 2005), the relevant government regulatory agencies and community organizations have become interested in the economics of dolphin excursions. Currently, only a few firms offer excursions and since they are generally small, privately owned firms, complete data are neither recorded nor ready to be released without affecting business confidentiality (Boehle, 2007). Therefore, a stated preference survey is the most appropriate to examine the economics of dolphin excursions in Hawaii.

3.1 Survey design

The online survey contains three sections: the first and last sections contain questions about the respondents' overall experience in Hawaii and their demographic information, respectively. The middle section presents the conjoint exercise. Dolphin excursion attributes and levels within each attribute were based on focus group discussions with individuals involved in the industry as well as potential participants. The survey was fielded primarily in Waikiki, Oahu and Kailua-Kona, Hawaii. Individuals were intercepted in these areas between December 2011 and February 2012. A total of 172 individuals agreed to participate in the survey and among these, 148 of them completed usable questionnaires. Once agreed to participate, respondents were escorted to a booth where they can access the fully self-administered online survey. Table II reports the descriptive statistics for several representative demographic variables. As expected, the sample was generally composed of tourists, primarily from the US mainland, with relatively high income and educational levels.

In the conjoint design, one of the most relevant attribute is price. After obtaining information about the prices for dolphin excursions across the state, six levels of price were chosen ranging from \$50 to \$300 with an equal difference of \$50. This range covers the existing range of excursion prices. Several other attributes were also used to differentiate excursions in the market place, including the type and size of excursion boats, the activities with dolphins, and whether the provider offers a guarantee to see dolphins. Each of these attributes has more than one possible outcome or level. The type of excursion boat includes inflatable zodiacs, motorized boats, or sailing catamaran, and its size may be either small (less than 20 passengers), medium (between 20 and 30 passengers), or large (above 30 passengers). Activities with dolphins refer to the level of interaction the participants may expect to have with the spinner dolphins. This attribute also contains three levels: viewing the dolphins from boat, snorkeling with the dolphins, or scuba diving with them. The guarantee serves as insurance since participants are allowed a second trip free of charge if they do not see at least one dolphin.

These attributes and their corresponding levels were then arrayed in an experimental design. There are a total of 324 possible combinations, i.e., profiles of excursion options, that can be formed by these attributes ($6 \times 3 \times 3 \times 3 \times 2$). It is unrealistic to ask respondents to evaluate all combinations. A fractional factorial design could greatly reduce the number of profiles to be evaluated while maintaining the identification of the underlying utility parameters. Nevertheless, the total number of profiles generated by a fractional factorial design can still be large for one person to evaluate. As a result, a blocked fractional factorial design (Box *et al.*, 2005) was adopted to generate five groups of choice sets. Following Adamowicz *et al.* (1994), the design limited the size of each group to contain six unique choice sets. In other words, the blocked fractional factorial designed generated a total of 30 choice sets (each containing two profiles). The design had 100 percent D-efficiency.

In addition to these two profiles, a third option was added to each choice set, which gives respondents an opportunity to indicate if they are not willing to choose either one of the first two options. In the survey, each respondent was assigned to only one group (six choice sets) to reduce the cognitive burden (Adamowicz *et al.*, 1994). Respondents were instructed to indicate their choice in all six choice sets. Figure 1 displays such a choice set as it was presented in the survey. In a study where the sample size is confined such as the current analysis, in order not to confound the choice sets respondents faced with their socioeconomic or cognitive characteristics, groups were randomly assigned to respondents.

Variable	Mean	SD	Definition
US	0.730	0.444	1 for US residents; 0 otherwise
HI	0.277	0.448	1 for Hawaii residents; 0 otherwise
MALE	0.493	0.500	1 for male; 0 otherwise
AGE	37.615	13.082	Years of age
INCOME	62,770.323	32,756.145	Annual income before tax
EDU	15.345	2.485	Years of education

Note: $n = 148$

Table II. Descriptive statistics for representative demographic variables

Features	Option A	Option B	Option C
Boat Type	Motor	Zodiac Inflatable	I will not choose either A or B (not take a dolphin excursion)
Boat Size	Medium (21-30 passengers)	Small (20 or less passengers)	
Activity	View	SCUBA	
Guarantee	No	No	
Price	$100	$250	
I would like to choose (Choose only one)	❑	❑	❑

