CHOICE MODELLING - AN EXERCISE IN ENVIRONMENTAL VALUATION

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1.0 Introduction

Stated preference techniques are now a common means of assessing values (Morrison, Blamey, Bennett and Louviere 1996). These techniques draw on the use of survey instruments to assess preferences, in contrast to preferences that are revealed in the course of market transactions. There is growing interest in the use of discrete choice models to assess stated preferences, where respondents are presumed to make choices between discrete alternatives that maximise their utility. Developing from the fields of market research, economics and psychology, these models have been more recently applied to environmental problems. Rolfe and Bennett (1996) outline a choice modelling (CM) approach that provides some estimates of the willingness to pay (WTP) of Australians for rainforest conservation.

Choice modelling involves people being asked in a questionnaire to indicate their preferred choice from two or more scenarios, each made up of a small number of attributes that vary to make the scenarios different. Performing a number of choice experiments provides data that enable the researcher to estimate the contribution of different attributes to the choices made. This then enables predictions to be made about choices, and hence value. The CM process involves the estimation of a model that tries to explain the behavioural process underlying choice. Use of the technique is attractive because it enables a more realistic modelling of the range of choices facing individuals (compared to other stated preference techniques), and can provide indications of both relative and absolute value.

A potential weakness of CM is that its outcomes are dependant on the inherent model specification. In the basic multi-nomial logit (MNL) format used to estimate the relationship between the attributes and choice probability, the assumption made is that the effects of the various attributes are additive in the underlying utility function. However, choices may also be influenced by interactions between attributes, and by various socio-economic factors. More accurate models can often be built by including these other significant factors. Because there is a circular process of model specification, experimental design, analysis of results, and then model re-specification, the estimation process is necessarily an iterative one.

Models can also be specified according to a hierarchal decision process, where choices are nested under successive layers of particular attributes. For example, the first level of decision for somebody contemplating a weekend's recreation may be between various activities. Once the choice has been made between fishing, boating or swimming, then the next layer of choice may be between different locations. Of course, the decision process may follow a different pathway. Perhaps the first choice is where to go for the weekend (location), and then what to do (activity). The process by which choice options are narrowed down by considering only a limited number of attributes at a time is called nesting.

Nested logit (NL) models are popular in the analysis of demands in areas such as recreation (Kling and Herrige 1995), travel (Hensher 1991) and housing (Weisbrod, Lerman and Ben-Akiva 1980). This is because the models are able to allow varying levels of correlation between selection alternatives. For example, an attribute such as number of fish caught may offer a significant explanation of choices involving fishing, but have no relevance to boating and swimming options. Different levels of cost and travel time need to be used in travel models involving bus, car and air travel options. Nested logit models enable the inclusion of option specific attributes (number of fish caught under the fishing choice), or attributes that vary between certain ranges under a particular branch of a nesting structure (low travel times in the fly option). As well as reflecting the physical constraints that govern many choices, NL models are often popular because they are seen to reflect consumer decision paths (Kling and Herriges 1995). For various reasons, people do make path dependant choices. For example, someone may first choose between driving to the beach or staying home and going to the movies for their weekend relaxation. Having decided on the latter, they then look up the paper to see what movies there are being screened to choose from.

Nested logit models appear to be highly relevant to stated preferences for environmental goods. This is partly because environmental issues are complex and prolific. People responding to environmental choices often use decision trees as efficient ways of narrowing down options and making choices. Thus they may simplify the range of choices according to whether the issue affects them or their family personally, affects their health, appears to carry high levels of risk, and so on.

As well, people often make choices about environmental issues from low levels of knowledge or incentive, and can simplify the decision process by using a sequence of decisions to make choices. They may restrict their choices to issues that they might be interested in, or take their decision cues from what their neighbours said. Social conventions and moral guidelines often reflect defaults for making quick decisions. Perhaps they respond only to issues that they feel some responsibility for, or issues that they think might affect their employment prospects. A nested model can reflect these sequence of decisions, and thus estimate the relevant choice model more accurately.

The researcher though faces two main difficulties in choosing a NL model. The first is to specify the correct structure for nesting. While it may be clear that number of fish caught nests under the fishing option, it is not at all obvious whether the weekender's first choice is between activity or location. Because there are usually a number of possible pathways to a complex decision, large numbers of nesting structures often need to be considered.

The second difficulty is to show that a NL model provides better estimates of utility maximisation than other model specifications (such as MNL). Because the researcher is trying to condense the very large pool of reasons why people make particular choices into a concise number of attributes of the particular choice, socio-economic characteristics of the people involved, and the various choice pathways that are available, it would be possible to construct many different models that explain the same choice. To show the advantages of NL models, it is usually necessary to consider how well the various models satisfy the statistical constraints underlying their application.

In this paper these issues are explored with relation to CM and a particular application to an environmental issue, the estimation of conservation values held by Australians for international rainforests. In the next section, the CM technique is described and some reasons advanced for why preference formation for environmental issues may involve a sequence of choice processes. In section three the nested logit model, the statistical process involved in the CM technique, is described more fully, particularly in relation to some of the assumptions underlying the application of the model. In section four the development of a nested logit model to model demands for rainforest conservation is outlined. Section five concludes the paper.

2.0 Choice Modelling and Preference Formation

Choice modelling developed from the work of Louviere and Hensher (1982), Louviere and Woodworth (1983) and Louviere (1988) out of a more general field of market research techniques loosely referred to as conjoint analysis. In CM, respondents are asked to make a sequence of discrete choices from sets of alternatives. Drawing on random utility theory (Thurstone 1927, McFadden 1974), it is assumed that each alternative chosen yields the highest utility. However, the outside observer cannot observe those utilities directly, and thus must explain the behaviour in terms of some systemic (explainable) component and a random error component. Assuming that the error terms follow an extreme value (Gumbel) distribution implies that a logistic model is applicable (McFadden 1974). This form is preferred for computational reasons.

The systematic component of choices is explained by reference to the attributes within each alternative selected relative to those rejected, following Lancaster's (1977) work on demand characteristics. Each discrete choice then can be explained as a preferred combination of attributes such as quantity and price, together with the random error term. The CM researcher allows each attribute to vary across two or more levels to generate differences between scenarios. Respondents choose a profile in a choice modelling set with the most attractive package of the attributes at their differing levels. Repeating the choice experiment with slight changes in the profiles of various alternatives can provide enough data to estimate the contribution of various attributes to successful choices.

Selection of several attributes for a good and allowing each to vary across a number of levels means that there is a very large number of slightly different ways of describing the one good. In the first rainforest example reported below (Appendix 1), we have one attribute (location) varying across eight levels, and a further six attributes varying across four levels. The combination of possible profiles is given by $8^1 x 4^6$ 32 768

An experimental design process is usually employed to determine which profiles to present to respondents in their choice sets. Selection of two or more profiles for the choice sets needs to be made on some systematic basis. The selection has to not only be a sample of the full set of possible profiles, but has to consider which alternatives are included in each set. As well, selection needs to allow the researcher to test for possible interactions. This is done by ensuring that the various combinations of interest are orthogonal (independent) within the design matrix.

