Accounting for latent attitudes in willingness-to-pay studies: the case of coastal water quality improvements in Tobago

Stephane Hess* Nesha Beharry-Borg †

August 15, 2011

Abstract

The study of human behaviour and in particular individual choices is of great interest in the field of environmental economics. Substantial attention has been paid to the way in which preferences vary across individuals, and there is a realisation that such differences are at least in part due to underlying attitudes and convictions. While this has been confirmed in empirical work, the methods typically employed are based on the arguably misguided use of responses to attitudinal questions as direct measures of underlying attitudes. As discussed in other literature, especially in transport research, this potentially leads to measurement error and endogeneity bias, and attitudes should rather be treated as latent variables. In this paper, we illustrate the use of such an Integrated Choice and Latent Variable (ICLV) model in the context of beach visitors' willingness-to-pay for improvements in water quality. We show how a latent attitudinal variable, which we refer to as a pro-intervention attitude, helps explain both the responses from the stated choice exercise as well as answers to various rating questions related to respondent attitudes. The incorporation of the latent variable leads to important gains in model fit and substantially different willingness-to-pay patterns.

Key words: Integrated Choice and Latent Variable (ICLV) model; discrete choice; latent attitude; coastal water; beach recreation; taste heterogeneity

1 Introduction

Mathematical structures belonging to the family of discrete choice models[1] are widely used in the study of human behaviour, including in environmental economics. These models are estimated on data containing information on real world choices or data from hypothetical choice scenarios (stated choice). They explain individual choices on the basis of the concept

*Institute for Transport Studies, University of Leeds, s.hess@its.leeds.ac.uk

†Sustainable Resources Institute, University of Leeds, N.C.Beharry-Borg@leeds.ac.uk

[1]For a comprehensive overview, see Train (2009).

of utility maximisation; decision makers evaluate the various alternatives that are available to them and choose the one that provides them with the greatest utility (or smallest disutility). The utility of an alternative is a function of attributes of the alternative and characteristics of the decision maker. This includes both observable variables, such as socio-demographic characteristics, and unobservable components that need to be estimated by the analyst. The main emphasis is on the sensitivities of the respondent to changes in the attributes, commonly referred to as tastes or marginal utilities. A large portion of the research effort in choice modelling has focussed on explaining differences across respondents in these taste parameters, either in a deterministic manner by linking them to socio-demographic characteristics, or through an appropriate random specification of any *unobserved* heterogeneity, such as in a Mixed Multinomial Logit (MMNL) model.

In this paper, we discuss the role that underlying (and unobserved) attitudes may have in driving such heterogeneity, in the context of a study looking at beach visitors' willingness-to-pay for improved coastal water quality in Tobago. This is in line with a growing realisation, across diverse fields, that differences in preferences across respondents are at least in part driven by underlying attitudes and personal convictions. Analysts routinely capture information relating to such attitudes through direct questions included in surveys, typically of the form asking respondents to what extent they agree with specific statements. Such information is potentially a powerful asset in characterising heterogeneity across respondents. However, the way in which this can best be accommodated in our existing modelling frameworks is not straightforward, a point largely ignored in a number of fields. The aim of the present paper is to highlight this issue in the context of the environmental economics field.

The main misunderstanding in large parts of the literature is that responses to attitudinal questions are seen as direct measures of attitudes. This would lead to the temptation to directly incorporate these responses as explanatory variables in models (cf. Morey, 1981; Milon and Scrogin, 2006; Green, 1984; Harris and Keane, 1998). However, a growing literature, especially in transport research (Ben-Akiva et al., 1999; Ashok et al., 2002; Ben-Akiva et al., 2002; Bolduc et al., 2005), argues that this leads to two distinct problems. Firstly, these answers, often referred to as indicators, are themselves clearly only a function of underlying attitudes, rather than a direct measure of attitudes, and their use as explanatory variables is thus possibly affected by measurement error. More importantly however, there is an argument that the responses to attitudinal questions are likely to be correlated with other unobserved factors that enter the error term of the models. This thus leads to potential problems with endogeneity bias.

A second approach that has been used to incorporate attitudes is through the use of a latent class framework[2]. This has been done in a number of ways. Firstly, the approach taken by Boxall and Adamowicz (2002) and Beck et al. (2010) assumes that the probability than an individual belongs to a certain class is a function of his or her attitudinal questions. Alternatively, one may also make use of only the attitudinal data without the choice data to estimate the latent classes (Morey et al., 2006, 2008). Examples of this approach outside of the environmental economics field include Yamaguchi (2000),

[2]For details on latent class models, see for example Greene and Hensher (2003).

Eid et al. (2003), Thacher et al. (2005), and Menezes and Bartholomew (1996). Related to this is a third approach where both the choice data and attitudinal data have been used to estimate the probability that an individual belongs to a certain class (Breffle et al., 2005). Another approach taken to integrate attitudinal data is through cluster analysis, which deterministically places each individual into a specific class, as opposed to the latent class model that only probabilistically assigns an individual to a class (Morey et al., 2008). Examples of environmental applications that use cluster analysis include Aldrich et al. (2007), Baker and Burnham (2001), and Pennings and Leuthold (2000).

All of the approaches discussed above rely to various degrees on responses to attitudinal indicators as variables in the models. However, as highlighted above, responses to such attitudinal questions are simply functions of underlying attitudes rather than direct measures of attitudes. Their inappropriate use as explanators thus places analysts at risk of producing results affected by measurement error and endogeneity bias. Importantly, such approaches are also inapplicable when there is an interest in using the models in forecasting, where no information on the responses to attitudinal questions would be available for the forecast period.

The aim of the present paper is to highlight recent progress in choice modelling to move away from such inappropriate model specifications and to discuss the use of these new methods in the context of environmental economics research. This emerging body of work, grounded in the developments of Ben-Akiva et al. (1999), Ashok et al. (2002), Ben-Akiva et al. (2002), and Bolduc et al. (2005), recognises that responses to attitudinal questions are not a direct measure of attitudes, but that they, along with the actual choices, are driven by underlying attitudes that are not observed by the analyst. The attitudes are thus treated as latent variables that are used as explanatory variables in modelling the observed (or stated) choices along with the response to attitudinal question. The key distinction with other work is thus that the responses to attitudinal questions are themselves a dependent variable in the overall model, rather than an explanatory variable as in earlier efforts. For this reason, the model is not directly comparable to approaches that incorrectly treat such indicators as explanatory variables. Importantly, as the indicators are no loner explanatory variables, the resulting model can also be used in forecasting. Given that it jointly models the response to choices and attitudinal questions through latent variables, the resulting structure is referred to as the Integrated Choice and Latent Variable (ICLV) model, and examples of applications include Johansson et al. (2005), Fosgerau and Bjørner (2006), Johansson et al. (2006), Temme et al. (2008), Alvarez-Daziano and Bolduc (2009), Abou-Zeid et al. (2010), Daly et al. (2011b), and Yáñez et al. (2010).

With the exception of the work of Alvarez-Daziano and Bolduc (2009), the ICLV model seems to have been largely ignored in the field of environmental economics, where arguably more bias-prone methods continue to be used. In the present paper, we provide an overview of the technique, and present an application in the context of studying respondents' willingness-to-pay (WTP) for visiting beaches with improved water quality in Tobago. In particular, we hypothesise that in addition to the marginal sensitivities, there is an underlying attitude towards payment for water quality improvements that helps characterise respondents' behaviour in this survey. Our empirical results confirm that both the choices and the responses to various attitudinal questions are indeed influenced by a latent variable, which we define as a pro-intervention attitude. Our results show how this leads to greater insights into behaviour. In particular, we show how respondents who are more *pro-intervention* have higher WTP measures. We also show how male respondents and respondents with postgraduate education are more pro-intervention, while the opposite is the case for national respondents.

The remainder of this paper is organised as follows. Section 2 gives an overview of the ICLV methodology. This is followed in Section 3 by the empirical application carried out for this paper. Finally, Section 4 presents a summary and the conclusions of the research.

2 Modelling methodology

Given the recognition that an analyst can only capture part of the utility of an alternative, the utility U_{int} of alternative i for respondent n in choice situation t is made up of a deterministic component V_{int} and a remaining random component ε_{int}. In the presence of a random component, we move to a probabilistic framework, in which the probability of choosing an alternative increases with its utility, and where the probability of choosing alternative i (out of I alternatives) is given by:

$$P_{int} = P\left(U_{int} \geq U_{jnt},\ j = 1, \ldots, I\right). \tag{1}$$

The specific form of this probability function depends on the assumptions made for the distribution of the error term.

The modelled component V_{int} is a function of the estimated vector of sensitivities β and the attributes of the alternative i, such that:

$$V_{int} = f\left(\beta, x_{int}\right), \tag{2}$$

where typically, a linear in parameters specification is used, i.e. $f\left(\beta, x_{int}\right) = \beta' x_{int}$.

The estimation of a model of this type requires data on actual or stated choices as well as all explanatory variables used in the specification, whether they relate to the alternatives or to the respondent. The aim of estimation is to find values of β that best explain the choices in the data. In particular, we need to maximise the likelihood function which is given by:

$$L\left(\beta\right) = \prod_{n=1}^{N} \prod_{t=1}^{T} P_{j^*_{nt}}\left(\beta, x_{nt}\right) \tag{3}$$

where j^*_{nt} refers to the alternative chosen by respondent n in choice task t, and where the modelled probability is conditional on the estimated parameters β, and the vector x_{nt} which describes all alternatives as faced in choice task t. In practice, it is more convenient to work with the log-likelihood (LL) function, given by taking the logarithm of Equation 3.

