

Title: Eliciting public values for management of complex marine systems: an integrated choice experiment

Running head: Valuing complexity in marine environments

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Abstract: To accurately capture how the public values marine environmental management, we need valuation approaches that can accommodate the complexity of environmental systems and human interaction with them. Coherently representing this complexity in an evaluation means that we can inform the socially optimal allocation of marine resources among competing uses, such as fisheries, industry and environmental protection. Integrated choice experiments (ICE) provide a systematic approach to valuing large numbers of attributes, and we use it to value eight marine ecological and recreational features at Moreton Bay, South-East Queensland. The ICE employed two sub-experiments: ecological and recreational, to reduce cognitive load for respondents. We compare the ICE approach with a full-profile discrete choice experiment, with all eight attributes. The ICE had greater face validity than the traditional format. We find large, positive willingness to pay for the provision of recreational features and habitat protection, although with some diminishing marginal effects.

Introduction

The marine environment is subject to increasing competition and degradation (Doney et al. 2012; Gunderson, Armstrong, and Stillman 2016). For example, there is increasing competition for the use of marine resources by commercial (Costello et al. 2016) and recreational fishers (Ihde et al. 2011), industry (such as the renewable energy sector e.g. Wilding et al. (2017)), and for conservation (Lubchenco and Grorud-Colvert 2015). To understand the socially optimal allocation of marine resources among these different users, we need to understand how the public values management of the marine environment. Non-market valuation is used to measure the economic value of, or social welfare generated by, public goods such as the marine environment. In particular, stated preference approaches such as discrete choice experiments (DCEs) are used where non-use values might be important, such as the existence values of marine biodiversity. However, the marine environment is a complex system, which does not lend itself easily to applications such as DCEs (Carson and Louviere 2011). DCEs—despite remaining among the most popular ways of conducting non-market valuation (see, for example, Chen, Liekens, and Broekx 2017; Czajkowski et al. 2017)—cannot capture the full complexity of marine environments because they can only assess a limited number of attributes and their levels at a time. Therefore, if we rely on traditional applications of these and other existing methods, the public's preferences for marine management are likely to be poorly understood. To accurately capture the public's values for marine management, we need valuation approaches that can account for the complexity of the marine environment. Only through this understanding can we balance the needs of the community with the needs of industry and environmental conservation.

This paper explores how the complexity of the marine environment can be captured in a non-market valuation exercise. We trial an integrated choice experiment (ICE) (Molin and

Timmermans 2009) approach to identify what the public is willing to pay to protect marine habitats and for the provision of marine-recreational features. The ICE framework is based on theories of information integration, and differentiates between higher order concepts and their constituent parts. By using an ICE, we can assess a large number of attributes within a single modelling framework, and hence more fully represent the complexity of the good—the marine environment—being valued.

The issue of how to deal with a large number of attributes in a valuation study is not new, and there are several approaches that have been applied in the past (for a review see Rao, Kartono, and Su (2009)). For example, Pascoe et al. (2013) employ the Analytic Hierarchy Process to generate relative rankings over a large number of attributes of a fishery. A limitation of the approach is that it does not deliver marginal values in a monetary framework. Alternatively, one can employ partial profile choice experiments (e.g. Chrzan 2010; Green 1974), where respondents see only a subset of the attributes in each choice set (implicitly all other attributes are assumed to be equal across options, and hence irrelevant to choices, assuming no attribute interaction effects).

Ideally, a large number of attributes would be used to value the marine environment (Pascoe and Doshi 2017; Torres and Hanley 2016). However, evidence suggests that increasing the number of attributes increases complexity of the choice task (Johnston et al. 2017). As respondents must process more information, the probability that they rely on relevance strategies (Hensher 2006) or develop other coping strategies (heuristics) (Johnston et al. 2017) increases. The implications of relying on relevance or other coping strategies is that some information provided in the choice sets (through attributes and their levels) may not enter into respondents' decision-making process, i.e. attribute non-attendance. The expected behavioural response in such a situation is for respondents to invoke a rule to guide their

choices, e.g. only focus on the most important attributes to them, which will likely vary among respondents. As a result, process heterogeneity increases—heterogeneity in respondent’s underlying decision process—which potentially increases model uncertainty as well (Hensher and Greene 2010). The modelling strategies that researchers have adopted to address attribute non-attendance (in the absence of self-reported information on attendance) include a latent class approach with a finite mixing panel model (Hensher and Greene 2010; Scarpa et al. 2009) and a Bayesian approach with a continuous mixing panel model (Scarpa et al. 2009). More recent advances to address attribute non-attendance include the use of eye-tracking technologies to develop a measure of visual attendance, which is then used as a model regressor (Chavez, Palma, and Collart 2017).