The contribution of the various attributes to successful choices in a CM experiment is analysed with the MNL model. This model essentially calculates the logarithm of the odds that a particular choice will be made. One general form of a discrete choice model is given by:

$$\log (\text{Prob (Option 1)}) / (1-(\text{Prob (Option 1)}) = \text{Beta1} + \text{Beta2.Z2} \ldots + \text{BetaxZx} \quad (1)$$

where the Z's represent the attributes of the choice sets (Pindyck and Rubinfeld 1981). The information revealed from varying the attribute levels within choice sets and correlating that with frequency of choice allows the researcher to estimate the coefficients for each attribute. The development of specialised software applications over the last decade has allowed researchers to vary several attributes simultaneously and disaggregate impacts on choice relating to each attribute.

The coefficients reported relate to the odds that a particular choice will be made rather than to the utility contributed by each attribute. Clearly though, there is a strong relationship between the two. The use of price as one attribute enables the researcher to estimate where respondents are indifferent between changes in price and compensating changes in another attribute. An estimate of the dollar value of the contribution made to utility by each attribute can be made by taking the ratio between the particular attribute coefficients and the price coefficient. Because CM is based on the Random Utility Model, the behavioural model that is derived through CM in the logit format can be used to compute WTP measures which are consistent with welfare measures derived from utility maximisation (McConnell 1995). This means that WTP estimates derived from CM are consistent with consumer surplus measures.

Care must be taken though in extrapolating results because they derive from the odds generated within the specified set of attributes. This means that any values derived are relative to the scenarios in the choice sets, and hence reflect marginal values associated with changes from some implicit base line. For example, the primary outcome of a CM exercise is to give the WTP for changes in the level of an attribute (such as an increase in the area of rainforest conserved from 100 hectares to 1000 hectares). Absolute measures of value can only be generated if well defined base conditions are included in the choice options.

Several refinements are necessary to ensure accurate results in the CM process (Louviere 1988, Carson et al 1994). First, the addition of a constant alternative (usually a "No Choice" option) ensures a standard reference point for choice sets and allows them to be combined for data analysis. As well, the constant alternative (if well defined) can enable absolute measures of value to be estimated. Second, the options to choose from may be labelled with specific names (such as Vanuatu and Far North Queensland in the rainforest conservation profiles). This implies that the choices may also depend on the alternatives given in each choice set (an alternative specific model) rather than simply on the attributes of the profiles chosen (as is assessed in a generic model).

Third, the accuracy of the underlying utility function can be tested by checking for violations of the assumptions regarding the application of the logit model. All logit models are based on the assumption that the error terms associated with each attribute are independently and identically distributed with extreme value distribution (Gumbel distribution). These assumptions in turn rest on the Irrelevance from Independent Attributes assumption (IIA) of discrete choice models, which holds that the attributes are independent. The probability of choosing an option is independent of any other alternatives that might exist, depending only on the alternatives presented within a choice set.

There are two avenues for testing this assumption. The first is by testing whether choices are influenced by the attributes of alternate profiles in the choice sets. Significant cross effects would suggest that the attributes are not independent. The second test is to respecify the model with a smaller number of choices and to check that the ratios of attribute coefficients remain unchanged (as they should if their relative contribution to the probability of choice remains unchanged). Violations of the IIA assumptions indicate that other factors are influencing the choice process, and mean that the researcher should look for significant interactions between attributes, heterogeneous factors, and nesting models to improve the explanatory power of the function.

This basic explanation of the CM process presupposes that the good to be valued can be described concisely in terms of several attributes that can be chosen at various levels. Rolfe and Bennett (1996) report that tropical rainforests can be characterised in terms of seven attributes: location, area, rarity, special features, effect on local populations, potential to visit, and the price of conservation. Profiles need to be easily understood by respondents, as well as being realistic and credible. Carson et al (1994) suggest that respondents may need some explanations and "warm-up" choice tasks to be able to process the information and make accurate tradeoffs. As well, there are practical limits to the number of attributes, levels, profiles within a choice set and the number of choice sets that can be presented to respondents. While it is possible to increase any one of these factors above a generalised average, compensating reductions in other factors are usually necessary to maintain respondent interest and comprehension.

The rainforest conservation issues reported in Rolfe and Bennett (1995, 1996) provides some indication of why NL models may be applicable in these CM exercises. There appear to be four broad groups of reasons why respondents to CM surveys may use decision pathways to make choices between alternatives: complex choices, default responses, 'soft' institutional patterns, and non-participation.

The first reason derives from the complexity of choices facing individuals. Although only seven attributes have been used to describe rainforest profiles, the background knowledge and understanding of respondents means those profiles trigger complex tradeoffs. In order to make choices, respondents may progressively rank their decision criteria, such as Australian/overseas, rare/not rare, so as to reduce the complexity of comparisons.

A particular way in which respondents to CM surveys may handle complex decision processes is to assign "indicator" status to one or more attributes. Focus groups and pretesting have revealed that some people will choose one particular attribute as the main signal for "value" within each profile. For example, some people may focus on rarity as the attribute that best imparts the key environmental status of a profile. These respondents then would select only profiles between profiles that had the extremely rare or perhaps the fairly rare attribute levels. Some respondents indicated that price was an "indicator attribute", saying that they only picked between the low cost options. Others looked for positive effects on the local people as a key component of profiles.

However, one key finding of the focus groups held (reported in Rolfe and Bennett 1995) was that Australians distinguished very strongly between support for conservation of Australian rainforests, and support for conservation of rainforests overseas. There were a number of reasons for this. Some related to use values - the potential to visit, resources for the tourism industry, and so on. Some related to feelings of ownership and responsibility, and the commonly expressed sentiment that "we should look after our own back yard first". Other reasons related to the uncertainty about the possibility of Australians influencing conservation in other countries, and doubt about whether appropriate institutional structures existed in some countries.

However, it is likely that part of the explanation for the strong distinction between Australian and overseas locations lies in the second broad group of reasons why decisions may be nested - the default decisions. In this case, decision rules are adopted to avoid complex decision processes. Rather than using a series of decision steps as a logical way of handling complex information, people may employ decision steps as a quick way of making choices and avoiding complex tradeoffs. The use of "indicator attributes" may reflect this search for some means of making quick choices.