It is now quite common practice to as part of the survey work also collect responses to a number of attitudinal questions, typically in the form of asking respondents to what extent they agree with certain statements. Let us assume that we capture K such indicators, given by I_{kn}, $k = 1, \ldots, K$. As highlighted in the introduction, a number of authors have stressed the importance of recognising that these responses are not direct measures of the actual attitudes, but rather functions of the attitudes, and that in addition, the answers by respondents given to these questions may be highly correlated with other unobserved factors. The simple deterministic inclusion of these indicators in our model would thus put us at risk of measurement error and endogeneity bias.

Nevertheless, we wish to make use of attitudinal information to better explain the differences in sensitivities across respondents. Rather than relying on such a deterministic approach, we recognise that the actual attitudes are unobserved, and that the responses to attitudinal questions as well as the actual choices are potentially influenced by these attitudes.

A single model may potentially make use of multiple such latent attitudes, but for the sake of simplicity of notation (and consistent with the later application), we rely on just a single such variable. Specifically, we define the latent attitude for respondent n as:

$$\alpha_n = l\left(\gamma, z_n\right) + \eta_n, \tag{4}$$

where $l\left(\gamma, z_n\right)$ represents the deterministic part of α_n, with z_n being a vector of socio-demographic variables of respondent n, and γ being a vector of estimated parameters, and where a decision on the specification of $l\left(\right)$ needs to be taken (e.g. linear). The term η_n is a random disturbance, which we assume follows a Normal distribution across respondents, with a zero mean and a standard deviation of σ_α, say $g\left(\eta\right)$.

This latent variable α_n is then interacted with parameters in our choice model. As an example, we might rewrite Equation 2 as:

$$V_{int} = f\left(\beta, \tau, x_{int}, \alpha_n\right), \tag{5}$$

where τ is a vector of parameters that interact α_n with β and x_{int}. Our model is then estimated by integration over the random components in α, i.e. rewriting Equation 3 as:

$$L\left(\beta, \tau, \sigma_\alpha\right) = \prod_{n=1}^{N} \int_\eta \prod_{t=1}^{T} P_{j^*_{nt}}\left(\beta, \tau, x_{nt}, \alpha_n\right) g\left(\eta\right) \mathrm{d}\eta \tag{6}$$

However, this specific treatment of α_n is no different from a standard random coefficients approach such as in a Mixed Logit model, and makes no use of the additional information gathered with the help of the attitudinal questions. Once again, rather than just using these indicators I_{kn}, $k = 1, \ldots, K$ as explanatory variables, we use them as dependent variables in a second component of the model, and make them dependent on the latent variable α_n. This use of α_n in the choice model as well as measurement model components means that the estimation of α_n is informed both by the data on choices and the data on responses to attitudinal questions. This approach thus integrates choice models with latent variable models resulting in an improvement in the understanding of preferences as well as explanatory power. A main benefit of using a latent variable approach is to avoid the risk of bias of the type that may arise when using indicators of attitudes (or other subjective measures) as explanatory variables in the utility function. What is more, problems with measurement errors can be overcome by looking at a set of factors that have their origin in a latent variable, rather than a simple one-to-one correspondence.

The measurement model component is given by a set of equations that use the values for the attitudinal indicators as dependent variables. In particular, we have that the value for the k^{th} indicator for respondent n is modelled as:

$$I_{kn} = \delta_{I_k} + \zeta_{I_k} \cdot \alpha_n + \upsilon_{kn}, \tag{7}$$

where δ_{I_k} is a constant for the k^{th} indicator, ζ_{I_k} is the estimated effect of the latent variable α_n on this indicator, and υ_{kn} is a normally distributed disturbance, with a mean of zero and a standard deviation of σ_{I_k}. To avoid the estimation of unnecessary parameters, the mean of each indicator can be subtracted from the original indicator variables prior to model estimation, thus meaning that all indicators are centred on zero, obviating the need to estimate δ_{I_k} $\forall k$. As mentioned above, the indicators are typically responses to attitudinal questions, with a finite number of possible values (e.g. scale of 1 to 5). The use of a continuous specification despite the discrete nature of the outcomes for the indicator variables is thus a simplifying assumption but is in line with common practice, even in advanced literature, and is thus also maintained in this paper. The potential for using ordered logit structures for the measurement model is discussed by Daly et al. (2011b).

The log-likelihood function for this model is composed of two different components, the probability of the observed sequence of choices, and the probability of the observed responses to the attitudinal questions[3]. In our joint model, we let $L_n(y_n \mid \beta, \tau, \alpha_n)$ give the likelihood of the observed sequence of choices for respondent n (y_n), conditional on the vector of taste coefficients β, the vector of interaction parameters τ, and the latent variable α_n, which itself is a function of γ and its random component η. This likelihood will thus be a product of discrete choice probabilities, with the specific form depending on model assumptions.

Next, let $L(I_n \mid \zeta_I, \sigma_I, \alpha_n)$ give the probability of observing the specific responses given by respondent n to the various attitudinal questions, conditional on the parameter vector ζ_I (grouping together $\zeta_{I_k},\ k = 1, \ldots K$), the vector of standard deviations σ_I (grouping together $\sigma_{I_k},\ k = 1, \ldots K$), and a specific realisation of the latent variable α_n. It can be seen that this probability is given by a product of Normal density functions, i.e.

$$L(I_n \mid \zeta_I, \sigma_I, \alpha_n) = \prod_{k=1}^{K} \phi(I_{kn}), \tag{8}$$

where:

$$\phi(I_{kn}) = \frac{1}{\sigma_{I_k}\sqrt{2\pi}} \cdot e^{-\frac{\left(I_{kn} - \zeta_{I_k} \cdot \alpha_n\right)^2}{2\sigma^2_{I_k}}}. \tag{9}$$

Both $L(y_n \mid \beta, \tau, \alpha_n)$ and $L(I_n \mid \zeta_I, \sigma_I, \alpha_n)$ are conditional on a specific realisation of the latent variable α_n. Given the random component in α_n, we thus need to integrate over

[3]As mentioned earlier, if model estimation makes use of the choice model component on its own (i.e. Equation 6), we are left with a model with purely random heterogeneity.

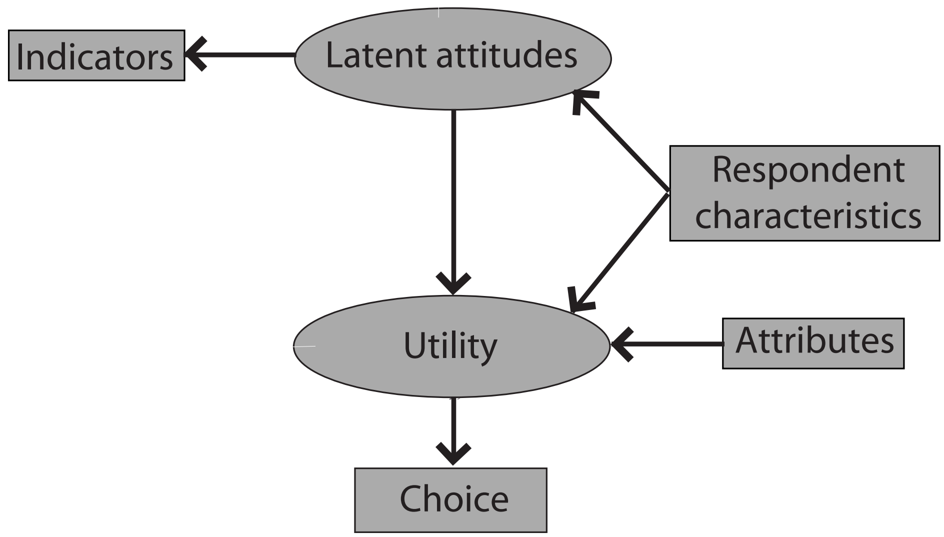

Figure 1: Structure of ICLV model

the distribution of η, i.e. $g(\eta)$, and the combined log-likelihood function is thus given by:

$$LL(\beta, \tau, \zeta_I, \sigma_I, \gamma) = \sum_{n=1}^{N} \ln \int_{\eta} L(y_n \mid \beta, \tau, \alpha_n) \, L(I_n \mid \zeta_I, \sigma_I, \alpha_n) \, g(\eta) \, \mathrm{d}\eta \tag{10}$$

where this is integrated over the distribution of η, the random component in the latent variable, and where $n = 1, ..., N$ is the index over respondents. Both components of this log-likelihood function are clearly also dependent on the specification of the latent variable, i.e. Equation 4. For identification reasons, the standard deviation of the random component of the latent variable α needs to be fixed, i.e. we set $\sigma_\alpha = 1$. Estimating the two components simultaneously rather than sequentially leads to efficiency, where sequential estimation only achieves consistency.

An illustration of the proposed model structure is given in Figure 1 where observed components are shown in rectangles and unobserved components are shown in ellipses. As shown in the graph, respondent characteristics (socio-demographics) affect both the latent attitude variable and the utility function. The utility is also a function of measured attributes. The latent variable drives the response to the indicator questions, while it also affects the utility function and thus the probabilities for the various alternatives.