To avoid attribute non-attendance, and other biases caused by choice tasks with a high cognitive burden, conventional wisdom holds that DCE designs should include a limited number of attributes (Johnston et al. 2017). Within the literature, there are examples of how this has constrained previous marine valuation studies. For example, Norton and Hynes (2014) identified that 11 attributes were required to fully value the non-market benefits arising from implementation of the EU Marine Strategy Framework Directive. However, these had to be aggregated to six attributes to lower the cognitive burden on respondents (Norton and Hynes 2014). In contrast, by employing an ICE approach, in our study we were able to incorporate a large number of attributes to better approximate the complexity of a marine environment. This allowed us to improve understanding of how the community views management of a local marine ecosystem. By identifying economic values for marine conservation and recreational use, we can compare the public’s value for marine management outcomes with those of marine industries—including fisheries. This knowledge allows marine managers to make informed decisions about the allocation of marine resources amongst different user groups to maximise social welfare.

In this research, we developed an ICE that assessed community values for marine ecological features and recreational services in Moreton Bay, Queensland, Australia (see Figure 1). Through focus groups, we identified that marine conservation and recreational service provision were two key features of a well-managed marine environment for the community. This result gave us two ‘constructs’—higher-order concepts each encompassing a number of attributes—to develop into sub-experiments in our integrated approach: an ecological construct (sub-experiment-eco) and a recreational construct (sub-experiment-rec). As ICE has not previously been applied in the environmental literature, an additional survey (full profile-experiment) was also developed that included all attributes in a single DCE, so we could compare the ICE with a traditional approach.

[Figure 1: approximate location]

We successfully implemented the ICE approach in this context, and found that the results had greater face validity than those generated by the DCE that included all attributes simultaneously. We found that the South-East Queensland population had large and positive willingness to pay (WTP) values for protection of marine habitats and provision of recreational services. Our results show that among the ecological attributes assessed, the surveyed population had highest value for *hard substrate* areas, and diminishing marginal values for increasing levels of protection for *vegetated habitats* and the *outer bay*. Among the recreational services assessed, WTP was highest for *beach cleanliness*. These values can be compared with the value of commercial and recreational fishing or marine energy extraction to identify zoning of the marine environment to maximise social welfare.

In what follows we provide an overview of the theory behind the ICE approach, before describing the process used to identify the main ways the South-East Queensland population viewed successful management of marine areas. We provide details of the survey design and

analysis performed before presenting results and discussing how our approach could be used in environmental applications and the advantages of doing so.

Methods

In this research, our prior was that a full profile-experiment (see Survey design) was too complex for respondents to process (Zhang et al. 2015); and this justified our use of an ICE. We identified eight management attributes to include in our DCE—more than are normally considered in the literature. For example, in their review of marine protected area (MPA) valuations, Torres and Hanley (2016) describe numerous choice experiment applications where the number of attributes used to describe the marine system ranged between two and five (plus a cost attribute). Some of these studies had a straight ecological (Börger et al. 2014; Boxall et al. 2012) or recreational (Wielgus et al. 2009) focus. Others considered recreational use attributes with a view to how they related to conservation objectives (Sorice, Oh, and Ditton 2007), or focused on ecological improvements while acknowledging that these had both use and non-use related values associated with them (e.g. Rogers 2013; Rolfe and Windle 2012). Still others incorporated both recreational and ecological outcomes in the same choice experiment, but through attributes that broadly represented each. For example, Wallmo and Edwards (2008), Wattage et al. (2011) and Glenn et al. (2010) each included an attribute on allowable uses within MPAs and one on coverage of MPAs for protection of marine ecology. Our ICE approach allows for an inclusive scope of recreation and ecological outcomes. In what follows, we describe the ICE approach in detail before describing the survey design and data analysis.