It seems likely that some of the respondents who focused on Australian rainforests were using this as a default mechanism to narrow their choice options. People generally had much higher levels of knowledge about Australian rainforests and conservation issues than ones overseas. As well, focus group participants suggested that they felt more comfortable supporting issues "close to home" where they tended to have more knowledge, control and potential to benefit themselves from improvements In contrast, respondents often seemed more reluctant to support more distant issues where they had lower levels of knowledge and understanding

This general issue of comprehension becomes particularly important in cases where respondents have limited knowledge or experience in designing the relevant preferences and making choices Environmental issues provide a good example of this uncertainty The level of knowledge and comprehension about both specific and general environmental issues varies widely across society It is problematic to "super-inform" respondents about a particular issue because this means that they are no longer a representative sample of the population (Rolfe 1996) Indeed, one of the main attractions of CM is its ability to "disguise" the particular item of interest within an array of similar goods Rather than "super informing" respondents the researcher has to find ways of describing goods (and structuring profiles) that invoke common understanding among respondents

The lack of experience and understanding may mean that respondents to CM surveys on environmental issues will often default to decision paths and other processes in order to make choices People buying normal consumption goods draw on a wealth of prior experience and market information to help them in their decisions Markets (such as a housing market) also help to provide information about how other people have made choices and valued the relevant attributes In a CM survey though, respondents are often being asked to make choices where they have little background knowledge or prior experience and almost no information about how other people have made choices As well, the tradeoff amounts (prices) are generally small and hypothetical The opportunity costs for incorrect decisions are probably perceived to be low These factors suggest that stated preferences for relatively unknown goods are more likely to be formed on the basis of informal decision rules and default cues than would preferences for well-understood commercial items

An example may help to illustrate this problem Consumers buying eggs may focus on the attributes of size price freshness, and production method Repeated buying experience means that they are able to easily balance the varying contributions of these factors to their eventual choice A CM analysis of egg demand would enable the estimation of the demand function for eggs in terms of those attributes In a case where respondents are asked to choose between different rainforest protection profiles though, it may be very difficult to weigh up the influence of the various attributes simultaneously In this cases, respondents may choose some form of a nested decision process to arrive at their preferred option For example they may choose between support for an Australian or an international rainforest Once that decision has been made (and the number of alternatives reduced), the respondent focuses on the other attributes to make a final choice Of course they may choose again to focus on a single attribute (such as rarity), in order to reduce the pool of available choices further

A third important reason why respondents to CM surveys on environmental issues may use a hierarchy of decision rules to structure their choices relates to the involvement of 'soft' institutional rules, particularly in the form of ethical and moral influences Many of the choices that people make are recurrent In order to make these choices efficiently, people use a range of frameworks to indicate the appropriate decisions These frameworks include habits, social conventions and norms, moral constraints and more substantive ethical guidelines

In one way, people making choices reflect the constraints of limited rationality (Simon 1957) It is perhaps better to think of them as decision optimisers, who draw on a variety of tools, including background knowledge, patterns of previous decisions, the information at hand, and other cues and default rules to make the necessary choices Moral and ethical frameworks are often very important reference structures for people, especially when faced with new or unusual choices The development of many environmental movements with ethical, philosophical and religious themes reflects this movement back to first principles in order to make choices These developments suggest that preferences are ranked into "higher" and "lower" preferences, and that decisions follow a general structure of satisfying the ethical or "higher" preferences first, and then considering the "lower" preferences.

Respondents in a CM exercise may structure their initial level of choices according to some ethical or moral framework Some of the survey results on rainforest conservation (Rolfe and Bennett 1996) suggested that when rainforests were not clearly specified, some participants were using ethical and moral frameworks to rank all rainforests as equally important. However, tests showed that when attributes for rainforest conservation were included, respondents were able to indicate their preferred choices between options. These results indicate that while ethical and moral frameworks can be a significant influence, they have largely avoided in the surveys reported below because choices have been essentially limited to the one good, rainforest conservation, and that has been adequately described through the seven attributes used.

The fourth reason why it may be important to model decision pathways for environmental choices is non-participation (Morey, Rowe and Watson 1993). Many people may not be interested in environmental issues, or may only be interested in a particular group of issues. The decision not to support particular rainforest conservation profiles may have been made at much earlier stages (i.e. "don't support environmental issues", "I'm not interested in rainforests"), and a simple comparison of a profile to a no choice option may not effectively model the no choice process.

While these broad groups of reasons exist why nested decision processes are likely to be involved in environmental issues, there is no mandate for correlation. It is quite possible that many choices involving environmental issues can be made without considering various attributes in sequence. The analysis of decisions about the environment can not automatically rest on assumptions about structured decision processes, but should at least involve a consideration of whether such processes improves explanatory power.

3.0 Nested Logit Models

There are a number of reasons why nested logit models may be a suitable functional form for the analysis of discrete choice data. The most common of these relate to cases where the odds of occurrence varies for different groups of attributes and level combinations. For example, in a discrete choice model exploring travel choices, a combination of air travel and short distance but a long travelling time is not realistic. Nesting travel attributes under an initial choice of air or car travel provides a means of tailoring attribute levels to realistic situations.

The second main function for NL models is to represent the decision process that respondents have used. Thus respondents may step their choice of rainforests according to location and then rarity, and then other factors, using each step to reduce the group of alternatives. NL is also a process that deals well with non-participants, choices between dissimilar goods and activities, and between different groups of users (Kling and Herriges 1995). The NL structure helps to represent these decision paths, and thus more closely models choice behaviour. NL models also help to present respondents with large amounts of information, as information can be tailored to specific versions.

The NL model is a generalised form of an extreme value error distribution which allows alternatives to be grouped internally to reflect correlations within (but not between) those subgroupings (Kling and Herriges 1995). The odds that alternative i will be selected is divided into two components reflecting the probability that the mode (or nest) to which i has been assigned will be chosen, and the conditional probability that i will be chosen given that the correct mode has already been selected. More formally, (following Kling and Herriges 1995)

$$(1) \quad P_i(v) = Q_{m(i)} P_{i|m(i)}$$

where v denotes the utility associated with alternative i and $m(i)$ assigns the alternative to a particular mode or nest. The variable Q_k denotes the probability that mode k is selected, and the variable $P_{i|m(i)}$ represents the conditional probability that alternative i is selected given that mode m has already been chosen. In turn

$$(2) \quad P_{i|m(i)} = \frac{\exp(v_i/\theta_{m(i)})}{I[m(i)]}$$

and

$$(3) \quad Q_{m,k} = \frac{E[m(k)]^{\theta_m}}{\sum_{k=1}^{M} E[k]^{\theta_k}}$$

where

$$(4) \quad E[k] = \sum_{j \in \text{alternatives}} \exp(v_j/\theta_k)$$

The parameter θ is the dissimilarity parameter (or inclusive value coefficient) associated with mode k (Kling and Herriges 1995).

In a typical analysis, the researcher hypothesises a particular nesting structure, chooses variables for inclusion in the model, and estimates the model (Kling and Thomson 1996). It is common to choose nests according to some physical or activity constraint, where the researcher must make assumptions about the correlation between different alternatives. For example, a travel analysis may be structured according to mode of travel (car, air, train, bus). In other cases, researchers may try to structure nests according to how they believe people structure their decision trees. But because there is no defined pathway for establishing a nest structure, the basis for establishing a model is at the discretion of the researcher.

The difficulty is that the alternatives are only correlated from the perspective of the researcher, and the nesting structure chosen may arise from misunderstandings on the researcher's part rather than from an accurate modelling of respondents' decision processes (Kling and Thomson 1996, Train, McFadden and Ben-Akiva 1987). As we move away from cases where physical constraints clearly influence the probabilities attached to different groupings of options towards more general instances where decision processes are merely hypothesised to allow various sub-groupings of alternatives, the more random the choice becomes of a nesting structure. There are two challenges. The first is to show that a nesting model has more explanatory power than a more general MNL model. Here the challenge is to show that people have used structured preference trees to make decisions, rather than weighing up the various attributes in a profile simultaneously. The second difficulty is to determine which nesting structure is preferred among alternatives. An associated difficulty here is that various estimation procedures can be used, ranging from sequential estimation through to different types of simultaneous (full information maximum likelihood or FIML) estimations (Kling and Thomson 1996). These issues are explored in the following sections.