In addition to the parameters for the standard model, the use of this model thus entails the estimation of the vector of interaction parameters τ, the parameters of the measurement equations ζ_{I_k} $\forall k$, the socio-demographic interaction terms γ used in the structural equation for the latent variable, and the standard deviations of the normally distributed υ_{kn} terms (having normalised the standard deviation of η_n, i.e. σ_α, to 1). If we have random heterogeneity in the β coefficients that is not linked to α through τ, additional layers of integration need to be added, and we would have:

$$LL(\Omega, \tau, \zeta_I, \sigma_I, \gamma) = \sum_{n=1}^{N} \ln \int_{\beta} \int_{\eta} L(y_n \mid \beta, \tau, \alpha_n) \, L(I_n \mid \zeta_I, \sigma_I, \alpha_n) \, g(\eta) \, m(\beta \mid \Omega) \, \mathrm{d}\eta \, \mathrm{d}\beta, \tag{11}$$

where $\beta \sim m(\beta \mid \Omega)$, with Ω being a vector of parameters to be identified.

3 Empirical application

3.1 Data

The data used in this analysis were drawn from a sample of beach visitors in Tobago. The objective of the survey was to determine the non-market values for improvements to the coastal water quality. Respondents were asked to imagine a day out at the beach and choose their most preferred beach alternative based on specific improvements in water quality attributes. The data used in this paper were collected with a view to eliciting sensitivities for attributes specifically related to the activity of snorkelling, where respondents were selected based on whether they had ever participated in snorkelling. Full details of the survey can be found in Beharry (2008), with previous applications using this dataset given by Beharry-Borg et al. (2009) and Beharry-Borg and Scarpa (2010).

The survey was administered in the departure lounge of the national airport in 2005 through face to face interviews. The airport was chosen as it was deemed to be the best location to provide a convenient sample of snorkellers who were foreign visitors, local visitors (Trinidadians) and residents (Tobagonians). We acknowledge that one of the limitations of our dataset was that it was administered at the airport when respondents were about to leave the country thus potentially leading to responses that were not incentive compatible. Interviewing respondents at this stage of their trip was however deemed necessary because it was important that they were asked about their beach experience after they had participated in recreation at the beaches. An additional point worth noting is that the majority of tourists had a long waiting period in the airport with only limited facilities in the departure lounge. From this perspective, the survey actually provided a point of focus which allowed visitors to be more attentive and spend time on thinking about their responses. Any survey that was improperly completed or that the interviewer thought was unreliable was not included in the final sample - this was the case for seven respondents.

The questionnaire comprised four subsections. The first section contained questions about the frequency of use of beaches in Tobago, the frequency of activities enjoyed at the beach, attitudes towards coastal water quality payment options, and preferences for beach characteristics. The second section contained the valuation scenario. Each respondent was asked to choose between two beach alternatives with a fee for usage, and a third alternative, which was to visit neither of the proposed beaches and involved no monetary contribution. This gave respondents the option to choose neither of the alternatives if the attribute levels were not sufficiently desirable to them. The two chargeable beaches differed on the basis of nine coastal water related attributes, while the fee attribute was

A DASH (-) represents that there is no program to control the levels of this factor at the beach

	BEACH A	BEACH B	NEITHER BEACH
Boats (near coastline)	-	2 Boats or less	I Choose to Visit Neither Beach
Marine Protected Area (absence or presence)	-	YES, TO VISIT ONLY, NO FISHING	
Coastline Development (hotels and homes)	Less than 25% developed	-	
Average Bathing Water Quality (chance of an ear infection)	Reduced chance	Increased chance	
Water Clarity (down to seabed)	Up to 10 meters	-	
Plastics (per 30meters of beach)	Less than 5 pieces	Up to 15 pieces	
Number of Snorkellers (per group)	-	Up to 15 per group	
Level of Coral Cover	Up to 45% coral cover	15% coral cover	
Abundance of Fish	Up to 60 fishes	-	
Contribution Fee (TT$)	TT$10.00	TT$25.00	TT$0
I would choose to visit	☐	☐	☐

TT$10.00 = US$1.40 = £0.90 **TT$25.00 = US$4.00 = £2.27**

Figure 2: Sample choice set for snorkeller experiments

described as a beach contribution fee. This monetary contribution would be paid to a non governmental organisation and be used to help with specific programmes designed to improve the level of coastal water quality on the island. Three levels were used for each of the nine policy intervention attributes according to the intensity of proposed improvement. After an initial detailed description, the three levels were referred to as 'high' level of policy action, 'low' level of policy action, and 'no' policy action (i.e. *status quo*). Figure 2 shows an example of a choice set while Table 1 contains a list of attributes and definitions.

Responses from 198 individuals were analysed in the present study, where, with each respondent facing 9 choice scenarios, a sample of $1,782$ observations was obtained. Eleven percent of the sample were local visitors and residents while 89 percent were international visitors. The average household income was TT$339,431[4], 53% of the sample were males, 46% had a university degree, and 65% were aged between 18 and 40.

In order to determine attitudes towards coastal water quality protection and use by visitors and locals, the respondents were asked a number of attitudinal questions. For each question, the responses were collected on a five point Likert scale ranging from *strongly agree* (1) to *strongly disagree* (5). The questions were introduced by a statement that read "As part of this research we are interested in what you think about certain aspects of the coastal zone, in particular the beaches and its environs". Six individual statements were used as follows:

I_1**:** The quality of the water around the coast is affected by activities on the land

[4]The equivalent in UK currency would be £33,238.14.

I_2: Tourism is important for the economy of Tobago and to maintain a higher coastal water quality non national visitors should make a monetary contribution

I_3: To maintain a higher coastal water quality nationals and residents should make a monetary contribution

I_4: To maintain a higher coastal water quality nationals, residents and non nationals should make a monetary contribution

I_5: The government is fully responsible for the maintenance of coastal water quality and the state of the beaches in Tobago

I_6: Everyone can benefit from better coastal water quality and we should do our part to keep it clean

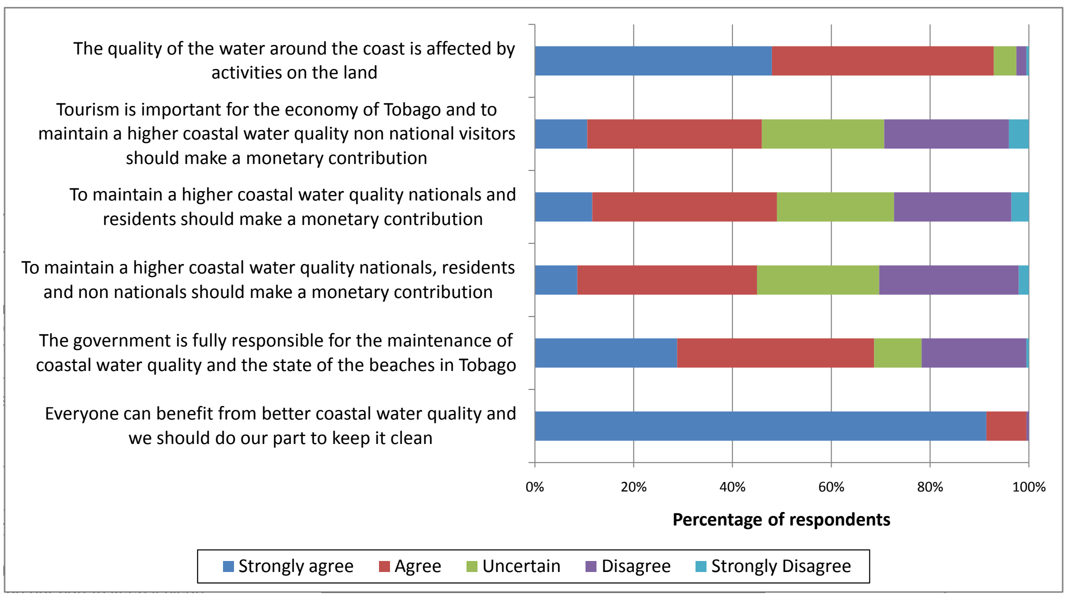

Figure 3: Attitudes towards paying for coastal water quality improvements

As shown in Figure 3, most of the respondents agreed that the quality of coastal water is affected by activities on the land and that everyone would benefit from its improvement. On the other hand, there is significantly greater heterogeneity when looking at respondents' views in terms of who (if anyone) should bear financial responsibility for improving coastal water quality. It is these latter indicators that will be used in the present analysis.