Figure 1.
Sample choice set

Respondents' preferred alternatives were obtained after they completed the conjoint experiment. The attributes and their corresponding levels were then all given to the respondents and they were asked to select a level for each attribute that they would prefer to see if they were to participate in a dolphin excursion. Figure 2 gives the question used in the survey. The goal was to use the information contained in this question to enhance the performance of the analysis. Below you have an opportunity to "build" your

Attribute	Available Levels
Boat Type	❑ Zodiac inflatable ❑ Motor boat ❑ Catamaran sail boat
Boat Size	❑ Under 20 passengers ❑ 20-35 passengers ❑ Over 35 passengers
Activity	❑ View dolphins from boat ❑ Snorkel with dolphins ❑ Scuba with dolphins
Guarantee	❑ Yes ❑ No
The MAXIMUM price you would be willing to pay	❑ $50 ❑ $100 ❑ $150 ❑ $200 ❑ $250 ❑ $300 ❑ Other values (please specify) ________________

Figure 2.
Question eliciting self-constructed preferred alternative

own favorite dolphin excursion trip. You can do so by selecting one level for each attribute, including the price. We understand that we all want to pay as little as possible for things we like but at this moment we would like to ask you if you were to pay for your ideal trip, what would be the highest price you could accept. In other words, what would be the MAXIMUM price you would be willing to pay for your ideal trip.

Ready *et al.* (2006), for example, created a computer-aided dynamic conjoint experiment in which respondents were asked to choose their own levels for each product attribute, excluding price. The price level associated with the profile the respondents identified was then calculated using estimated, pre-built continuous cost functions based on the chosen levels of each attribute. These authors argue that this approach elicits an incentive compatible with the true willingness to pay for each attribute. In a sense, as the authors noted, their study uses a conjoint analysis framework with a continuous rather than discrete choice format. Nunes *et al.* (2004) on the other hand, used a conjoint experiment with a pair-wise comparison between two alternatives in a choice set. Deviating from the conventional approach, the price of the second alternative was left to the respondents to specify with no restriction as to the price range respondents could consider. This approach embedded a hedonic evaluation task within a conjoint analysis. As the authors noted, this method incorporates the advantages of both approaches. Netzer and Srinivasan (2007) and Liu *et al.* (2007) studied a similar approach in marketing context.

Unlike previous studies, in this dolphin excursion analysis, discrete levels for all attributes, including the price, were adopted. This ensured that the levels for all attributes were consistent between the conjoint experiment and the follow-up question. Attributes for the preferred alternative in both conjoint experiment and the follow-up question can then be compared and the difference can be measured. Including the difference in a standard choice model established the linkage between the two types of choices made in this survey.

In a conjoint experiment choice set, respondents indicated their preferred alternative by selecting between the two options in the set. If the alternative was not identical to the respondents' preferred alternative, then the respondents had to make some compromises in order to be willing to accept the alternative. If such a compromise could not be made, respondents were expected to select the choose-none option. In the construction of the preferred alternatives, respondents were not limited by alternatives in a particular choice set. They could build their own alternative by choosing the appropriate level for each attribute. The difference between the attribute levels between the constrained and the unconstrained choices may reveal the trade-offs the respondent made and thus be used to improve the analysis of the conjoint experiment data. The online survey provides the necessary condition where respondents could use an animated "build your own excursion" tool to construct their preferred tour. The internet makes this tool realistic and believable to survey participants in a setting that mimics online storytelling (Hsiao *et al.*, 2013).

3.2 Empirical analysis

The building blocks of the models are random utility. In the conjoint experiment, suppose alternative j, which individual i chose in the t-th choice set, was featured by attribute levels summarized into a vector $\mathbf{X}_{ijt}$, the indirect utility in this case can be written as:

$$U_{ijt} = \mathbf{X}_{ijt}\alpha + e_{ijt} \quad (1)$$

where α and e_{ijt} are unknown coefficients and a random error term, respectively. The difference between the attributes suggested in this stage and those in the follow-up stage can be included in the model in two different ways. First, one could consider the total number of attributes that are different between the two alternatives (alternative *jt* and the self-constructed preferred alternative), denoted by variable TD. The smaller variable TD is, the more closely the two alternatives resemble each other.