3.1 The Independence of Irrelevant Alternatives Assumption

One attractive feature of the NL model is that it offers a partial solution to the impact of the Independence of Irrelevant Alternatives (IIA) assumption of the MNL model. This assumption is necessary for the MNL model as a consequence of adopting the independent and identically distributed (IID) extreme value error distribution (Carson et al 1994, Ben-Akiva and Lerman 19[illegible]). The IID assumption holds that the distribution of the random components of utility (the error terms) are both independent from each other and follow identical distributions. The implication of this is that each element in a set of alternative choices is independent from each other. The IIA assumption implies that for a specific individual, the ratio of choice probabilities for any two alternatives should be independent of other choices available.

An example may help to explain the IIA assumption. Let the probability of two particular choices from a possible set be given as $P_i(C_n)$ and $P_j(C_n)$. Under the IIA assumption, the ratio of these probabilities ($P_i(C_n)/P_j(C_n)$) is held to remain constant no matter what other alternatives exist. When alternatives are added or deleted from the choice set, the probability of choices i and j change in tandem and the ratio of those probabilities should remain constant. If however an alternative is added that shares some characteristics of either i or j, it is unlikely that the probability of that factor remains relatively unchanged. The standard example is the addition of a different coloured bus to a choice of transport options, and treating that addition as an independent alternative. The IIA assumption is likely to be violated in this case because the consumers would simply view red and blue buses as interchangeable. Violation of the IIA assumption indicates that the IID conditions for MNL have not been met and that the application of the logit model is not valid.

It is unlikely that alternative choices are ever completely independent Indeed, the issues of most interest are generally cases where alternatives are substitutable or complementary to some extent There are several ways of minimising the impact of the IIA assumption on the application of the logit model (Carson et al 1994) One is to respecify the attributes used to mininise the potential for interactions A second is to use the "mother logit" function (McFadden 1974, Louviere 1988) which can explicitly capture interactions between attributes A third is to design a heterogeneous model that identifies the effects of respondent attributes (such as age or income) on preference selection Another option is to use the NL function, which allows correlation to occur within (but not between) groups of alternatives

Kling and Thomson (1996) use a recreation example of three activities (boating, fishing and picnicking) at three possible sites to illustrate the latter There are nine options in total, and two ways to nest the options The first is to group the three sites together for each activity (i e choose the activity first, and then the site) The IIA condition applies to each sub-group of sites nested under activities, but does not apply to activities across the three sub-groups Alternatively, if activities are nested under sites, the IIA condition applies to each sub-group of activities, but not between the sub-groups The probability of boating at site 1 should be independent of the probability of fishing at site 1, but not necessarily of the probability of boating at site 2

Indications of IIA violations are available through an analysis of cross-alternative effects These effects suggest that the choices made for a particular alternative have been significantly influenced by variations in the attributes of other alternatives (rather than being explained by the variations in the attributes of the alternative in question) Thus significant cross-alternative effects may suggest that the IIA properties have not been met, and therefore that the IID assumptions do not hold A more formal way of testing for IIA violations is to calculate a model, recalculate it with a smaller number of choice parameters involved and compare ratios of choice alternatives available in both models (McFadden, Tye and Train 1977 Hausman and McFadden 1984) Variations in the ratios will indicate that the IIA conditions are not being met (McFadden 1974 Hausman and McFadden 1984, Ben-Akiva and Lerman 1994) This in turn indicates that the IID conditions are not being satisfied, and that the application of the MNL model is incorrect

There are a range of other tests that can be used to detect violations of the IIA assumption (McFadden, Tye and Train 1977, McFadden 1987) One specialised test is the lagrange multiplier test for omitted variables which is an appropriate test for IIA violations in NL models (McFadden 1987)

3.2 The Advantages of Nested Logit Models

The use of a NL model helps to avoid problems with IIA violations This becomes especially important when a "no choice" constant option is added to sets of CM profiles It appears that the addition of this option does tend to influence the respondents' choices of alternatives, implying that a NL model or other complex choice model is necessary for analysis (Olsen and Swait 1993, cited in Carson et al 1994) This means that for many CM requirements a NL model may be superior to a MNL model simply because of its improved ability to meet the IIA requirements

NL models allow alternatives to be grouped in a manner that allows the choice of alternatives to be correlated within, but not between, groups (Kling and Thomson 1996) This means that problems of correlation between particular attributes can be circumvented by nesting those attributes into separate groups The IIA conditions still apply between groups, but not within them For example, if the choice of weekend activities lies between fishing, swimming and boating at three separate sites, there are nine different options available A MNL format would treat those nine options as independent, meaning that IIA conditions must hold between each of the alternatives If though the activities are nested under the location choice, then the IIA conditions would apply between location choices and to the choice of activity at each location, but not to the same activity across the different sites Train, McFadden and Ben-Akiva (1987) show that when the substitution rate among nests (i e from one location to another) differs from the substitution rates within nests (i e from one activity to another) then a nested model is a more accurate specification

However, no clear decision rule exists to establish preference for a NL model over other logit models (such as a "mother logit" function) that meet IIA requirements. Kling and Thomson (1996) use welfare measures and associated likelihood statistics to compare MNL, sequential estimation and NL models. While the log likelihood figures show little difference between MNL and NL models in this case, the advantage of the NL models in more easily satisfying IIA assumptions possibly provides them with some advantage.

Log likelihood ranking exercises are generally used as the best available "goodness of fit" statistic to compare MNL models. Log likelihood ratio tests provide a similar function to chi-square statistics, and reflect the 'goodness of fit' of the CM data to the estimated logit function. Significantly larger absolute values of log likelihood functions indicate a model with higher explanatory power.

4.0 The Case Study - Australian Values for International Rainforest Protection.

Choice modelling is an iterative process because of the need to make assumptions about the functional form in order to use an experimental design process. Continued experiments provide more information about the goodness of fit and IIA violations of the hypothesised functional form, and thus enable the researcher to estimate more accurate models.

The case study at hand reflects this iterative approach. The good to be valued, international rainforest protection, was described in terms of seven attributes. These were location, area, rarity, ability to visit, effect on local people, special features and the price of conservation. Each attribute could vary across several levels. For example, area might vary across three levels of 100, 1000, and 10,000 hectares. The attributes and levels were selected through a process of focus groups and pretests (Rolfe and Bennett 1995, 1996). Choice modelling was chosen as an appropriate valuation technique because the issue of interest, conservation of rainforests in Vanuatu, could be embedded within a group of other similar goods. By varying location across several countries, Vanuatu was effectively disguised as the location of interest.

Experimental design was used to select and combine profiles into choice sets from the large pool of possible combinations of attributes at varying levels. Three successive surveys have been run in Brisbane by REARK Research. These surveys involved 100, 100 and 200 respondents respectively. Results from the surveys were coded and analysed. Results from analysis using LIMDEP are presented in the appendices.