Table 1: Attribute definitions, levels and variable names

Attribute	Definition	Variable Names and Levels	
Number of boats	Number of recreational and fishing boats near the coastline	BTS1_Low_Policy BTS2_High_Policy No policy option (status quo)	Up to seven boats allowed near coastline Up to 2 boats allowed near coastline No policy to limit the number of boats near the coastline
Marine protected area (MPA)	Presence of type of marine protected area	MPA1_Low_Policy MPA2_High_Policy No policy option (status quo)	A marine protected area where you can (tour, swim, snorkel, dive) and fish A marine protected area where you can (tour, swim, snorkel, dive) but no fishing No policy that enforces restrictions on activities in an MPA
Coastline development	Percentage of coastal development on the coastline	DEV1_Low_Policy DEV2_High_Policy No policy option (status quo)	Up to 75% development allowed on the coastline Up to 25% development allowed on the coastline No policy that limits the development activities on the coastline
Average bathing water quality	Risk of contracting an ear infection from swimming in polluted water	WQ1_Low_Policy WQ2_High_Policy No policy option (status quo)	Increased chance of contracting an ear infection from swimming in polluted water Reduced chance of contracting ear infection from swimming in polluted water No policy that indicates the quality of the bathing water
Clarity	Level of vertical visibility	CLAR11_High_Policy CLAR2_Low_Policy No policy option (status quo)	Vertical Visibility of up to 10 metres Vertical Visibility of up to 5 metres No policy that ensures clarity of coastal water
Plastic debris	Number of plastics per 30 metres of coastline	PLAS11_Low_Policy PLAS2_High_Policy No policy option (status quo)	Up to 15 pieces per 30 metres of coastline allowed Less than 5 pieces allowed per 30 metres of coastline allowed No policy that ensures that plastic litter is picked up
Number of snorkellers	Number of snorkellers allowed per group	SNO1_Low_Policy SNO2_High_Policy No policy option (status quo)	Up to 15 snorkellers allowed per group or per instructor Up to 5 snorkellers allowed per group or per instructor No policy that limits size of snorkeller groups
Coral Cover	Percentage of coral cover available for viewing while snorkelling	CORAL1_High_Policy CORAL2_Low_Policy No policy option (status quo)	Can view up to 45% coral cover while snorkelling Can view up to 15% coral cover while snorkelling No policy to ensure that coral cover is at a certain level
Abundance of Fish	Number of fish species available for viewing while snorkelling	FISH1_High_Policy FISH2_Low_Policy No policy option (status quo)	Can view up to 60 species of fish while snorkelling Can view up to 10 species of fish while snorkelling No policy to ensure that number of fish species is at a certain level
Fee	Contribution fee to beach authority	FEE	TT$10, TT$20, TT$25

3.2 Model and estimation

In our analysis, two different models were estimated; A) a Multinomial Logit model (MNL) as base model; and B) an Integrated Choice and Latent Variable (ICLV) model[5].

The use of the MNL model instead of more flexible structures such as Mixed Multinomial Logit (MMNL) in part reflects our belief that the MNL model is still the point of departure for the majority of choice modelling applications. Our aim in the present paper is to illustrate the way in which taste heterogeneity can be linked to underlying attitudes, rather than focussing solely on gains in explanatory power. A comparison with a standard random parameter logit model (i.e. one in which the taste heterogeneity is not linked to underlying latent attitudes) would have been interesting, but the specification of such a model involves numerous decisions on specification (e.g. which parameters are random, what distributions are used, whether we have correlation between parameters). The decisions made would have a significant impact on the comparisons with the ICLV model, and would have distracted from the key message of the paper, namely how to appropriately make use of data from attitudinal questions in choice model applications in environmental applications. For example, a comparison between the ICLV model used here and a MMNL model with random heterogeneity in all coefficients would not have been appropriate, given that in our ICLV specification, we in effect have a single random term that applies in different degrees for the various coefficients. We would thus have had to allow for a completely new level of heterogeneity within the ICLV model that is not linked to the latent attitude. The use of up to nineteen different random parameters would almost surely also have been beyond the realm of feasibility with the data at hand. The exploration of such structures is left as a direction for future research.

3.2.1 Model A: base model

We let V_{jnt} give the modelled utility for alternative j in choice situation t for respondent n, where the utilities for the first two alternatives are given by:

[5]All models were coded in Ox4.2 (Doornik, 2001). Estimation of ICLV models is also possible in the new version of Biogeme which is freely available at biogeme.epfl.ch

$$
\begin{aligned}
V_{jnt} = {} & \beta_{\text{BTS1\_Low\_Policy}} \cdot \text{BTS1\_Low\_Policy}_{jnt} + \beta_{\text{BTS2\_High\_Policy}} \cdot \text{BTS2\_High\_Policy}_{jnt} \\
& + \beta_{\text{MPA1\_Low\_Policy}} \cdot \text{MPA1\_Low\_Policy}_{jnt} + \beta_{\text{MPA2\_High\_Policy}} \cdot \text{MPA2\_High\_Policy}_{jnt} \\
& + \beta_{\text{DEV1\_Low\_Policy}} \cdot \text{DEV1\_Low\_Policy}_{jnt} + \beta_{\text{DEV2\_High\_Policy}} \cdot \text{DEV2\_High\_Policy}_{jnt} \\
& + \beta_{\text{WQ1\_Low\_Policy}} \cdot \text{WQ1\_Low\_Policy}_{jnt} + \beta_{\text{WQ2\_High\_Policy}} \cdot \text{WQ2\_High\_Policy}_{jnt} \\
& + \beta_{\text{CLAR1\_High\_Policy}} \cdot \text{CLAR1\_High\_Policy}_{jnt} + \beta_{\text{CLAR2\_Low\_Policy}} \cdot \text{CLAR2\_Low\_Policy}_{jnt} \\
& + \beta_{\text{PLAS1\_Low\_Policy}} \cdot \text{PLAS1\_Low\_Policy}_{jnt} + \beta_{\text{PLAS2\_High\_Policy}} \cdot \text{PLAS2\_High\_Policy}_{jnt} \\
& + \beta_{\text{SNO1\_Low\_Policy}} \cdot \text{SNO1\_Low\_Policy}_{jnt} + \beta_{\text{SNO2\_High\_Policy}} \cdot \text{SNO2\_High\_Policy}_{jnt} \\
& + \beta_{\text{CORAL1\_High\_Policy}} \cdot \text{CORAL1\_High\_Policy}_{jnt} + \beta_{\text{CORAL2\_Low\_Policy}} \cdot \text{CORAL2\_Low\_Policy}_{jnt} \\
& + \beta_{\text{FISH1\_High\_Policy}} \cdot \text{FISH1\_High\_Policy}_{jnt} + \beta_{\text{FISH2\_Low\_Policy}} \cdot \text{FISH2\_Low\_Policy}_{jnt} \\
& + \beta_{\text{fee}} \cdot \text{Fee}_{jnt} \qquad (12)
\end{aligned}
$$

where $j = 1, 2$ and where e.g. $\text{BTS1\_Low\_Policy}_{jnt}$ represents the value (either 0 or 1) of the BTS1_Low_Policy attribute for alternative j in choice situation t for respondent n. The estimates for the associated parameter show the relative valuation with respect to the base scenario, where no policy is in operation. The modelled utility for the third alternative is set to 0 in this specification. Attempts to include a specific status quo constant for this third alternative led to unsatisfactory results in terms of WTP indicators, a point discussed further in the Appendix, which also raises questions about the wisdom of the widespread use of such constants in environmental valuation work.

3.2.2 Model B: Latent attitude model (ICLV)

In our ICLV model, we hypothesise that there is an underlying latent attitude towards a chargeable policy intervention (CPI) which varies across respondents and which at the same time explains the responses to the attitudinal questions listed in Section 3.1. In particular, we refer to this latent variable as α_{CPI}, where, for respondent n, we have:

$$\alpha_{\text{CPI},n} = l(\gamma, z_n) + \eta_n, \qquad (13)$$

where z_n is a vector of socio-demographic variables of respondent n, γ is a vector of estimated parameters, and where η_n follows a Normal distribution across respondents, with a zero mean, and a variance set to 1 for identification reasons.

The utility function for alternatives 1 and 2 as given in Equation 12 is rewritten as follows for this model:

$$
\begin{aligned}
V_{jnt} = & (\beta_{\text{BTS1\_Low\_Policy}} + \tau_{\text{BTS}} \cdot \alpha_{\text{CPI},n}) \cdot \text{BTS1\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{BTS2\_High\_Policy}} + \tau_{\text{BTS}} \cdot \alpha_{\text{CPI},n}) \cdot \text{BTS2\_High\_Policy}_{jnt} \\
& + (\beta_{\text{MPA1\_Low\_Policy}} + \tau_{\text{MPA}} \cdot \alpha_{\text{CPI},n}) \cdot \text{MPA1\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{MPA2\_High\_Policy}} + \tau_{\text{MPA}} \cdot \alpha_{\text{CPI},n}) \cdot \text{MPA2\_High\_Policy}_{jnt} \\
& + (\beta_{\text{DEV1\_Low\_Policy}} + \tau_{\text{DEV}} \cdot \alpha_{\text{CPI},n}) \cdot \text{DEV1\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{DEV2\_High\_Policy}} + \tau_{\text{DEV}} \cdot \alpha_{\text{CPI},n}) \cdot \text{DEV2\_High\_Policy}_{jnt} \\
& + (\beta_{\text{WQ1\_Low\_Policy}} + \tau_{\text{WQ}} \cdot \alpha_{\text{CPI},n}) \cdot \text{WQ1\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{WQ2\_High\_Policy}} + \tau_{\text{WQ}} \cdot \alpha_{\text{CPI},n}) \cdot \text{WQ2\_High\_Policy}_{jnt} \\
& + (\beta_{\text{CLAR1\_High\_Policy}} + \tau_{\text{CLAR}} \cdot \alpha_{\text{CPI},n}) \cdot \text{CLAR1\_High\_Policy}_{jnt} \\
& + (\beta_{\text{CLAR2\_Low\_Policy}} + \tau_{\text{CLAR}} \cdot \alpha_{\text{CPI},n}) \cdot \text{CLAR2\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{PLAS1\_Low\_Policy}} + \tau_{\text{PLAS}} \cdot \alpha_{\text{CPI},n}) \cdot \text{PLAS1\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{PLAS2\_High\_Policy}} + \tau_{\text{PLAS}} \cdot \alpha_{\text{CPI},n}) \cdot \text{PLAS2\_High\_Policy}_{jnt} \\
& + (\beta_{\text{SNO1\_Low\_Policy}} + \tau_{\text{SNO}} \cdot \alpha_{\text{CPI},n}) \cdot \text{SNO1\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{SNO2\_High\_Policy}} + \tau_{\text{SNO}} \cdot \alpha_{\text{CPI},n}) \cdot \text{SNO2\_High\_Policy}_{jnt} \\
& + (\beta_{\text{CORAL1\_High\_Policy}} + \tau_{\text{CORAL}} \cdot \alpha_{\text{CPI},n}) \cdot \text{CORAL1\_High\_Policy}_{jnt} \\
& + (\beta_{\text{CORAL2\_Low\_Policy}} + \tau_{\text{CORAL}} \cdot \alpha_{\text{CPI},n}) \cdot \text{CORAL2\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{FISH1\_High\_Policy}} + \tau_{\text{FISH}} \cdot \alpha_{\text{CPI},n}) \cdot \text{FISH1\_High\_Policy}_{jnt} \\
& + (\beta_{\text{FISH2\_Low\_Policy}} + \tau_{\text{FISH}} \cdot \alpha_{\text{CPI},n}) \cdot \text{FISH2\_Low\_Policy}_{jnt} \\
& + (\beta_{\text{fee}} + \tau_{\text{fee}} \cdot \alpha_{\text{CPI},n}) \cdot \text{Fee}_{jnt} \qquad (14)
\end{aligned}
$$

The latent variable $\alpha_{\text{CPI},n}$ is incorporated in the utility function through interaction with the fee coefficient as well as the coefficients associated with the different levels of policy intervention. The various τ parameters show the shift in the sensitivity towards the interventions as a function of the latent attitude. Initial results showed that it was not necessary to use separate interaction terms for the two different levels of policy intervention for a given attribute, suggesting that any underlying pro-intervention attitude has similar impacts on the desire for the two levels of intervention, i.e. moving away from the no-intervention scenario.

The final component of the model is given by the measurement equations for the attitudinal indicators. In particular, we have that the value for the k^{th} indicator for respondent n is modelled as:

$$I_{kn} = \zeta_{I_k,\text{CPI}} \cdot \alpha_{\text{CPI},n} + \upsilon_{kn} \qquad (15)$$

where all indicators were centred on zero, thus avoiding the estimation of the constants previously shown in Equation 7. Here, $\zeta_{I_k,\text{CPI}}$ is the estimated effect of the latent attitude $\alpha_{\text{CPI},n}$ on this indicator, and υ_{kn} is a normally distributed disturbance, with a mean of zero and a standard deviation of σ_{I_k}.

In addition to the parameters estimated for the standard model, the estimation of this ICLV model thus entails the estimation of the 10 interaction terms (grouped together into the vector τ), $\zeta_{I_k,\text{CPI}}\ \forall k$, the socio-demographic interaction terms γ, and the standard deviation of the normally distributed υ_{kn} terms (having normalised the standard deviation of η_n to 1).

As highlighted in Section 2, the log-likelihood function for this model is composed of two components. Firstly, $L\left(y_n \mid \beta, \tau, \alpha_{\text{CPI},n}\right)$ gives the likelihood of the observed choices of respondent n (y_n), conditional on the vector of taste coefficients β, the vector of interaction parameters τ, and a specific realisation of the latent attitude $\alpha_{\text{CPI},n}$. This likelihood is a product of MNL probabilities, using the utility specifications from Equation 14. Secondly, $L\left(I_n \mid \zeta_{I,\text{CPI}}, \sigma_I, \alpha_{\text{CPI},n}\right)$ gives the probability of observing the specific responses given by respondent n to the various attitudinal questions, conditional on the parameter vector $\zeta_{I,\text{CPI}}$ (grouping together $\zeta_{I_k,\text{CPI}},\ k = 1, \ldots K$), the vector of standard deviations σ_I (grouping together $\sigma_{I_k},\ k = 1, \ldots K$), and a specific realisation of the latent attitude $\alpha_{\text{CPI},n}$. This is given by a product of normal density functions as shown in Equation 8.

In combination, the log-likelihood function is thus given by:

$$LL\left(\beta, \tau, \gamma, \zeta_{I,\text{CPI}}, \sigma_I\right) = \sum_{n=1}^{N} \ln \int_{\eta} L\left(y_n \mid \beta, \tau, \alpha_{\text{CPI},n}\right) L\left(I_n \mid \zeta_{I,\text{CPI}}, \sigma_I, \alpha_{\text{CPI},n}\right) g\left(\eta\right) \mathrm{d}\eta_n \quad (16)$$

where this is integrated over the distribution of η_n, the random component in the latent attitude $\alpha_{\text{CPI},n}$. Unlike the base MNL model, this structure, through the placement of the integral, explicitly accommodates the repeated choice nature of the data by working with sequences of choices rather than individual choices.

The log-likelihood in Equation 16 is not directly comparable to that from the MNL model. Indeed, while the MNL log-likelihood gives the probability of the observed sequence of choices for all respondents, the function in Equation 16 gives the probability of observing the sequence of choices seen in the data for all respondents *and* the specific responses observed to the various attitudinal statements. However, there is clearly interest in seeing whether the incorporation of the latent attitude in the choice model allows the combined structure to better explain the observed choices. This comparison is made possible by taking the final estimates for β, γ and τ obtained by maximising Equation 16, say β^*, γ^* and τ^*, and using them inside the log-likelihood function for the choice model component on its own, given by:

$$LL_{\text{choice}}\left(\beta^*, \tau^*, \gamma^*\right) = \sum_{n=1}^{N} \ln \int_{\eta_n} L\left(y_n \mid \beta^*, \tau^*, \alpha_{\text{CPI},n}\right) g\left(\eta_n\right) \mathrm{d}\eta_n, \quad (17)$$

where $L\left(y_n \mid \beta^*, \tau^*, \alpha_{\text{CPI},n}\right)$ gives the probability of the sequence of choices observed for respondent n, conditional on the estimates for β^*, τ^*, and a specification realisation of $\alpha_{\text{CPI},n}$, which is a function of γ^*, where the function is then integrated over the random component in the distribution of $\alpha_{\text{CPI},n}$, i.e. η[6].

[6]With the only link between $L\left(y_n \mid \beta, \tau, \alpha_{\text{CPI},n}\right)$ and $L\left(I_n \mid \zeta_{I,\text{CPI}}, \sigma_I, \alpha_{\text{CPI},n}\right)$ being α_n, we can indeed see that, conditional on a given realisation of α_n and given estimates for the various model parameters,

3.3 Results

In this section, we present the estimation results for the two models used in the analysis. The main estimation results are presented in Table 2, while Table 3 shows the WTP measures computed from these models. Unless explicitly stated, the notation used is that introduced in previous sections.

3.3.1 Main estimation results

The estimation results for the base model showed that, relative to the base scenario (i.e. no specific policy), respondent have a dislike of beaches with up to 7 boats near the coastline (BTS1), with a preference for beaches with up to 2 boats (BTS2), although this is only significant at the 91% level. There is a small preference for a marine protected area (MPA) allowing fishing (over the base scenario, but only significant at the 87% level), with a strong preference for the MPA which does not allow fishing (MPA2). Respondents prefer low levels of development (DEV2) to the base scenario, which in turn is preferred to high levels of development (DEV1). There is a strong preference for reduced risk of infection (WQ2), with the base scenario being preferred to a high risk of infection (WQ1), while, in terms of water clarity, there is a preference for beaches with a vertical visibility of up to 10 metres (CLAR1), with a dislike of beaches with only up to 5 metres vertical visibility (CLAR2). Respondents have a dislike of beaches with up to 15 pieces of plastic per 30 metres of coastline (relative to the base scenario), with a preference for beaches with under 5 pieces of plastic (PLAS2). The two coefficients for the number of snorkellers are only significant at the 85% level for SNO1 and the 81% level for SNO2 respectively. There is a strong preference for high levels of coral cover (CORAL1), while the base situation is preferred over low cover (CORAL2), where this is only significant at the 81% level. While there is a preference for beaches with up to 60 species of fish being visible while snorkelling (FISH1), there is essentially no difference between the base scenario and beaches with low numbers of species of fish (FISH2). Finally, fee increases have the expected negative impact on utility.

We next turn our attention to the ICLV model, reported in the second part of Table 2. Attempts were made to incorporate all six attitudinal indicators in Equation 15, but significant effects were only observed for I_2, I_3, and I_4, i.e. the three questions directly relating to the monetary contributions. Attempts were also made to incorporate socio-demographic attributes in the latent attitude model in Equation 13, and we observed interactions with gender (γ_{male}, significant at the 93% level), whether a respondent had a postgraduate degree ($\gamma_{\text{postgraduate}}$, significant at the 92% level), and whether a respondent was a national (γ_{national}, significant at the 91% level). No effect was observed for age and income.