Second, a difference measure can be calculated to monitor whether each attribute is different between the two alternatives. This measure resembles the disagreement measures in a similarity scale commonly seen in the literature of cluster analysis (Edinger *et al.*, 2000). If two chosen alternatives differ on the q-th attribute, variable ID_q equals one and if they do not differ, ID_q equals zero. These individual attribute difference measures can be collected into a vector **ID** and included into the model. For the third alternative offered in each choice set, the choose-none option, similar difference measures can still be calculated, except that this option does not contain any of the attributes levels considered.

Equations (2) and (3) describe the two approaches including TD and **ID**, where β and ‹ are unknown coefficients:

$$U_{ijt} = \mathbf{X}_{ijt}\alpha + \mathrm{TD}\beta + e_{ijt} \tag{2}$$

$$U_{ijt} = \mathbf{X}_{ijt}\alpha + \mathbf{ID}\gamma + e_{ijt} \tag{3}$$

The difference measures can be used to gauge preference reversals as well. If an alternative offered in the conjoint experiment is identical to the self-constructed preferred alternative, the individual is expected to choose this alternative. A preference reversal occurred, if this did not happen. The coefficients in the three equations can be estimated assuming proper distribution assumption of the error terms. If all errors follow an iid Gumbel distribution, a conditional logit model can be applied to each choice set.

4. Results

Discussion in this section summarizes the preference reversal by survey respondents, presents the parameter estimates and highlights the welfare implications.

4.1 Preference reversal

Following the conventional definition provided by Grether and Plott (1979), preference reversal occurs when an alternative offered in a choice set is identical to that one constructed by respondents themselves in the follow-up question, but the alternative was not chosen in the conjoint experiment. A high rate of preference reversal may indicate the survey was not properly designed or implemented and is therefore subject to framing effect, which undermines the validity of the results. Considering all quality and price attributes included in this study, a total of ten alternatives that appeared in the conjoint experiment were identical to a respondent's self-constructed, preferred alternative. Among these ten, two indicated preference reversal. The opportunity to identify preference reversal provides another justification for including price levels in the self-constructed alternatives that were identical to the levels used in the conjoint experiment. Use of the same alternatives ensures that the two stages can be matched.

At the same time, respondents may not choose the alternative they identified as the preferred option but instead select one that is slightly different due to a price discount.

If price is excluded from the comparison, the sample contains a total of 50 cases in which the alternative offered in the conjoint experiment is the same as the preferred alternative constructed by the respondents. Among these 50 cases, 17 appear to be cases of preference reversal. However, in three cases a slightly different alternative was chosen likely because of a large price discount. The rate of preference reversal that can be unambiguously defined under these two approaches are 30 percent (3/10) and 28 percent (14/50), respectively, which are well within the range given in many behavioral studies. Ready *et al.* (2006) found the rate of preference reversal was between 20 and 30 percent depending on different question formats.

4.2 Choice model results

Table III reports the three estimated logit models generated by Equations (1)-(3). The first model presented is the conditional logit model based on the standard conjoint data from the survey. Variables ZODIAC and MOTOR are dummy variables for the type of boat where sailing catamaran is omitted to avoid singularity. Both are negative and significant indicating that the sailing catamaran is the most preferred type of boat. Similarly for the size of the excursion vessel, the variables SMALL and MEDIUM are dummy variables with large being omitted. As suggested by the signs of these variables, they both are preferred to a large boat. For activities involved in an excursion, snorkeling/swimming (variable SWIM) and scuba diving (variable SCUBA) with dolphins are both positive and significant. This suggests that participants generally enjoy interactive dolphin activities to viewing the animals from the boat. A guarantee is likely to receive positive response as signified by the positively significant variable GARNT. Price on the other hand has a negative coefficient in the utility function as expected.