The first survey used a simple MNL form, hypothesising that the attributes were independent and additive. Although the resulting model for the groups of attributes (Appendix 2) showed strong goodness of fit characteristics (log likelihood = -1558), tests indicated that the IIA assumptions did not hold. As well, the model did not conform to expectations because the coefficient for price is positive when it would be expected to be negative.

More accurate results can also be generated by estimating the MNL model for the specific levels of each attribute (Appendix 3). Here the coefficients have been estimated for each particular level used in the model, and can be used to estimate part-worth utilities for particular profiles. The model exhibits a strong correlation to expected results, with the coefficients for Australian locations being positive, the coefficients for the subjective attributes generally increasing with amount (apart from *visits*), and the price coefficient being negative (implying that as price increases, the odds of selection falls). However, the goodness of fit for this model is much lower than for the generic model reported in Appendix 2.

There were several reasons why the estimated model may have violated the IIA assumptions. The first option explored was that heterogeneous factors may have significantly impacted on choices. Age, sex, income, occupation and level of education are just some of the factors that may have influenced a sub-group of respondents to support particular options. Crosstabulations between socio-economic data and the choices made were performed with chi-square tests to ascertain if the IIA violations had arisen from heterogenous factors. These tests revealed only small levels of correlation, indicating that the IIA violations had occurred because of other reasons.

The possibilities that interactions or a nested decision process may have been responsible for the violations could not be tested on the basis of the experimental design parameters used in the first survey. It was hypothesised that location was the most likely attribute to be involved in interactions and decision tree processes, partly because location represented a series of labels (country names) in the experiment. The first survey restricted choices in each set for respondents to only two countries.

For many respondents, this restriction in choice may have influenced outcomes for two main reasons. The first is that if respondents were using some decision rule process involving location to make choices, then the changing pairs of countries presented in each set of profiles may have generated the use of varying decision rules. For example, if respondents were keen to nest their choice of rainforest preservation between Australian and overseas locations, this decision rule was not available when only overseas locations were presented. Thus if location is a key attribute (either for nesting or interaction purposes), its presentation in this survey may not have encouraged the use of consistent decision rules.

In a similar vein, the arbitrary presentation of pairs of countries may have impacted on the selection of the *no choice* option. Respondents may have employed different decision rules to take a *no choice* option according to the locations presented. Some indication of bias can be gained from comparison to an earlier result in the same survey, where a large majority of respondents indicated that they would prefer to buy an environmental friendly good (phosphate free laundry detergent) rather than donate money to preserving rainforest in another country (Solomon Islands). Yet the same respondents then selected many of the overseas rainforest preservation choice options, rather than nominating the *no choice* option that their earlier answers would indicate. This suggests that a substantial scope effect may be present when choice sets are restricted to narrow limits.

The second survey addressed some of these problems by including six profiles (one for each country involved) plus a *no choice* option. Restricting *place* to six levels, and the other attributes to three levels enabled a powerful experimental design to be generated. An example of a choice set for the second survey round is presented in Appendix 4. This survey was designed to test for the two other groups of explanations for IIA violations by using a 'Mother Logit' experimental design that enabled interactions and nested models to be estimated. For example, potential interactions between location and the other attributes could be estimated by ensuring that these interactions were orthogonal (independent) within the experimental design.

The results from this survey were first used to estimate explicitly the interactions between location and other attributes. No highly significant interactions were found, which suggests that respondents choosing between relatively unknown or unfamiliar goods will use simple additive utility functions to pattern their choices.

Testing for a nested process was more complex. Appendix 5 shows the results for the generic model which exhibit very strong goodness of fit characteristics (log likelihood -1378[1] This indicates that giving respondents more choices in each set improves the consistency of the choice process, and hence the statistical fit of the results. These data were then used in alternate nesting structures, and log likelihood results used to rank the outcomes. The model that fitted best (with a log-likelihood of -1359.1) had two stages of choice between not making a choice or supporting a rainforest, and then under the latter, between supporting the *Far North Queensland* option or an overseas option[2]. Some prior indication of this result can be seen in Appendix 5, where the coefficients for the overseas locations are reasonably similar, and the coefficient for *Far North Queensland* is quite different. This suggested that respondents might be nesting their choices between Australian and overseas rainforests. An example of a nesting analysis is given in Appendix 6, where respondents were assumed to make a three way first level choice between an Australian rainforest, an overseas rainforest, or no support. The restricted log likelihood figure of -1592.3 suggests that this nesting model provides a better fit than the MNL model reported in Appendix 5. However, because only one Australian rainforest was included in this survey, this hypothesis needed to be tested further with a following survey.

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[1] The price coefficient should be negative. The profile codes for price were inadvertently swapped, leading to a reversal in the sign.

[2] We remain indebted to Dr Joffre Swait from the University of Florida for conducting these tests.

The model specified for the second survey also failed to satisfy IIA tests, suggesting that some correlation between alternatives was still present. When one of the choices available (*Far North Queensland*) was omitted and the model recalculated (Appendix 7), some of the changes in ratios of other choices were significant.

The third survey was designed to allow a better testing of the nesting process to occur. In a similar survey to the preceding one, respondents were asked to choose between six locations and a *no choice* option. There were three Australian locations (*Far North Queensland, South East Queensland* and *New South Wales*) and three overseas locations (*Vanuatu, South America,* and *Indonesia*). An example of a choice set is presented in Appendix 8, and the results of the general MNL model are presented in Appendix 9.[5]

Results for a three way nested model that allows choices to be grouped between Australian rainforests, overseas rainforests, or a *no choice* option are presented in Appendix 10. This shows that *Far North Queensland* is the most preferred location, followed by *South East Queensland* and *Northern New South Wales*, and then the overseas locations. This nested model is a better fit than the MNL model (restricted log-likelihood of -1843.471), and the nested model for the second survey. These results show that the explanatory power of CM data can be improved by adoption and development of nested logit models.

As well as yielding higher log likelihood values, the nested logit model for the third survey meets the IIA requirements more closely. Appendixes 11 and 12 show the results for the MNL model and the nested model with *Far North Queensland* dropped. The MNL model clearly violates the IIA tests. For example, the ratio of *rarity* to *price* changes from 3.59 to 5.08, and the ration of *visit* to *special* changes from 1.26 to 2.23. In contrast, the nested model shows much smaller changes for the same ratios. The *rarity* to *price* ratio changes from 3.72 to 3.62, and the *visit* to *special* ratio changes from 1.78 to 1.65 when the Far North Queensland choice is dropped from the model.

4.1 Implications of the Case Study Results

The case study discussed above shows that both that explanatory power of a model and confidence in its application can be improved by using a nesting structure. The nesting structure used focuses on location and the *no choice* options as first level choices. Although the choice for these nesting structures was based on the outcomes of the focus groups and pretests, they should not be considered as the only possible nesting structures. For example, alternate decision pathways involving *rarity* and *effect on locals* may also be possible, and these could be tested to ensure that they did not offer more significant explanations.

Development of the nesting process has also helped to address a major issue for discrete choice models - the problem of scope. Broadly defined, scope tests are designed to ensure that WTP measures are sensitive to the amount of the good being offered. Scope tests not only encompass statistically significant changes to WTP that result from changes in quantity, but also 'plausibly responsive' judgements of the validity of results (Smith and Osbourne 1996).