Integrated choice experiments

Integrated Choice Experiments (ICE) are an extension of the Hierarchical Information Integration (HII) approach (Louviere 1984), both of which can be applied in cases where there are large numbers of attributes in a choice problem (Molin and Timmermans 2009). Conceptually, the models assume that respondents follow a hierarchical decision process when faced with a complex decision. Explicitly, they propose that respondents: (1) classify attributes into higher order “constructs”; (2) make an assessment of the value of these constructs; and (3) make choices based on the values of the constructs rather than the attribute levels *per se*. Respondents are assumed to value constructs similarly, even if each respondent has a different view of what constructs are composed of. In an early example that investigated determinants of supermarket choice (Louviere and Gaeth 1987), the authors defined four higher order constructs: price, quality, selection and convenience—convenience was defined by 11 attributes, including travel time from home, availability of parking, and checkout speed, etc. When comparing supermarkets it was assumed that an assessment was first made of “convenience” based on the 11 attributes, and the other three constructs similarly, and then an assessment of the supermarket as a whole was made based on the levels of the four constructs. Integrated choice experiments have been used in several fields including transport (Keuchel and Richter 2011), residential markets (note, as hierarchical information integration) (Vyvere, Oppewal, and Timmermans 1998), and marketing (Oppewal, Louviere, and Timmermans 1994). When applied empirically, respondents are required to complete sub-experiments where they evaluate only elements of the overall problem, and then these sub-experiments are combined to give an overall analysis. We now outline our implementation of the ICE approach.

In our context, we assume that residents in the Moreton Bay area consider two higher level constructs when considering management changes in the Bay: the impact of management changes on ecological outcomes, and the impact of management changes on recreational outcomes. This assumption was based on results from focus groups (see next section). It is important in the design of the ICE that the constructs are independent; that is, that changes in an attribute can only influence one construct, and not many. Here we define the ecological construct in terms of areas of different ecosystems that are afforded protection, while the recreational construct is defined in terms of recreational services such as beach closures, accessibility etc. It is possible that beach closure due to water quality may also be associated with (temporary) environmental impacts, but the environmental constructs are defined in terms of protection from human use, rather than ecological quality per se.

Within an ICE sub-experiment a respondent is presented with a description of the situation being valued with the attributes for one construct, and a summary ‘rating’ for the other(s) (note that although in this case we consider only two constructs, in principle there could be n , leading to n sub-experiments in total). The construct rating can either be provided on a numerical scale (Molin and Timmermans 2009) or as categorical descriptions (i.e. Vyvere, Oppewal, and Timmermans (1998), who use “fair”, “good” and “very good” to describe housing constructs). We include an additional variable, *cost*, which could be considered as a single attribute that appears in all sub-experiments. The sub-experiments are designed as choice experiments, where a series of choice scenarios are presented to respondents, who are required to choose between the multiple alternatives presented in each scenario. As shown in Figure 2, sub-experiments differ by which construct is represented in full by attributes, and which by a summary rating. The different sub-experiments can each be allocated to different respondents, reducing cognitive load.

[Figure 2: approximate location]

In our case, the two sub-experiments were: “sub-experiment-rec”, where the ecological construct is defined by four attributes and the recreational construct is given as a rating; and “sub-experiment-eco”, where the recreational construct is defined by four attributes, and the ecological construct is given as a rating. However, it is important that respondents have some concept of what a rating score for ‘recreation’ or ‘ecological condition’ means before they are asked to evaluate them in a choice experiment. We achieved this in the survey by first asking respondents to complete rating questions for the *condition* of the constructs, described below in ‘ICE construct rating’. Each sub-experiment in the ICE can be treated as a separate experiment, with discrete choices explained using conditional logit models. However, the advantage of the ICE is that one can concatenate all of the data, and estimate a model as if it had been derived from a full profile-experiment. In this way, there is a single model of utility rather than several. It should be noted that, although it would be possible to generate estimates of willingness to pay for the constructs, these would have limited empirical value, as they relate to an index that may be difficult to ground in physical terms. However, these are not required, as the concatenated model generates WTP estimates for all non-construct attributes.