Variable	Logit without difference Coeff.	*t*-ratio	Logit with overall differences Coeff.	*t*-ratio	Logit with individual differences Coeff.	*t*-ratio
ZODIAC	−0.371	−2.230	−0.265	−1.547	−0.397	−2.064
MOTOR	−0.220	−1.806	−0.159	−1.267	−0.090	−0.702
SMALL	0.593	3.784	0.544	3.383	0.595	3.680
MEDIUM	0.240	1.662	0.339	2.261	0.300	1.944
SWIM	0.405	3.644	0.379	3.330	0.382	3.367
SCUBA	0.288	2.019	0.406	2.753	0.580	3.533
GARNT	0.525	4.790	0.302	2.613	0.032	0.204
PRICE	−0.007	−11.080	−0.008	−11.371	−0.008	−11.538
CNONE	−1.040	−6.287	−1.084	−6.449	−1.159	−6.773
TD			−0.525	−3.807		
TDSQUARE			0.041	1.958		
ID-ZODIAC					−0.034	−0.240
ID-MOTOR					−0.453	−4.294
ID-SMALL					−0.221	−2.186
ID-MEDIUM					−0.027	−0.218
ID-SWIM					−0.261	−2.759
ID-SCUBA					−0.574	−3.909
ID-GARNT					−0.620	−4.116
LL	−850.149		−824.809		−815.986	
Adj. ρ^2	0.093		0.119		0.126	
AIC	1,718.298		1,671.618		1,663.972	

Table III. Model estimation results

Variable CNONE is a constant representing the choose-none alternative in each choice set and denotes an excursion that is not captured by the variables currently included in the model. In other words, CNONE represents a trip on a large sailing catamaran that offers viewing dolphins from the boat with no guarantee. This variable is negative and significant indicating that forgoing the opportunity to participate in a dolphin excursion has negative utilities to the respondents in general.

The second and third models both include attribute difference measures. Following the argument that was previously presented, price was excluded when the difference measures for these two models were calculated to allow respondents to trade-off attribute differences with the price. In addition, including price in the difference may introduce a nonlinear impact of price on the utility function, which complicates the welfare calculation. Both models that include difference measures offer significant improvement in model fit as suggested by the adjusted ρ^2 statistic and the AIC measure.

In the second model, all variables in the conventional analysis are included. The estimated parameters are consistent with the first model except that ZODIAC and MOTOR are no longer significant. The second model considers the overall number of differences between the attributes in an alternative offered in a conjoint choice set and the self-explicated, preferred alternative. To account for possibility of a nonlinear relationship, variables TD (total differences) and TD squared are included and they are both significant. Judging by the signs of these difference measures, one can conclude that holding other factors constant, the more an alternative offered in a conjoint experiment differs from the respondents' preferred alternative, the more this alternative will be discounted in calculating the respondent's overall utility, lowering the probability of being chosen. Moreover, the positive sign associated with the squared term suggests that the magnitude of change in utility along this overall difference measure is decreasing as TD increases.

Instead of overall difference measures, the third model incorporates dummy variables indicating whether an attribute in the conjoint experiment is different from the self-constructed preferred alternative. These variables are marked by prefix ID. This model fits the data better than the second model with generally consistent parameter estimates for each attribute. One noticeable difference is that the variable GARNT is no longer significant. Five of the seven additional difference variables are significant. All five significant variables are negative suggesting that, holding other factors constant, if an attribute displayed by an alternative in the conjoint experiment is not what the respondents have expected, the utility associated with the attribute will be reduced. The interpretation of each difference dummy variable will become clearer when the welfare measures are discussed in the following section.

Lastly, all three models were estimated in the framework of a conditional logit model. As discussed previously, more sophisticated modeling kernels, such as a latent class or a random parameter specification, can be superimposed on these models. Similarly, more variables, such as respondents' demographic and/or attitudinal characteristics may also be included. However, the main point of this paper is to show that the additional information about attribute differences introduced in the two types of choices can be used to better understand choice behavior. Additional efforts to developing the modeling framework may improve the fit of the model, but will not further the argument already presented here.

4.3 Welfare measures

Calculating the estimated marginal values associated with each attribute allows the implication of each choice model on welfare to be examined. Several authors have shown that marginal values are determined by the ratio between the coefficient of an attribute and the absolute value of the coefficient of the price variable. Table IV gives these marginal values for each model. The standard deviations are calculated using simulation with 10,000 replications. The value for BASE refers to the value of a baseline excursion with features included in the variable CNONE, i.e. a large sailing catamaran with dolphin viewing only and no guarantee. The values of other attributes are measured relative to this base trip. For example, the first logit model estimates that a zodiac inflatable boat is valued about $50 less than a catamaran by a potential customer.