CM is an effective technique for addressing many scope issues. This is because the good to be valued can effectively be 'disguised' within an array of alternatives. In the rainforest conservation studies, the item of interest, rainforest conservation in Vanuatu, was presented as one alternative in Australian and international rainforest conservation options.

Yet there were some indications from the first survey that issues of scope may have influenced results. As noted above, the first survey gave only two rainforest options (and a *no choice* option) with each

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[5] As in the second survey, price has been incorrectly coded, leading to a reversal in the sign. The price coefficients in the results for the third survey should all be negative.

choice set. This may have artificially restricted the scope of the choice set because respondents may have focused on the two options presented, setting aside other rainforest conservation alternatives and other environmental goods (as well as perhaps a wider range of substitute goods) that they may have wished to support. Some evidence for this came from the low support registered in the same survey for international rainforest conservation when the alternative was an environmental friendly consumer good, as opposed to the high support for rainforest conservation registered in the CM sets.

NL models provide a means of addressing some of these scope issues (Horowitz 1993). This has been demonstrated in the second and third survey where the choice sets have been effectively widened to include a greater number of choices, and a wider range of Australian rainforest conservation options. This process could be continued by introducing other landscapes to be conserved (such as wetlands, rangelands and marine areas), or other environmental issues that could be supported (such as a reduction of pollution). Embedding the good to be valued within a wider set of alternatives helps to capture the diversity of choices that people face, and can allow more accurate choice pathways to be used (Horowitz 1993).

However, an iterative approach is necessary to build complex nesting models because of the exponential relationship between the number of possible nesting levels and the number of pathway choices. This means that it is most efficient to examine particular stages of a nesting structure in separate experiments. In the experiments reported above, the successful modelling of a nested relationship between the seven attributes used to describe international rainforest conservation provides a base to explore more complex nesting structures.

The application of the nesting model reported in Appendix 12 can be demonstrated by generating a WTP amount for a change in the location of a rainforest conservation area. This marginal value can be calculated by taking the difference between the coefficients of two locations and dividing by the price coefficient. For example, the marginal value of moving from a New South Wales location to a Far North Queensland location is[4]

-(.400 - -1.586) / -.187 = $6.41

The marginal value of moving from a Vanuatu location to a Far North Queensland location is given by

-(.400 - -2.672) / -.187 = $16.43

In this way, CM can be used to build up profiles of values of environmental changes, and thus aid decision makers in choices.

5.0 Conclusions.

There are four main conclusions that can be drawn from these results and analysis. The first is that nested logit models may be important ways of modelling choices that people make for environmental goods. This is because of reasons dealing with the complexity of issues and information, the possible use of default or quick decision rules by people, the possible reliance on 'soft' institutional rules (such as moral and ethical guidelines) to make choices, and the need to model the various nonparticipation options that people face.

The second conclusion is that the application of NL models may improve the explanatory power of CM outcomes. This has been demonstrated in the rainforest conservation studies with the iterative approach to model building and subsequent increase in 'goodness of fit' statistics.

The third conclusion is that the use of nested logit in modelling environmental choices may help to reduce problems in model application as represented by potential IIA violations. Again, the rainforest

[4] The surveys were conducted in Brisbane, which possibly explains why the Queensland locations rate more highly than the New South Wales one.

conservation studies demonstrate how selection of more accurate nesting models also improve compliance with the underlying logit model assumptions

The fourth conclusion is that the construction of nesting models provides a pathway for extending the range of goods and choices that can be presented to survey respondents. This widening of the choice set enables the researcher to address problems of scope, and ensure that the item of interest is embedded within wide array of alternatives and substitutes. The development of nested decision options promises to make CM a very powerful analytical tool for evaluation of complex goods.

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Appendix 1. Sample Choice Set for First Survey

Q 8 I would now like you to make some choices between proposals to protect a number of different areas of rainforest. A number of different rainforest sites around the world have been selected that will be affected by development within the next two years unless protection measures are enacted. In order to find out where people think we should start, a series of options have been offered which are variations of the actual sites.

Please tell me which option you prefer, or if you think that neither option is worthwhile. When making your choices, please keep in mind what you would realistically do within your budget, and treat each pair as an independent event. By asking people to make choices between these scenarios, it can be worked out what type of rainforests people think are more important, and where we should start with protection measures.

SCENARIO CHOICE 1

Option 1 ***2,500 hectares in Thailand***	***Option 2*** ***2,500 hectares in Africa***
• Extremely rare	• Somewhat rare
• Visits possible but moderate access and few facilities	• Easy to visit with full facilities
• No local people	• Protection of rain forest means local people will be worse off
• Special landscapes as well as plants and animals	• No special features
$50 donation required	$10 donation required

Please indicate preference:

(Tick one)

[1] *Option 1*

[2] *Option 2*

[3] ***I would not support either option***

Appendix 2. MNL model results for first survey

° Discrete choice (multinomial logit) model °
° Iterations completed 5 °
° Log likelihood function -1558 765 °
° Log-L for Choice model -1558 7648 °
° R2 1-LogL/LogL* Log-L fncn R-sqrd RsqAdj °
° No coefficients -1845 6686 0 15545 0 10650 °
° Constants only -1689 6244 0 07745 0 02408 °
° Response data are given as frequencies °
° Number of obs 64 skipped 0 bad obs °

Variable	Coefficient	Standard Error	z b/s e	P[Z'oz]	Mean of X
B PLACE	-0 11219	0 16163E-01	-6 941	0 00000	
B AREA	0 18263	0 32799E-01	5 568	0 00000	
B RARE	0 27990	0 33221E-01	8 425	0 00000	
B VISIT	0 53065E-01	0 31190E-01	1 701	0 08897	
B LOCALS	0 26964	0 34151E-01	7 895	0 00000	
B SPEC	0 13268	0 28908E-01	4 590	0 00000	
B PRICE	0 04970E-01	0 28810E-01	2 206	0 00098	

Appendix 3 Alternative specific model for first survey

Variable	Coefficient	Std error	T
Intercept	-.149849e+01.	.234485e+00	-6.3906
Locations			
Vanuatu	-.161982e+00	.980987e-01	-1.6512
Far North Qld	738807e+00	.104018e+00	7.1027
Qld/NSW Border	.558046e+00	.104985e+00	5.3155
Papua New Guinea	-.165136e+00	.106839e+00	-1.5457
South America	.118455e+00	.108047e+00	1.0963
Africa	-.162219e+00	.102575e+00	-1.5815
Thailand	-.599584e+00	.117226e+00	-5.1148
Indonesia	-.326407e+00	.105970e+00	-3.6213
Area			
Logarea	.147962e+00	.238158e-01	6 2128
Rarity			
Not rare at all	-.557608	.0712662	-7.8243
Somewhat rare	-.127279	.0653375	-1.9480
Fairly rare	.105086	.0684166	1.5360
Extremely rare	.535415	.0683401	8 2363
Visits			
No visits allowed	-.202140	.0708846	-2 8517
Visits allowed	-.00113105	.0651942	-.0173
Visits possible	.192025	.0702895	2 7319
Easy to visit	.011240	.0687894	.1371
Locals			
Locals worse off	-.652196	.0771546	-8 4531
No locals affected	-.0216819	.0642467	-.3375
Locals can stay	.249736	.0607821	4 1087
Locals better off	424131	.0673945	4 6819
Special features			
No special features	-.38462	.0685934	-5.6073
Special landscapes	-.0136031	.0668037	-.2036
Special plants and animals	.156569	.0676558	2 3142
Special landscapes and plants and animals	.241655	.0676846	3.4967
Price			
Lprice	-.192839	.0436730	-4.4155