Attributes

Following advice from marine ecologists, we defined four ecological attributes based on the 20 possible habitat types in Moreton Bay: *vegetated habitats*, the *outer bay*, *loose* and *hard substrate* areas. Four levels of protection were selected for each ecological attribute, defined as the percentage of the attribute area zoned as a marine national park. The current protection level for each attribute varied from 15-18% and this level was set as the status quo. One

lower (10%) level, and two higher (25 and 30%) levels were also included for each ecological attribute.

Four recreational attributes were selected so that the number of attributes in both constructs was the same. These were guided by the focus groups, but with an effort made to avoid any confounding issues between marine protection and recreation: outcomes for marine protection were designed to be influenced by changes in marine zoning while recreation attributes were focussed on outcomes that could be achieved through terrestrial-based management. This led to length of walkways accessing the coast (15-60km), signage (defined as low, medium or high), days of beach closure per year (5-15) and cleanliness of beaches (distance in metres between items, 1-10m) being selected for the recreational construct. The payment vehicle for the cost attribute was defined as higher local council and state taxes, payable annually for five years. Attribute levels are reported in Table 1.

[Table 1: Approximate location]

ICE construct ratings

In addition to the attributes, the sub-experiments also contained ratings of the *condition* of the constructs (see Figure 2). The ecological and recreational condition construct ratings were defined on a 10-point scale (with 1 equal to the lowest value, and 10 the highest possible value). The ecological (recreational) rating needed to be defined by the ecological (recreational) attributes and their levels. A rating task was used to ‘train’ respondents to be consistent in what they perceived the construct rating to mean. We describe this rating task using the sub-experiment-eco.

First, respondents were provided with a description of the four ecological attributes, including the four percentage levels of protection. Respondents were asked to indicate which level of each attribute represented the ‘best’ for them. This resulted in a ‘build your own’ profile of

the most preferred level of protection for all four habitat types (Johnson, Orme, and Pinnell 2006).

Second, respondents were presented with four rating questions (Figure 3 shows an example). In each of these questions, the online survey was programmed to auto-populate the best possible outcome based on the respondent's most preferred attribute levels from the 'build your own' profile. Respondents were told that this profile was scored as a 10 (i.e. optimal). Using this profile as a reference point, respondents were then asked to rate two other profiles out of 10. The levels of the attributes varied in these two profiles, according to an experimental design (see Survey design below).

Third, once respondents had completed the four separate rating questions they were asked to score the current ecological quality of Moreton Bay, again on a scale of 1-10, as an assessment of how they perceived the 'status quo'.

By completing the rating tasks respondents had some context to understand the implications of the different rating values when they were used as an attribute in the DCE (e.g. Figure 4). The status quo level of the construct shown in the DCE was based on the individuals' assessment. The recreational construct rating was determined in an equivalent process.

[Figure 3: approximate location]

[Figure 4: approximate location]

Survey design

The ICE survey versions first presented respondents with the rating exercise, followed by the choice experiment. For sub-experiment-rec, that meant respondents were first provided with the recreational attribute descriptions and associated rating questions, followed by a description of the ecological attributes and a choice experiment containing those ecological

attributes with a recreational condition construct rating. For sub-experiment-eco, the respondents completed a rating exercise on the ecological attributes, and then a choice experiment containing the four recreational attributes with an ecological condition construct rating. Respondents were also asked a series of debriefing questions, plus questions capturing standard socio-demographics, recreational activities etc.

For the full-profile survey, there was no rating exercise. Instead all eight attributes were described for both the ecological and recreational constructs, and respondents were presented with a choice experiment consisting of these eight attributes plus a cost attribute. Figure 5 gives an example of the full-profile valuation task.

[Figure 5: approximate location]

Both ICE and full-profile DCE scenarios were constructed using S efficient designs in Ngene, with 48 choice sets blocked into six blocks of eight questions for the DCE. The design involved two alternatives and a status quo. The construct rating (of ecological or recreational condition) questions were also designed to be evaluated as a choice question, with 24 questions blocked into six sets of four, with two alternatives in each set.

Sample description and data management

The sub-experiments and full profile-experiment each received between 500 and 506 complete responses. Each respondent saw eight choice scenarios after the training exercises, and it is the choice scenario responses that are the subject of analysis here. Note that samples for each sub-experiment and the full profile-experiment were mutually exclusive. Samples were collected from an online panel in February and March 2017. Respondents were residents of South-East Queensland local government areas and summary statistics for the final samples and South-East Queensland region (for comparison) are presented in Table 2.