In the second model, holding other factors constant, features of an offered excursion can differ from participants' preferred features. As measured by the total number of different attributes between these two alternatives, variable TD can range from one to seven, excluding price. Table IV reports the welfare implications for the number of attributes offered that differ from the participants' self-constructed, preferred alternative. As shown, if an excursion differs from the preferred by one attribute or variable TD = 1, participants would require a $57 discount on average, as compensation. The compensation required increases as more attributes deviate from the preferred alternative, although the increase in compensation rises at a slower rate. When total differences are between six and seven, the required compensation stabilizes. These changes in value are based on the number of differences introduced and are not directly related to the specific attributes offered by an excursion.

In the third model, individual difference variables are included for each attribute and three sets of values can be calculated for each attribute. The first set is reflects a situation in which the attribute appears in the excursion offered but not in the self-constructed preferred alternative. This is labeled in Table IV as "Offered, Not Expected" for model three. Using a zodiac inflatable boat as an example, offered

	Logit without differences		Logit with overall differences		Logit with individual differences					
					Offered, not expected		Offered, expected		Not offered, expected	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
BASE[a]	141.263	22.496	139.449	21.605			143.875	21.074		
ZODIAC	−49.952	22.332	−33.889	21.896	−53.428	21.955	−48.964	23.699	−4.464	18.016
MOTOR	−30.101	16.996	−20.542	16.507	−67.837	19.330	−11.307	15.908	−56.530	13.768
SMALL	79.975	19.786	69.508	19.636	45.767	23.681	73.441	18.931	−27.674	12.703
MEDIUM	32.357	19.861	43.355	19.771	33.859	21.153	37.220	19.280	−3.361	15.528
SWIM	55.028	16.040	48.847	15.277	14.912	18.757	47.631	14.656	−32.719	12.111
SCUBA	38.568	19.274	52.096	18.583	0.305	20.771	72.099	20.044	−71.794	18.837
GARNT	71.094	15.045	38.764	14.817	−73.189	36.044	3.930	19.792	−77.119	19.295
TD = 1			−57.161	13.375						
TD = 2			−114.322	26.751						
TD = 3			−155.316	32.690						
TD = 4			−185.530	34.484						
TD = 5			−204.966	33.785						
TD = 6			−213.623	34.333						
TD = 7			−211.501	41.754						

Note: [a]BASE refers to an excursion with large sailing catamaran that only offers viewing and with no guarantee

Table IV.
Marginal values

and not expected for both ZODIAC and ID-ZODIAD would equal one. The second set of values reflects a situation in which an attribute is both expected and displayed in the alternative offered. These values are given under "Offered, Expected" and using the same example, ZODIAC equals one and ID-ZODIAC equals zero. The third set of values suggests an attribute was expected but not offered and is listed under label "Not Offered, Expected" in Table IV. Under this condition, for a zodiac boat, ZODIAC is zero and ID-ZODIAC is one. The last possible situation occurs when an attribute was not expected and not offered so that the marginal values collapse into the BASE value. The formula used for determining the marginal values is the same as in the first model.

Clearly, when an attribute is offered in an excursion and a respondent's preferred alternative includes the attribute, the marginal value of this attribute is close in value to what was estimated using the other two models. On the other hand, if an attribute differs from the self-constructed, preferred alternative, the estimated value of the attribute greatly differs from its estimated value using the other two models. For some attributes such as boat size and activities offered, the change is large enough to reverse the signs of some marginal values. Furthermore, for the two cases, offered/not expected and not offered/expected, which both suggest a situation in which the alternative offered and the preferred alternative differ, the magnitude of the values associated with corresponding attributes are not symmetric. This last model demonstrates that in standard conjoint analysis where respondents' self-explicated, preferred alternative is not jointly considered, the result generated only captures one type of value, i.e. offered/expected, underlining the choice behavior. Incorporating this simple additional information significantly broadens the understanding of welfare implications for respondents with different types of preferences without including any of their personal characteristics.