Statistics

L(ZERO):	-607.49		
L(BETA):	-264.15		
-2(L(0)-L(B)):	686.68	D F.:	22
RHOSQ	.56518		

Appendix 4. **Sample Choice Set for second survey**

SCENARIO CHOICE 1

Option 1 - Vanuatu

- 100 hectares
- Fairly rare
- Easy to visit with full facilities
- No local people
- Special landscapes

$50 DONATION REQUIRED

Option 2 - Far North Queensland

- 10,000 hectares
- Extremely rare
- Visits possible but moderate access and few facilities
- Protection of rainforest means local people will be better off
- Special landscapes

$10 DONATION REQUIRED

Option 3 - Papua New Guinea

- 10,000 hectares
- Not rare at all
- No visits allowed
- No local people
- Special landscapes

$50 DONATION REQUIRED

Option 4 - South America

- 10,000 hectares
- Extremely rare
- Easy to visit with full facilities
- No local people
- Special landscapes

$5 DONATION REQUIRED

Option 5 - Thailand

- 100 hectares
- Extremely rare
- No visits allowed
- Protection of rainforest means local people will be better off
- Special landscapes as well as plants and animals

$5 DONATION REQUIRED

Option 6 - Indonesia

- 10,000 hectares
- Not rare at all
- No visits allowed
- No local people
- Special landscapes

$50 DONATION REQUIRED

Please indicate preference:
(Tick one)

1	*Option 1*	2	*Option 2*
3	*Option 3*	4	*Option 4*
5	*Option 5*	6	*Option 6*
	I would not support any option		

Appendix 5. 2nd Survey, MNL model

° Discrete choice (multinomial logit) model °
° Iterations completed 5 °
° Log likelihood function -1378 472 °
° Log-L for Choice model -1378 4718 °
° R2 1-LogL/LogL* Log-L fncn R-sqrd RsqAdj °
° No coefficients -1751 3191 0 21290 0 19297 °
° Constants only -1491 4203 0 07573 0 05233 °
° Response data are given as frequencies °
° Number of obs 81 skipped 0 bad obs °

Variable	Coefficient	Standard Error	z b/s e	P[¦Z¦oz]	Mean of X
B VANUAT	-2 3935	0 22318	-10 724	0 00000	
B FNQ	-0 64387	0 18563	-3 469	0 00052	
B PNG	-2 5329	0 22778	-11 120	0 00000	
B SA	-2 3310	0 22388	-10 412	0 00000	
B THAI	-2 6164	0 23106	-11 324	0 00000	
B INDO	-2 6088	0 23545	-11 335	0 00000	
B AREA	0 26879	0 51891E-01	5 180	0 00000	
B RARE	0 64576	0 58386E-01	11 060	0 00000	
B VISIT	0 11476	0 54473E-01	2 107	0 03514	
B LOCALS	0 51255	0 55849E-01	9 177	0 00000	
B SPEC	0 94474E-01	0 53332E-01	1 771	0 07649	
B PRICE	0 17964	0 53995E-01	3 327	0 00088	

Appendix 6. 2nd Survey, Three Way Nest between FNQ, overseas and No Choice.

° Iterations completed 27 °
° Log likelihood function -1378 460 °
° Restricted log likelihood -1592 290 °
° Chi-squared 427 6693 °
° Degrees of freedom 13 °
° Significance level 0 0000000 °
° Ry 1-LogL/LogL* Log-L fncn R-sqrd RsqAdj °
° No coefficients -1592 2903 0 13429 0 11050 °
° Constants only -1491 4203 0 07574 0 05034 °
° At start values -1751 3191 0 21290 0 19127 °
° Response data are given as frequencies °
° Hessian was not PD Using BHHH estimator °
° The model has 2 levels °
° Number of obs 81, skipped 0 bad obs °

Variable	Coefficient	Standard Error	z b/s e	P[¦Z¦oz]	Mean of X
Attributes in the Utility Functions					
B VANUAT	-2 4290	0 33225	-7 311	0 00000	
B FNQ	-0 63937	0 18098	-3 533	0 00041	
B PNG	-2 5693	0 33713	-7 621	0 00000	
B SA	-2 3666	0 34205	-6 919	0 00000	
B THAI	-2 6506	0 33654	-7 876	0 00000	
B INDO	-2 7029	0 34053	-7 937	0 00000	
B AREA	0 26843	0 52337E-01	5 129	0 00000	
B RARE	0 64391	0 58579E-01	10 992	0 00000	
B VISIT	0 11457	0 55079E-01	2 080	0 03751	

Appendix 7. 2nd Survey, MNL model with FNQ dropped

```
° Discrete choice (multinomial logit) model °
    ° Maximum Likelihood Estimates            °
    ° Dependent variable           Choice    °
    ° Number of observations          81     °
    ° Iterations completed             5     °
    ° Log likelihood function    -1384.575   °
    ° Log-L for Choice  model    -1384.5745  °
    ° R2=1-LogL/LogL* Log-L fncn R-sqrd RsqAdj °
    ° No coefficients -1751.3191 0.20941 0.19110 °
    ° Constants only  -1491.4203 0.07164 0.05014 °
    ° Response data are given as frequencies  °
    ° Number of obs     81, skipped  0 bad obs °
```

Variable	Coefficient	Standard Error	z=b/s.e.	P[|Z|>z]	Mean of X
B VANUAT	-1.7587	0.12459	-14.115	0.00000	
B PNG	-1.8960	0.13156	-14.411	0.00000	
B SA	-1.6887	0.12164	-13.883	0.00000	
B THAI	-1.9770	0.13602	-14.535	0.00000	
B INDO	-2.0185	0.13801	-14.625	0.00000	
B AREA	0.20953	0.48645E-01	4.307	0.00002	
B RARE	0.55657	0.51095E-01	10.893	0.00000	
B VISIT	0.53619E-01	0.50827E-01	1.055	0.29146	
B LOCALS	0.42946	0.49585E-01	8.661	0.00000	
B SPEC	0.42487E-01	0.50535E-01	0.841	0.40049	
B PRICE	0.10945	0.49593E-01	2.207	0.02731	

Appendix 8. Sample Choice Set for third survey

SCENARIO CHOICE 1

Option 1 - Vanuatu
• 10,000 hectares
• Extremely rare
• Easy to visit with full facilities
• Protection of rainforest means local people will be worse off
• Special landscapes
$10 DONATION REQUIRED