We note that the percentage of female respondents is a close match in the sub-experiment-rec sample, and slightly higher than the South-East Queensland average in the other two samples. The median income for South-East Queensland falls squarely within the median-income of all three samples, and age distributions across the samples are generally representative, although the sampled population is slightly over-representative of 31-45 year olds (24-27% versus 19%) and slightly under-representative of over 75 year olds (3-4% versus 8%). The percentage of respondents with a university degree is higher in the sampled populations relative to the census average (39-45% versus 21%). However, we note that our sample does not include 15-19 year olds, and thus will overstate the percentage of the sample with a university degree relative to the census data.

We ‘cleaned’ the data based on speed of completion (median time was approximately 15 minutes across the three versions: sub-experiments -eco and -rec and the full profile-experiment), and evidence of ‘protest’ responses. In the first case, we dropped respondents who completed the survey in under seven minutes. In the second case, respondents who selected the status quo for the seven final discrete choice questions were asked a follow-up question to identify those who legitimately preferred the status quo and those who were protesting (e.g. Subroy, Rogers, and Kragt 2018). Protest responses were identified as those who stated: ‘I don’t believe I should have to make these choices’ or ‘I believe funding to improve the recreational experience or to protect the habitats described for Moreton Bay should come from somewhere other than my own pocket’. Table 2 reports the sample numbers at each stage of the cleaning process, and the final sample used in estimation.

Within the samples there is a high level of participation in recreational activities, both water based and foreshore based (Table 2), implying a high level of engagement with the study region. As a possible screen for attribute non-attendance (Hensher and Greene 2010), we

included the de-briefing question “did you consider all of the attributes?” in each survey version. Responses to this question were remarkably consistent across all three versions (93-94% agreement, Table 2). Respondents were also asked whether they found any of the scenarios confusing or particularly difficult to answer. Again, the percentage of affirmative responses were very consistent across the three survey versions: between 25% (full-profile) and 29% (sub-experiments -eco and rec).

[Table 2: approximate location]

Analysis

All results were analysed in Stata (StataCorp 2015) with a mixed logit model—specified with a random, normally distributed, status quo coefficient. Under the mixed logit specification, the independence of irrelevant alternatives (IIA) assumption is relaxed by allowing alternatives to be correlated.

The utility function underlying choices is given by

$$U = \beta X + \varepsilon \quad (1)$$

where X is a set of attributes (the relevant individual attributes, construct rating, cost and ASC dummy), β a vector of parameters to be estimated and ε the random component to utility. Given an assumption of a Type I extreme value distribution for the random component, the probability that option i is selected out of a set of J alternatives is given by:

$$P(y = i) = \frac{\exp(\lambda \beta X_i)}{\sum_{j=1}^J \exp(\lambda \beta X_j)} \quad (2)$$

Where λ is the scale parameter, which is inversely related to the variance of the random component. λ and the parameters β are not uniquely identified, the convention is to normalise

by $\lambda=1$ (so that what is estimated and reported are normalised preference parameters). The partworths associated with attribute k are given by:

$$PW_k = -\frac{\beta_k}{\beta_{cost}} \quad (3)$$

i.e. the (negative) ratio of the attribute parameter and the monetary attribute. However, here we applied an alternative normalization and estimated models in WTP space (Scarpa, Thiene, and Train 2006), fixing the cost coefficient $\beta_{cost}=-1$, and freely estimating the (log of the) scale parameter, $\ln(\lambda)$. This means the attribute parameter estimates can be directly interpreted as WTP values. We also included a normally distributed random parameter for the ASC. This can either be interpreted as identifying heterogeneity in preferences, or an error effects model (Scarpa, Ferrini, and Willis 2005). We also tested whether there were any non-linear effects in the valuation of nominal attributes (e.g. ecological variables, *beach closure* and *cleanliness*, *length of walkways*). These were present for *length of walkways* and some ecological attributes. For the latter we included both the level of protection (measured in %) and a dummy variable for the highest level of protection at 30% (dummy variables identified as e.g. *hard substrate* (30)). We do not include any socio-demographics to explain heterogeneity in preferences—although we acknowledge that heterogeneity may be present, in the current presentation we are concerned with whether the ICE modelling approach can provide meaningful results, and how the sub-experiment sample average values compare to those from the full profile-experiment sample.