5. Conclusion

Given the popularity of recreational wildlife excursions, little work has been conducted to understand their economic values. For most existing work, even conjoint analysis is generally regarded as a realistic preference elicitation method (Sattler and Hensel-Börner, 2000), usually highly hypothetical scenarios are used in survey questions, which may cause choices made by respondents not representing their true preferences. Based on consumers' self-explicated excursion attributes, this research introduces a simple approach to enhance conjoint analysis. This relatively low-cost approach involves asking survey participants to specify their preferred alternatives using the same attributes and levels used in the conjoint analysis. The difference between these self-explicated preferred alternatives and those offered in conjoint experiment are then analyzed using various choice models. With the assist of an internet-based survey, the approach is straightforward to apply. Respondents are able to link the survey questions to their actual daily choices. The models used to analyze the data collected are also straightforward to apply on a modern computer.

Previous research investigated the strength of merging the self-explication approach and conjoint analysis and favored the combined method (e.g. Park *et al.*, 2008). However, these past studies usually involve highly sophisticated models. While also trying to enhance the conjoint analysis, this current study presents an approach that requires no additional modeling effort. Our study confirms the conclusion that incorporating the additional information from consumers' self-explicated alternative improves the analysis. Results show that although the extra effort involved in data collection is relatively small, the improvement in model fit, choice interpretation, and welfare calculation is sizable. The additional information enables the researcher to jointly consider an individual's choices at two separate stages. Thus, the proposed approach described in this paper can also serve as a method to test for preference consistency suggested by a particular data collection process.

Although this study does not intend to offer a theoretical explanation of choice behavior from a human judgment and decision-making perspective, opportunities exist for expanding the current research. For instance, research can be conducted to understand whether the proposed method may bring similar benefits in a choice situation respondents may be more familiar with, such as food or consumer products. It can be argued that in a familiar choice environment, consumers will have a better defined preferred alternative. Self-explication may be associated with less cognitive burdens and with higher precision, which in turn could strengthen the impacts of this approach. In another application, one may use respondents' characteristics to explain why they may choose certain levels of the attributes in the process of constructing their preferred alternative. Similarly, these characteristics may be used to describe their behavior based on the differences among alternatives in the two stages. With the increasing usage of internet-based surveys, this study offers a practical approach to improve data and analysis quality.

References

Adamowicz, W.L., Louviere, J. and Williams, M. (1994), "Combining stated and revealed preference methods for valuing environmental amenities", *Journal of Environmental Economics and Management*, Vol. 26 No. 3, pp. 271-292.

Archak, N., Ghose, A. and Ipeirotis, P.G. (2011), "Deriving the pricing power of product features by mining consumer reviews", *Management Sciences*, Vol. 57 No. 8, pp. 1485-1509.

Bateman, H., Louviere, J., Thorp, S., Islam, T. and Satchell, S. (2010), "Investment decisions for retirement savings", *Journal of Consumer Affairs*, Vol. 44 No. 3, pp. 463-482.

Batte, M., Hu, W., Woods, T.A. and Ernst, S. (2010), "Do local production, organic certification, nutrition claims, and product branding pay in consumer food choices?", selected paper, Agricultural and Applied Economics Association Annual Meeting, Denver, CO, July 25-27.

Ben-Akiva, M., McFadden, D., Garling, T., Gopinath, D., Walker, J., Bolduc, D., Borsch-Supan, A., Delquie, P., Larichev, O., Morikawa, T., Polydoropoulou, A. and Rao, V. (1999), "Extended framework for modeling choice behavior", *Marketing Letters*, Vol. 10 No. 3, pp. 187-203.

Bhat, C.R. and Gossen, R. (2004), "A mixed multinomial logit model analysis of weekend recreational episode type choice", *Transportation Research B*, Vol. 38 No. 9, pp. 767-787.

Boehle, K. (2007), "Valuation of spinner dolphin excursions in Hawaii", unpublished MS thesis, Joint Institute for Marine and Atmospheric Research and Department of Natural Resources and Environmental Management, University of Hawaii at Mānoa, Honolulu, HI.

Box, G.E.P., Hunter, J.S. and Hunter, W.G. (2005), *Statistics for Experimenters: Design, Innovation, and Discovery*, John Wiley, Hoboken, NJ.