In reporting the results of the ICLV model, we show the overall log-likelihood (cf. Equation 16) and the log-likelihood for the choice model component (cf. Equation 17),

---

we have that the log-likelihood of the overall model is the sum of the log-likelihood of the two separate model components. This statement clearly does not imply that sequential estimation would yield the same results as simultaneous estimation.

Table 2: Parameter Estimates for MNL and ICLV models

	MNL	ICLV
Respondents	198	198
Observations	1,782	1,782
par. (overall)	19	38
par. (choice model)	19	29
Null log-likelihood	-1,957.73	-1,957.73
Log-likelihood (overall)	-1,742.92	-2,425.00
Log-likelihood (choice model)	-1,742.92	-1,564.76
adj. ρ^2 (choice model)	0.1000	0.1859

	MNL est.	MNL t-rat.	ICLV est.	ICLV t-rat.
$\beta_{\text{BTS1\_Low\_Policy}}$	-0.1967	-2.34	-0.3269	-3.22
$\beta_{\text{BTS2\_High\_Policy}}$	0.1362	1.69	0.1488	1.56
τ_{BTS}	-	-	0.2480	2.56
$\beta_{\text{MPA1\_Low\_Policy}}$	0.1254	1.50	0.2987	2.97
$\beta_{\text{MPA2\_High\_Policy}}$	0.2892	3.58	0.4205	4.32
τ_{MPA}	-	-	0.1535	1.54
$\beta_{\text{DEV1\_Low\_Policy}}$	-0.4109	-4.74	-0.3722	-3.67
$\beta_{\text{DEV2\_High\_Policy}}$	0.3760	4.85	0.4502	4.83
τ_{DEV}	-	-	0.1920	1.95
$\beta_{\text{WQ1\_Low\_Policy}}$	-0.4209	-4.79	-0.5514	-5.15
$\beta_{\text{WQ2\_High\_Policy}}$	0.4590	5.85	0.5196	5.64
τ_{WQ}	-	-	0.0092	0.09
$\beta_{\text{CLAR1\_High\_Policy}}$	0.3113	3.92	0.3950	3.91
$\beta_{\text{CLAR2\_Low\_Policy}}$	-0.2145	-2.60	-0.2328	-2.25
τ_{CLAR}	-	-	0.3868	3.88
$\beta_{\text{PLAS1\_Low\_Policy}}$	-0.1656	-1.93	-0.2106	-2.09
$\beta_{\text{PLAS2\_High\_Policy}}$	0.5135	6.38	0.6951	7.15
τ_{PLAS}	-	-	0.0611	0.63
$\beta_{\text{SNO1\_Low\_Policy}}$	-0.1191	-1.45	-0.1948	-1.98
$\beta_{\text{SNO2\_High\_Policy}}$	0.1080	1.32	0.1919	1.92
τ_{SNO}	-	-	0.2260	2.38
$\beta_{\text{CORAL1\_High\_Policy}}$	0.4645	5.73	0.5058	4.94
$\beta_{\text{CORAL2\_Low\_Policy}}$	-0.1099	-1.30	-0.1649	-1.56
τ_{CORAL}	-	-	0.3966	3.95
$\beta_{\text{FISH1\_High\_Policy}}$	0.2401	2.95	0.3108	3.20
$\beta_{\text{FISH2\_Low\_Policy}}$	-0.0915	-1.09	-0.1130	-1.14
τ_{FISH}	-	-	0.2242	2.38
β_{Fee}	-0.0226	-5.78	-0.0289	-5.42
τ_{fee}	-	-	0.0209	3.38
γ_{male}	-	-	0.1400	1.81
$\gamma_{\text{postgraduate}}$	-	-	0.3888	1.74
γ_{national}	-	-	-0.3915	-1.67
$\zeta_{I_2,\text{CPI}}$	-	-	-0.2468	-3.04
σ_{I_2}	-	-	1.0308	19.52
$\zeta_{I_3,\text{CPI}}$	-	-	-0.2095	-2.55
σ_{I_3}	-	-	1.0393	19.61
$\zeta_{I_4,\text{CPI}}$	-	-	-0.2290	-2.91
σ_{I_4}	-	-	0.9838	19.49

alongside the associated adjusted ρ^2 measure. The results show that the ICLV model obtains far superior fit to the base model, confirming our hypothesis that at least part of the behaviour observed in the survey is a result of an underlying pro-intervention attitude of some respondents, where some of the gains could also be a result of correlation across choices for the same respondent that is accommodated through the specific location of the integral outside the product over choices in Equation 16. Additionally, we acknowledge that the comparison in terms of fit is not a level playing field, given that the MNL model does not allow for any random heterogeneity. In the remainder of this discussion, the main interest will be in the actual differences in implied sensitivities.

The signs for the main coefficients (β) are all identical to those obtained in the base model, where the detailed differences in terms of WTP implications are studies in Table 3. For some coefficients, increases in the level of statistical significance are observed, while for others, there are decreases. This is in part also a result of the fact that unlike the base model, this structure accommodates the repeated choice nature of the data.

In terms of the effect of the latent attitude on the parameters of the choice model, we can see that the impact on the fee sensitivity (τ_{fee}) is significant and positive, showing that respondents with a more positive value for the latent attitude have a less negative reaction to paying a fee. Similarly, the impact of the latent variable on the parameters associated with the nine intervention attributes are all positive, showing that respondents with a more positive value for the latent attitude have a stronger desire for such interventions. The actual impact varies across attributes, and is completely insignificant for two attributes, namely water quality and plastics, while it is only significant at the 88% level for the MPA intervention.

Turning next to the estimates for the measurement equations model, we observe that the standard deviations (σ_{I_2}, σ_{I_3}, and σ_{I_4}) are not significantly different from unity. The estimates for the marginal impact of the latent attitude $\alpha_{\text{CPI},n}$ on the response to the attitudinal questions shows that with any increase in the latent pro-intervention variable $\alpha_{\text{CPI},n}$, we obtain an increase in the degree to which respondents agree with the notion of making a monetary contribution (equivalent to a reduction in the Likert scale rating). The most negative value is obtained for $\zeta_{I_2,\text{CPI}}$, which relates to only non-nationals making a monetary contribution. The second most negative level is obtained by $\zeta_{I_4,\text{CPI}}$, which is the response to a statement that nationals and non-nationals should make a contribution, while the smallest effect is observed for the statement that only residents and nationals should make a contribution ($\zeta_{I_2,\text{CPI}}$). While the three estimates are very similar, and not significantly different from one another, it is still worth noting that the order of estimates is entirely consistent with expectations, given that the majority of the sample were non-nationals. Indeed, with a negative estimate equating to a greater willingness to accept monetary contributions, this is also highest for the statement that actually most relates to the sample of respondents used in this analysis.

Finally, in terms of socio-demographic interactions, we can see that male respondents have a more positive value for the latent attitude, i.e. are less opposed to making a monetary contribution. The same is the case for respondents with a postgraduate education, where the impact is even larger. On the other hand, respondents who are nationals of the islands have a more negative value for the latent attitude, i.e. are more opposed to making

Table 3: WTP Estimates (*vs.* base level of attribute)

		latent attitudes model (ICLV)		
	MNL	10^{th} percentile	median	90^{th} percentile
BTS1_Low_Policy	-8.71	-11.55	-11.38	-11.02
BTS2_High_Policy	6.03	-1.90	3.18	13.98
MPA1_Low_Policy	5.55	3.01	8.30	19.52
MPA2_High_Policy	12.81	5.49	12.03	25.92
DEV1_Low_Policy	-18.20	-14.79	-12.46	-11.36
DEV2_High_Policy	16.65	5.32	12.72	28.44
WQ1_Low_Policy	-18.64	-28.76	-16.93	-11.37
WQ2_High_Policy	20.33	10.36	15.86	27.54
CLAR1_High_Policy	13.79	0.34	9.95	30.38
CLAR2_Low_Policy	-9.50	-12.40	-9.27	-2.62
PLAS1_Low_Policy	-7.33	-9.55	-6.79	-5.48
PLAS2_High_Policy	22.74	12.89	20.94	38.05
SNO1_Low_Policy	-5.27	-8.44	-7.22	-4.62
SNO2_High_Policy	4.78	-0.59	4.62	15.71
CORAL1_High_Policy	20.57	2.39	13.29	36.45
CORAL2_Low_Policy	-4.87	-11.22	-7.25	1.19
FISH1_High_Policy	10.64	1.86	8.27	21.91
FISH2_Low_Policy	-4.05	-6.74	-4.70	-0.37

a monetary contribution. Aside from any correlation with income[7], this observation is not entirely surprisable as these respondents will be more accustomed to making free use of the beaches.

3.3.2 Willingness-to-pay estimates

As a next step in our analysis, willingness-to-pay (WTP) measures were computed from the estimates, giving the implied monetary valuation of the different policy measures. A positive WTP shows that respondents would be willing to pay more for visiting a beach with the relevant attribute (*vs.* a beach with the status quo value), while a negative WTP measure implies that the concerned attribute is seen as less desirable than the status quo. The results of this process are reported in Table 3, where the labels used are those from Table 1.