Results

We first present the results from sub-experiments -rec and -eco: the recreational and then ecological sub-experiments. We follow with an integrated model based on concatenated data from both sub-experiments, then present results from the full profile-experiment.

Sub-experiment-rec

The results of a mixed logit model for sub-experiment-rec (n=393, choice occasions =3144)—with ecological attributes and a rating for the *recreational condition* construct—are shown in Table 3. The results show that there is significant and positive WTP for protection of all habitat types with respect to the continuous variables. The coefficients for the dummy variables representing the highest level of protection (30%) for *loose* and *hard substrate* are not significant, implying that there is no decreasing marginal (or plateau) effect at that level. However, the coefficients for the 30% level of protection for the *outer bay* and *vegetated habitats* are negative and significant and demonstrate a plateau effect. Figure 6 shows the implied utility associated with increasing the level of protection for these two attributes has a ‘plateau’ effects: there is no increase in utility as one goes from the 25% to 30% level of protection (p values are 0.977 and 0.748 respectively for tests of differences between 25% and 30%.)

[Figure 6: approximate location]

Sub-experiment-eco

Results from sub-experiment-eco, with recreational attributes and a rating for the *ecological condition* construct, are shown in Table 3 (n=406, choice occasions=3241). We tested to see if *beach closure* and *beach cleanliness* needed to be treated as categorical variables and found that they could be included using the cardinal numbers. Individuals were willing to pay to

move to higher levels of *length of walkways* and *signage*, with the largest difference in utility associated with moving from the lowest to the second level, which is the status quo. This could be interpreted as a stronger preference to prevent a drop from the status quo compared to increasing the levels, which is consistent with other studies where individuals are generally more risk averse: they are willing to pay more to avoid a loss than they are willing to pay for an equivalent sized gain (Cleland, Rogers, and Burton 2015). Note that the *ecological condition* construct has a WTP that is about 2.5 times as large as the *recreational condition* construct from Table 3: generic improvements in *ecological condition* are valued more than twice as much as the *recreational condition*.

Concatenated Integrated Choice Experiment model

In Table 3 we present results from a single model with the two sub-experiment data sets (sub-experiments -eco and -rec) stacked together. We imposed that the scale parameter and variance of the status quo were the same (which is equivalent to imposing the same cost coefficient). Results (see Table 3) are very close to the previous two models (Table 3). In these results we have a single model that contains two measures of ecological value (the *ecological condition* and the four ecological attributes: *loose substrate*, *hard substrate*, *outer bay* and *vegetated habits* at their different levels) and the same for recreation.

[Table 3: approximate location]

Full profile-experiment

Table 3 also reports estimates for the model based on a design that presented all nine attributes in a single choice set: four ecological attributes, four recreational attributes and *cost*. A sample of 393 was available after cleaning (choice occasions=3144). The model specification used was similar to that estimated before: a random parameter for the status quo and estimated in WTP space. The coefficient for *beach closure* has a positive sign, but logic

would expect a negative sign—that increases in beach closure should decrease utility. *Beach cleanliness* is consistent with the previous results, but *length of walkways*, which in the previous model was increasing in utility across the three levels, now appears to have a reduction in utility as one moves from 30 to 60km. *Signage* levels medium and high have similar size values. The marginal effects for the ecological continuous variables look quite similar to the concatenated ICE model. Also in line with that model, the plateau effects for *outer bay* and *vegetated habitats* both imply that the utility associated with 30% protection is not statistically different to that of 25% (p values of 0.884 and 0.131 respectively). However, the results for *hard substrate* now implies a strong declining marginal effect at the 30% level of protection (p value of 0.002 for the difference between \$58.3 and \$37.6); where previously there was not one (see Figure 7).

[Figure 7: approximate location]

A remaining question is whether you can combine the models' concatenated ICE data with the full profile-experiment data to give a single model, with the same coefficients where appropriate. The answer is no: based on a Log Likelihood ratio test, there are systematic differences between the concatenated ICE data and the full profile-experiment data ($p < 0.001$). Given the changes in effect identified for *beach closure* and *hard substrate* this is not surprising.