Boxall, P.C. and Adamowicz, W.L. (2002), "Understanding heterogeneous preferences in random utility models: a latent class approach", *Environmental and Resource Economics*, Vol. 23 No. 4, pp. 421-446.

Chung, S. (2013), "The role of online informediaries for consumers: a duel perspective about price comparison and information mediation", *Internet Research*, Vol. 23 No. 3, pp. 338-354.

Deshazo, J.R. and Fermo, G. (2002), "Designing choice sets for stated preference methods: the effects of complexity on choice consistency", *Journal of Environmental Economics and Management*, Vol. 44 No. 1, pp. 123-143.

Edinger, E.N., Kolasa, J. and Risk, M.J. (2000), "Biogeographic variation in coral species diversity on coral reefs in three regions of Indonesia", *Diversity and Distributions*, Vol. 6 No. 3, pp. 113-127.

Farley, K., Thompson, C., Hanbury, A. and Chambers, D. (2013), "Exploring the feasibility of conjoint analysis as a tool for prioritizing innovations for implementation", *Implementation Science*, Vol. 8, pp. 56-66.

Fennell, G., Allenby, G.M., Yang, S. and Edwards, Y. (2003), "The effectiveness of demographic and psychographic variables for explaining brand and product category use", *Quantitative Marketing and Economics*, Vol. 1 No. 2, pp. 223-244.

Gilbride, T. and Allenby, G. (2004), "A choice model with conjunctive, disjunctive, and compensatory screening rules", *Marketing Science*, Vol. 23 No. 3, pp. 391-406.

Green, P.E. and Carmone, F.J. (1977), "Segment congruence analysis: a method for analyzing association among alternative bases for market segmentation", *Journal of Consumer Research*, Vol. 3 No. 4, pp. 217-222.

Green, P.E. and Rao, V.R. (1971), "Conjoint measurement for quantifying judgmental data", *Journal of Marketing Research*, Vol. 8 No. 3, pp. 355-363.

Green, P.E., Krieger, A.M. and Wind, Y. (2001), "Thirty years of conjoint analysis: reflections and prospects", *Interfaces*, Vol. 31 No. 3, pp. S56-S73.

Grether, D.M. and Plott, C.P. (1979), "Economic theory of choice and the preference reversal phenomenon", *American Economic Review*, Vol. 69 No. 4, pp. 623-648.

Hailu, A., Adamowicz, W.L. and Boxall, P.C. (2000), "Complements, substitutes, budget constraints and valuation", *Environmental and Resource Economics*, Vol. 16 No. 1, pp. 51-68.

Hauser, J.R., Toubia, O., Evgeniou, T., Befurt, R. and Dzyabura, D. (2010), "Disjunctions of conjunctions, cognitive simplicity, and consideration sets", *Journal of Marketing Research*, Vol. 47 No. 3, pp. 485-496.

Hearne, R.R. and Salinas, Z.M. (2002), "The use of choice experiments in the analysis of tourist preferences for ecotourism development in Costa Rica", *Journal of Environmental Management*, Vol. 65 No. 2, pp. 153-163.

Hsiao, K., Lu, H. and Lan, W. (2013), "The influence of the components of storytelling blogs on readers' travel intentions", *Internet Research*, Vol. 23 No. 2, pp. 160-182.

Hu, W. (2006), "Comparing consumer preferences and willingness to pay for non-GM oil using a contingent valuation approach", *Empirical Economics*, Vol. 31 No. 1, pp. 143-150.

Hu, W. (2007), "Bargains or rip-offs: reference price effects in conjoint demand", *Journal of Agricultural and Resource Economics*, Vol. 32 No. 2, pp. 462-475.

Hu, W., Chen, K.Z. and Yoshida, K. (2006), "Japanese consumers' perceptions on and willingness to pay for credence attributes associated with canola oil", *Journal of Agricultural and Applied Economics*, Vol. 38 No. 1, pp. 91-103.

Hu, W., Woods, T.A., Bastin, S., Cox, L. and You, W. (2011), "Assessing consumer willingness to pay for value-added blueberry products using a payment card survey", *Journal of Agricultural and Applied Economics*, Vol. 43 No. 2, pp. 243-258.