For the MNL model, we obtain point estimates for the WTP measures, obtained simply by dividing the appropriate coefficient through the fee coefficient, e.g. dividing $\beta_{\text{BTS1\_Low\_Policy}}$ by β_{Fee} for the first measure. On the other hand, for the ICLV model, all coefficients are interacted with the latent attitude. To this extent, the WTP measures also follow a random distribution. To take this into account, we generated $10,000$ draws for the latent attitude for each respondent, i.e. using $10,000$ individual-specific draws from η and combining them with the appropriate socio-demographic values as shown in Equation 13. Using the estimates for the individual β parameters and the interaction terms τ as shown in Equation 14, we then obtain $10,000$ draws for each coefficient for

[7]Income effects were not observed to be significant when incorporated directly in the model.

each respondent, and produce draws from the WTP distribution by dividing the draws for the 18 coefficients relating to the intervention measures by the draws for the fee coefficient. From the resulting distribution, we show the median as well as the tenth and ninetieth percentile points. This approach (rather than reporting means and standard deviations) is motivated by the fact that, with the reliance on Normal distributions, the moments of the WTP distributions are not defined (Daly et al., 2011a).

As a first observation, focussing on the MNL results, we can see that for those attributes where there is a bi-directional change, i.e. one policy is worse than the status quo while the other is better, there is evidence of asymmetry in response. However, there is no clear pattern which would suggest that losses are valued more negatively than gains are valued positively, as would be the case from a prospect theory viewpoint. In fact, if anything, the opposite is the case here. However, it is important to bear in mind that the difference in the attribute levels themselves is in many cases asymmetrical in relation to the status quo.

In the MNL model, the highest WTP is for up to 45% coral cover (CORAL1) and a low chance of infection (WQ2). Conversely, there is a strong opposition to high costal development (DEV1) and increased chance of infection (WQ1). The findings from the latent attitude model show high variation across respondents for some of the indicators, which is a direct result of the incorporation of the latent attitude, meaning that differences in WTP measures now arise across respondents. While some of the median values are similar to the MNL point estimates, this is not the case for others, e.g. DEV2 and CORAL1, where the absolute median values are visibly lower than the MNL point estimates. On the other hand, some of the values for the ninetieth percentile are substantially higher than the point values from the MNL model.

4 Discussion, future research and conclusions

The analysis reported in this paper has looked at the estimation of willingness-to-pay measures for coastal water quality improvements in Tobago. The notion of making a monetary contribution for what is typically regarded as a free resource is a contentious issue, and our expectation was that there would be a significant level of underlying heterogeneity in the attitudes towards such interventions.

In common with many other studies in the field, the survey used in the present work had collected responses from participants to a number of attitudinal questions. In past work, there has been a tendency to incorporate such responses directly in the models as explanatory variables. This treatment of such responses as error free measures of underlying attitudes disregards the point that these responses are in fact functions of unobserved attitudes, rather than direct manifestations.

In the theory section of the paper, we highlight how recent discussions, notably in the transport research literature, indicate that such approaches put analysts at risk of producing results affected by measurement error and endogeneity bias. We then show how a latent variable approach can be used in this context, allowing an analyst to make use of the responses to attitudinal questions while recognising the fact that the actual attitudes are unobserved. Specifically, a combined model is formulated in which responses to attitudinal questions are dependent variables in the same way as choices are in a traditional choice model. Both sets of dependent variables (responses to attitudinal questions and choices) are influenced by a latent variable, and the parameters of the model are obtained through simultaneous estimation of the two model components.

In the empirical part of the paper, we formulate the hypothesis that respondents have an unobserved underlying attitude towards policy interventions, where this has an impact on the fee sensitivity as well as the desire for the different types of policy interventions. Our results show that this latent attitude can indeed be used to explain both the stated choices and the responses to the attitudinal questions. Its incorporation in the models leads to very significant gains in statistical fit, but more importantly provides further insights into behaviour, leads to changes in the WTP measures, and shows the variation in these measures across respondents as a function of their underlying attitudes.

The results of the ICLV model suggest that different respondents are willing to pay different amounts for attributes associated with higher environmental quality such as the amount of coral cover that can be viewed when snorkelling or the abundance of fish species as well as for avoiding undesirable effects, such as a heightened chance of contracting an ear infection, or higher levels of coastal development. This has important implications for the calculation of aggregate benefits and their consequent use in cost-benefit analysis for coastal water quality improvement programs. Furthermore, the results show that male respondents and respondents with postgraduate degrees have a higher desire for intervention, with the opposite applying for national respondents. Here, there is arguably strong correlation with underlying differences in income, where attempts to directly incorporate income effects were however not successful.

Finally, as an aside, the analysis also revealed problems with the commonly adopted approach of using a constant for the *no choice* or *status quo* alternative, a point addressed in more detail in the Appendix.

While the results of this study are interesting in their own right, we believe that the findings further suggest that the ICLV model structure could be a very powerful tool in the field of environmental economics. Indeed, studies in this field aim to provide reliable WTP measures with a view to guiding prioritisation of policy initiatives, where underlying attitudes potentially drive a large extent of the heterogeneity often retrieved in such studies. Unlike approaches that incorporate responses to attitudinal questions as error free measures of attitudes, a technique that has been shown to be inappropriate, the ICLV model is not affected by measurement error and endogeneity bias as it recognises that attitudes are unobserved, and as it treats responses to attitudinal questions as dependent rather than explanatory variables. Additionally, the method can be used directly in forecasting, where the measurement part of the model can be dropped, i.e. forecasting solely using Equation 17, but conditional on the estimates obtained by maximising Equation 16.

There are a number of avenues for future work. These include the use of latent attitudes with an underlying MMNL (rather than MNL) model, i.e. allowing for additional random heterogeneity not linked to the latent attitude. Additionally, the method should be tested more widely on a set of different environmental case studies. Finally, it is important to acknowledge two possible drawbacks. The first relates to the computational complexity of estimating the model, especially when using simultaneous (and hence efficient) estimation. Future work should focus on making the method more widely applicable through making robust and efficient code widely available. Secondly, the performance of the model depends to a large extent on the quality of the information captured in the responses to the attitudinal questions. Often, these questions are included in surveys without specifically being aimed at the use in an ICLV structure. Future work should focus on producing guidance for good practice in this context.

Acknowledgements

The authors would like to thank Bhanu Patruni and Dimitris Potoglou for coding suggestions. The first author also acknowledges the support of the Leverhulme Trust in the form of a *Leverhulme Early Career Fellowship.* We also thank three anonymous referees for very helpful comments on an earlier version.

Appendix: effects of status quo constant

Studies in environmental economics and elsewhere often include a constant associated with any status quo or no choice alternative included in surveys, a point discussed for example by Hess and Rose (2008). In the data used for the present study, respondents had the option of indicating that they would not be willing to choose either of the two options presented to them in a given scenario. The estimation of a *status quo* constant may thus seem appropriate. However, an important point arises here, which we believe also applies more widely. In particular, it relates to the fact that in the present survey (and in many other such surveys), the status quo alternative involves no cost, while the choice of the remaining alternatives incurs a fee.

A status quo constant is in this context traditionally regarded as capturing inertia and status quo bias. The argument is that such a constant is needed so as to avoid a situation in which the presence of protest voters (i.e. respondents refusing to choose an option incurring a fee) will result in an inflated estimate of the cost sensitivity, and hence artificially low WTP measures. However, if the status quo alternative has a zero cost (or even just a lower cost than the two others), and the two other alternatives do not, as is the case here, then a status quo constant can in fact additionally be seen to capture cost sensitivity. In the extreme scenario where there is no inertia or protest voting, the status quo constant would then capture the effect of moving from the zero cost alternative to the cheapest charged alternative, while the estimated fee coefficient would relate only to the marginal cost sensitivity for differences in cost between the remaining alternatives. This would then however be of little use if we are interested in the WTP for improvements over the status quo scenario in individual components.

As an illustration, Table 4 shows results for a MNL model with the additional status quo constant, alongside the results for the MNL model from Section 3. The inclusion of the constant leads to an improvement in fit by 24.21 units, which is of course highly significant. But not only do we observe a drop in the significance level for the fee coefficient