Option 2 - Far North Queensland
• 100 hectares
• Not rare at all
• No visits allowed
• No local people
• Special landscapes as well as plants and animals
$10 DONATION REQUIRED

Option 3 - Northern NSW
• 1,000 hectares
• Not rare at all
• Easy to visit with full facilities
• Protection of rainforest means local people will be better off
• Special landscapes
$10 DONATION REQUIRED

Option 4 - South America
• 100 hectares
• Not rare at all
• Easy to visit with full facilities
• Protection of rainforest means local people will be worse off
• No special features
$10 DONATION REQUIRED

Option 5 - South East Queensland
• 100 hectares
• Extremely rare
• No visits allowed
• Protection of rainforest means local people will be better off
• No special features
$50 DONATION REQUIRED

Option 6 - Indonesia
• 1,000 hectares
• Not rare at all
• Visits possible but moderate access and few facilities
• Protection of rainforest means local people will be better off
• Special landscapes
$10 DONATION REQUIRED

Please indicate preference: (Tick one)

☐ 1	*Option 1*	☐ 2	*Option 2*
☐ 3	*Option 3*	☐ 4	*Option 4*
☐ 5	*Option 5*	☐ 6	*Option 6*
☐ -	*I would not support any option*		

Appendix 9. 3rd Survey, MNL model

° Discrete choice (multinomial logit) model °
° Iterations completed 5 °
° Log likelihood function -1378 472 °
° Log-L for Choice model -1378 4718 °
° R2 1-LogL/LogL* Log-L fncn R-sqrd RsqAdj °
° No coefficients -1751 3191 0 21290 0 19207 °
° Constants only -1491 4203 0 07573 0 05233 °
° Number of obs 81 skipped 0 bad obs °

Variable	Coefficient	Standard Error	z b/s e	P[¹Z¹oz]	Mean of X
B VANUAT	-2 3935	0 22318	-10 724	0 00000	
B FNQ	-0 64387	0 18563	-3 469	0 00052	
B NSW	-2 5329	0 22778	-11 120	0 00000	
B SA	-2 3310	0 22388	-10 412	0 00000	
B SEQ	-2 6164	0 23100	-11 324	0 00000	
B INDO	-2 6688	0 23545	-11 335	0 00000	
B AREA	0 26879	0 51891E-01	5 180	0 00000	
B RARE	0 64576	0 58386E-01	11 066	0 00000	
B VISIT	0 11476	0 54473E-01	2 107	0 03514	
B LOCALS	0 51255	0 55849E-01	9 177	0 00000	
B SPEC	0 94474E-01	0 53332E-01	1 771	0 07649	
B PRICE	0 17964	0 53995E-01	3 327	0 00088	

Appendix 10. Third Survey, Three Way Nest

° FIML Nested Multinomial Logit Model °
° Iterations completed 37 °
° Log likelihood function -1372 968 °
° Restricted log likelihood -1843 471 °
° Chi-squared 941 0074 °
° Degrees of freedom 14 °
° Significance level 0 0000000 °
° R2 1-LogL/LogL* Log-L fncn R-sqrd RsqAdj °
° No coefficients -1843 4714 0 25523 0 23314 °
° Constants only -1491 4203 0 07942 0 05212 °
° At start values -1751 3191 0 21604 0 19278 °
° Hessian was not PD Using BHHH estimator °
° The model has 2 levels °
° Number of obs 81 skipped 0 bad obs °

Variable	Coefficient	Standard Error	z b/s e	P[¹Z¹oz]	Mean of X
Attributes in the Utility Functions					
B VANUAT	-2 6716	0 23362	-11 435	0 00000	
B FNQ	0 40045	0 64538	0 620	0 53493	
B NSW	-1 5864	0 65329	-2 428	0 01517	
B SA	-2 6233	0 23665	-11 085	0 00000	
B SEQ	-1 6781	0 64798	-2 590	0 00960	
B INDO	-2 9540	0 24660	-11 979	0 00000	
B AREA	0 29771	0 57489E-01	5 179	0 00000	
B RARE	0 69923	0 66854E-01	10 459	0 00000	
B VISIT	0 13178	0 59815E-01	2 203	0 02759	
B LOCALS	0 57240	0 60933E-01	9 394	0 00000	
B SPEC	0 73916E-01	0 55651E-01	1 328	0 18411	
B PRICE	0 18749	0 58890E-01	3 184	0 00145	

Appendix 11. 3rd Survey, MNL model with FNQ dropped

° Discrete choice (multinomial logit) model °
° Iterations completed 5 °
° Log likelihood function -1384 575 °
° Log-L for Choice model -1384 5745 °
° R2 1-LogL/Logl * Log-L fncn R-sqrd RsqAdj °
° No coefficients -1751 3191 0 20941 0 19110 °
° Constants only -1491 4203 0 07164 0 05614 °
° Number of obs 81, skipped 0 bad obs °

Variable	Coefficient	Standard Error	z b/s e	P[Z°oz]	Mean of X
B VANUAT	-1 7587	0 12459	-14 115	0 00000	
B NSW	-1 8960	0 13156	-14 411	0 00000	
B SA	-1 6887	0 12164	-13 883	0 00000	
B SEQ	-1 9776	0 13602	-14 535	0 00000	
B INDO	-2 0185	0 13801	-14 625	0 00000	
B AREA	0 20953	0 48645E-01	4 307	0 00002	
B RARE	0 55667	0 51095E-01	10 893	0 00000	
B VISIT	0 53619E-01	0 50827E-01	1 055	0 29146	
B LOCALS	0 42946	0 49585E-01	8 661	0 00000	
B SPEC	0 42487E-01	0 50535E-01	0 841	0 40049	
B PRICE	0 10945	0 49593E-01	2 207	0 02731	

Appendix 12. 3rd Survey, three way nest with FNQ dropped.

° FIML Nested Multinomial Logit Model °
° Iterations completed 28 °
° Log likelihood function -1373 218 °
° Restricted log likelihood -1843 471 °
° Chi-squared 940 5071 °
° Degrees of freedom 13 °
° Significance level 0 0000000 °
° R2 1-LogL/LogL* Log-L fncn R-sqrd RsqAdj °
° No coefficients -1843 4714 0 25509 0 23462 °
° Constants only -1491 4203 0 07925 0 05395 °
° At start values -1751 3191 0 21590 0 19434 °
° Hessian was not PD Using BHHH estimator °
° The model has 2 levels °
° Number of obs 81, skipped 0 bad obs °

Variable	Coefficient	Standard Error	z b/s e	P[Z°oz]	Mean of X
Attributes in the Utility Functions					
B VANUAT	-2 6996	0 22841	-11 819	0 00000	
B NSW	-1 9720	0 13940	-14 146	0 00000	
B SA	-2 6528	0 23168	-11 450	0 00000	
B SEQ	-2 0629	0 14548	-14 180	0 00000	
B INDO	-2 9829	0 24084	-12 385	0 00000	
B AREA	0 29778	0 56669E-01	5 255	0 00000	
B RARE	0 69761	0 66311E-01	10 520	0 00000	
B VISIT	0 13441	0 58622E-01	2 293	0 02185	
B LOCALS	0 56905	0 60325E-01	9 433	0 00000	