Kramer, T. (2007), "The effect of measurement task transparency on preference construction and evaluations of personalized recommendations", *Journal of Marketing Research*, Vol. 44 No. 2, pp. 224-233.

Liu, Q., Otter, T. and Allenby, G.M. (2007), "Investigating endogeneity bias in marketing", *Marketing Science*, Vol. 26 No. 5, pp. 642-650.

Luce, D.R. and Tukey, J.W. (1964), "Simultaneous conjoint measurement: a new type of fundamental measurement", *Journal of Mathematical Psychology*, Vol. 1 No. 1, pp. 12-17.

McFadden, D. (1974), "The measurement of urban travel demand", *Journal of Public Economics*, Vol. 3, pp. 303-328.

Murray, K.B., Liang, J. and Häubl, G. (2010), "ACT 2.0: the next generation of assistive consumer technology research", *Internet Research*, Vol. 20 No. 3, pp. 232-254.

Netzer, O. and Srinivasan, V. (2007), "Adaptive self-explication of multi-attribute preferences", Research Paper No. 1979, Stanford University, Stanford, CA, available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1077434

Netzer, O., Toubia, O., Bradlow, E., Dahan, E., Evgeniou, T., Feinberg, F., Feit, E., Hui, S., Johnson, J., Liechty, J., Orlin, J. and Rao, V.R. (2008), "Beyond conjoint analysis: advances in preference measurement", *Marketing Letters*, Vol. 19 No. 3, pp. 337-354.

Nunes, P.A.L.D., Galvan, A. and Chiabai, A. (2004), "Combining stated choice methods and hedonic valuation: measuring the economic benefits from protecting the business activities from high water in Venice", selected paper, European Association of Environmental and Resource Economics, Budapest, June 25-28.

Park, Y., Ding, M. and Rao, V.R. (2008), "Eliciting preference for complex products: a web-based upgrading method", *Journal of Marketing Research*, Vol. 45 No. 5, pp. 562-574.

Ready, R., Fisher, A., Guignet, D., Stedman, R. and Wang, J. (2006), "A pilot test of a new stated preference valuation method: continuous attribute-based stated choice", *Ecological Economics*, Vol. 59 No. 3, pp. 247-255.

Richards, T., Hamilton, S.F. and Allender, W.J. (2014), "Social networks and new product choice", *American Journal of Agricultural Economics*, Vol. 96 No. 2, pp. 489-516.

Sattler, H. and Hensel-Börner, S. (2000), "A comparison of conjoint measurement with self-explicated approaches", in Gustafsson, A., Herrmann, A. and Huber, F. (Eds), *Conjoint Measurement: Methods and Applications*, Springer Verlag, Berlin, pp. 67-76.

Srinivasan, V. (1988), "A conjunctive-compensatory approach to the self-explication of multiattributed preferences", *Decision Sciences*, Vol. 19 No. 2, pp. 295-305.

Stanton, K. (2005), "Group wants limits on dolphin access: increased water traffic is disrupting the natural processes of spinner dolphins", *Honolulu Star Bulletin*, Honolulu US Census Bureau, available at: //starbuletin.com/2005/04/18/news/story7.html (accessed April 5, 2014).

State of Hawaii Department of Business, Economic Development and Tourism (2004), "2002 and 2003 Hawaii cruise industry impact study", available at: www.hawaii.gov/dbedt/info/visitor-stats/econ-impact/cruise-impact.pdf (accessed March 31, 2014).

Swait, J. and Adamowicz, W. (2001), "Choice complexity and decision strategy selection", *Journal of Consumer Research*, Vol. 28 No. 1, pp. 135-148.

Von Haefen, R.H., Massey, D.M. and Adamowicz, W.L. (2005), "Serial nonparticipation in repeated discrete choice models", *American Journal of Agricultural Economics*, Vol. 87 No. 4, pp. 1061-1076.

Vriens, M., Wedel, M. and Wilms, T. (1996), "Metric conjoint segmentation methods: a Monte Carlo comparison", *Journal of Marketing Research*, Vol. 33 No. 1, pp. 73-85.

Yoo, H. and Doiron, D. (2013), "The use of alternative preference elicitation methods in complex discrete choice experiments", *Journal of Health Economics*, Vol. 32 No. 6, pp. 1166-1179.

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