Table 4: Results with and without status quo constant

	MNL_A	MNL & status quo (SQ) dummy
par	19	20
Log-likelihood	-1742.92	-1718.71
Null log-likelihood	-1957.73	-1957.73
adj. rho^2	0.1000	0.1119

	est.	t-rat.	WTP	est.	t-rat.	WTP	ratio of WTP
$\beta_{\text{BTS1\_Low\_Policy}}$	-0.1967	-2.34	-8.71	-0.0915	-1.03	-7.99	0.92
$\beta_{\text{BTS2\_High\_Policy}}$	0.1362	1.69	6.03	0.2824	3.3	24.64	4.09
$\beta_{\text{MPA1\_Low\_Policy}}$	0.1254	1.5	5.55	0.2983	3.29	26.04	4.69
$\beta_{\text{MPA2\_High\_Policy}}$	0.2892	3.58	12.81	0.4847	5.55	42.3	3.3
$\beta_{\text{DEV1\_Low\_Policy}}$	-0.4109	-4.74	-18.2	-0.2531	-2.7	-22.09	1.21
$\beta_{\text{DEV2\_High\_Policy}}$	0.376	4.85	16.65	0.5608	6.66	48.94	2.94
$\beta_{\text{WQ1\_Low\_Policy}}$	-0.4209	-4.79	-18.64	-0.3012	-3.25	-26.29	1.41
$\beta_{\text{WQ2\_High\_Policy}}$	0.459	5.85	20.33	0.6211	7.41	54.21	2.67
$\beta_{\text{CLAR1\_High\_Policy}}$	0.3113	3.92	13.79	0.4967	5.7	43.35	3.14
$\beta_{\text{CLAR2\_Low\_Policy}}$	-0.2145	-2.6	-9.5	-0.05	-0.57	-4.37	0.46
$\beta_{\text{PLAS1\_Low\_Policy}}$	-0.1656	-1.93	-7.33	-0.0335	-0.37	-2.92	0.4
$\beta_{\text{PLAS2\_High\_Policy}}$	0.5135	6.38	22.74	0.6629	7.7	57.85	2.54
$\beta_{\text{SNO1\_Low\_Policy}}$	-0.1191	-1.45	-5.27	0.0195	0.23	1.7	-0.32
$\beta_{\text{SNO2\_High\_Policy}}$	0.108	1.32	4.78	0.2319	2.67	20.24	4.23
$\beta_{\text{CORAL1\_High\_Policy}}$	0.4645	5.73	20.57	0.6678	7.49	58.28	2.83
$\beta_{\text{CORAL2\_Low\_Policy}}$	-0.1099	-1.3	-4.87	0.069	0.76	6.02	-1.24
$\beta_{\text{FISH1\_High\_Policy}}$	0.2401	2.95	10.64	0.4427	4.91	38.64	3.63
$\beta_{\text{FISH2\_Low\_Policy}}$	-0.0915	-1.09	-4.05	0.0677	0.75	5.91	-1.46
β_{Fee}	-0.0226	-5.78	-	-0.0115	-2.65	-	-
δ_{SQ}	-	-	-	1.277	6.75	-	-

(t-ratio of 2.65 instead of 5.78), but the estimated fee sensitivity is also much lower, leading to much higher WTP measures. These WTP measures are in some extreme cases four times as large as for the base model, and are in many cases larger than the highest cost presented in the survey ($25). The results would thus wrongly tell us that respondents are willing to pay more for a single attribute (when compared to its base level) than the cost of the best combined set of attributes presented in the stated choice examples. This supports our hypothesis that such a constant risks capturing cost sensitivity, thus leading to a downwards bias in the estimated cost coefficient, and overstated WTP indicators.

References

Abou-Zeid, M., Ben-Akiva, M., Bierlaire, M., Choudhury, C., Hess, S., 2010. Attitudes and Value of Time Heterogeneity. In: Van de Voorde, E., Vanelslander, T. (Eds.), Applied Transport Economics - A Management and Policy Perspective. De Boeck Publishing, forthcoming, pp. 525–548.

Aldrich, G., Grimsrud, K., Thacher, J., Kotchen, M., 2007. Relating environmental attitudes and contingent values: how robust are methods for identifying preference heterogeneity? Environmental and Resource Economics 374, 757–775.

Alvarez-Daziano, R., Bolduc, D., 2009. Canadian consumers perceptual and attitudinal responses toward green automobile technologies: an application of Hybrid Choice Models, 2009 EAERE-FEEM-VIU European Summer School in Resources and Environmental Economics: Economics, Transport and Environment Venice International University.

Ashok, K., Dillon, W. R., Yuan, S., 2002. Extending discrete choice models to incorporate attitudinal and other latent variables. Journal of Marketing Research, 31–46.

Baker, G., Burnham, T., 2001. Consumer response to genetically modified foods: market segment analysis and implications for producers and policy makers. Journal of Agricultural and Resource Economics 26 (2), 387–403.

Beck, M., Rose, J., Hensher, D., 2010. Identifying response bias in stated preference surveys: attitudinal influences in emissions charging and vehicle selection. Institute of Transport and Logistics Sudies, University of Sydney.

Beharry, N., 2008. Valuing benefits of improved coastal water quality for beach recreationists in Tobago : A discrete choice experiment application. Ph.D. thesis, University of York, U.K.

Beharry-Borg, N., Hensher, D. A., Scarpa, R., 2009. An Analytical Framework for Joint vs Separate Decisions by Couples in Choice Experiments: The Case of Coastal Water Quality in Tobago. Environmental and Resource Economics 43, 95–117.

Beharry-Borg, N., Scarpa, R., 2010. Valuing quality changes in Caribbean coastal waters for heterogeneous beach visitors. Ecological Economics 69, 1124–1139.

Ben-Akiva, M., McFadden, D., Gärling, T., Gopinath, D., Walker, J., Bolduc, D., Börsch-Supan, A., Delquié, P., Larichev, O., Morikawa, T., et al., 1999. Extended framework for modeling choice behavior. Marketing Letters 10 (3), 187–203.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D. S., et al., 2002. Hybrid choice models: Progress and challenges. Marketing Letters 13 (3), 163–175.

Bolduc, D., Ben-Akiva, M., Walker, J., Michaud, A., 2005. Hybrid choice models with logit kernel: Applicability to large scale models. In: Lee-Gosselin, M., Doherty, S. (Eds.), Integrated Land-Use and Transportation Models: Behavioural Foundations. Elsevier, Oxford, pp. 275–302.

Boxall, P., Adamowicz, W., 2002. Understanding heterogeneous preferences in random utility models: A latent class approach. Environmental and Resource Economics 23, 421–446.

Breffle, W., Morey, E., Thacher, J., 2005. Combining attitudinal and choice data to improve estimates of preferences and preference heterogeneity: a FIML, discrete-choice, latent-class model, working Paper Department of Economics, University of New Mexico, Albuquerque.

Daly, A., Hess, S., Train, K., 2011a. Assuring finite moments for willingness to pay estimates from random coefficients models. Transportation, forthcoming.

Daly, A. J., Hess, S., Patruni, B., Potoglou, D., Rohr, C., 2011b. Using ordered attitudinal indicators in a latent variable choice model: A study of the impact of security on rail travel behaviour. Transportation, forthcoming.

Doornik, J. A., 2001. Ox: An Object-Oriented Matrix Language. Timberlake Consultants Press, London.

Eid, J., Langeheine, R., Diener, E., 2003. Comparing typological structures across cultures by multigroup latent class analysisa primer. Journal of Cross-Cultural Psychology 342, 195–210.

Fosgerau, M., Bjørner, T. B., 2006. Joint models for noise annoyance and willingness to pay for road noise reduction. Transportation Research Part B 40, 164–178.

Green, P., 1984. Hybrid Models for Conjoint Analysis: An Expository Review. Journal of Marketing Research 21, 155–169.

Greene, W. H., Hensher, D. A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. Transportation Research Part B 37 (8), 681–698.

Harris, K., Keane, M., 1998. A Model of Health Plan Choice: Inferring Preferences and Perceptions from a Combination of Revealed Preference and Attitudinal Data. To appear: Journal of Econometrics.

Hess, S., Rose, J., 2008. Should reference alternatives in pivot design SC surveys be treated differently? Environmental and Resource Economics 42, 297–317.

Johansson, M. V., Heldt, T., Johansson, P., 2005. Latent Variables in a Travel Mode Choice Model: Attitudinal and Behavioural Indicator Variables, working Paper Department of Economics, Uppsala University, Sweden.

Johansson, M. V., Heldt, T., Johansson, P., Jul. 2006. The effects of attitudes and personality traits on mode choice. Transportation Research Part A 40 (6), 507–525.

Menezes, L. D., Bartholomew, D., 1996. New developments in latent structure analysis applied to social attitudes. Journal of the Royal Statistical Society 1592 Series A, 213224.

Milon, J. W., Scrogin, D., 2006. Latent preferences and valuation of wetland ecosystem restoration. Ecological Economics 56, 162–175.

Morey, E., 1981. The demand for site-specific recreational activities: A characteristics approach. Journal of Environmental Economics and Management 8, 345–371.

Morey, E., Thacher, J., Breffle, W., 2006. Using angling characteristics and attitudinal data to identify environmental preference classes: A latent class model. Environmental and Resource Economics 34, 91–115.

Morey, E., Thiene, M., Salvo, M. D., Signorello, G., 2008. Using attitudinal data to identify latent classes that vary in their preference for landscape preservation. Ecological Economics 68, 536–546.

Pennings, J., Leuthold, R., 2000. The role of farmers behavioral attitudes and heterogeneity in futures contracts usage. Journal of Agricultural Economics 82 (4), 908–919.

Temme, D., Paulssen, M., Dannewald, T., 2008. Incorporating Latent Variables into Discrete Choice Models A Simultaneous Estimation Approach Using SEM Software. Business Research 1, 220–237.

Thacher, J., Morey, E., Craighead, W., 2005. Using patient characteristics and attitudinal data to identify treatment preference groups: a latent-class model. Depression and Anxiety 212, 47–54.

Train, K., 2009. Discrete Choice Methods with Simulation, second edition Edition. Cambridge University Press, Cambridge, MA.

Yamaguchi, K., 2000. Multinomial logit latent-class regression models: an analysis of the predictors of gender-role attitudes among japanese women. American Journal of Sociology 1056, 1702–1740.

Yáñez, M., Raveau, S., de D. Ortúzar, J., Nov. 2010. Inclusion of latent variables in mixed logit models: Modelling and forecasting. Transportation Research Part A 44 (9), 744–753.