Discussion

Our aim in this research was to explore a method that could capture the complexity of the marine environment in a non-market valuation exercise. Reliable information from non-market valuation approaches can enable managers to balance public values for the protection of the marine environment alongside values for other marine uses—including commercial

and recreational fishing. While as many as nine attributes have been previously included in environmental valuation studies (Norton and Hynes 2014), and 16 in health valuation (Marshall et al. 2010), it is generally recognised that including large numbers of attributes will increase cognitive burden—which may bias WTP estimates (Johnston et al. 2017). In marine valuations, however, large numbers of attributes are desirable because they allow us to better represent the complexity of the marine environment. Through an ICE, we were able to elicit the WTP of the South-East Queensland public for eight ecological and recreational attributes plus a cost attribute. By incorporating a large number of attributes, we were better able to represent the complexity of the marine environment in the valuation task.

To compare the ICE approach over a traditional discrete choice format, we conducted a full profile-experiment with all nine attributes. We hypothesized that in the full profile-experiment, respondents would struggle to compute the valuation task because it required them to make trade-offs between nine attributes (a cost attribute plus the eight recreational and ecological attributes). One might expect that increased complexity in the full profile-experiment would lead to the adoption of heuristics or other coping strategies. This increased complexity could increase the potential for attribute non-attendance between the sub-experiments and full profile-experiment. However, respondents indicated that this was not the case for them (see Table 2) when asked: “Did you consider all of the recreational and environmental features described in the scenarios when making your choices?”¹ Although the results from the full-profile mixed logit model showed greater similarities to sub-experiments -rec and -eco than we expected, they also demonstrate a number of anomalies. This was most obvious in the WTP value for *beach closure*—which was positive in the full profile-experiment (Table 3). This result is counter-intuitive as the *a priori* expectation is that respondents would not value increasing beach closures—a greater number of beach closures means they have fewer opportunities to visit the beach. Beach closures have relevance for the

sample as between 72% and 86% of respondents indicated that they have undertaken foreshore and water-based activities (respectively) in the Bay. This anomalous result suggests that respondents were unable to appropriately process nine attributes, and would most likely have had further difficulty computing additional attributes. This result supports our main conclusion—that ICE has greater face validity than a standard DCE when asking respondents to evaluate ecosystems with a large number of attributes, such as the marine environment.

The principle benefits of following an ICE approach are that a greater number of attributes can be valued than in a traditional DCE setting (Johnston et al. 2017) and that the trade-offs respondents make between higher-order constructs are captured (Molin and Timmermans 2009). The structure of ICE also provides an opportunity to understand how respondents process information when evaluating hypothetical scenarios. In these situations, respondents can employ heuristics to process the information required to evaluate their preferred choice. If some respondents employ different decision heuristics, for example, by ignoring all or some of the attributes they are evaluating, then model estimates will be erroneous and biased (Scarpa et al. 2009). These heuristics must therefore be captured through supplementary questions, or adaptations to model specifications (Scarpa et al. 2009). Using ICE, these heuristics can be investigated by interrogating how respondents conceptualise the relationship between attributes (and their levels) and constructs. In the present research, training questions helped respondents interpret constructs, but responses to training questions could also be analysed to validate how respondents aggregate attributes and their levels to identify construct values. Analysing the training questions to provide further insight into how constructs are processed by respondents is the next step in the present research. Alternative validation strategies have been employed by Oppewal, Louviere, and Timmermans (1994). In their tests, the attribute combinations defining a construct are evaluated on the same scale used to describe the experimentally varied decision construct evaluations (as described in

Molin and Timmermans 2009, p. 650). It is worth noting that, where ICE applications do not include any means to interrogate process heterogeneity, researchers must rely on the ICE assumption that constructs are universally interpreted, but with no way of validating that this is the case.

Following conventional wisdom, including large numbers of attributes in a single survey—where trade-offs can be explicitly observed—should bias WTP estimates (Johnston et al. 2017). In our results, this is demonstrated by the anomalous results for *beach closures* under the full profile-experiment. For some valuation exercises, it will not be possible to reduce a good to two constructs as we have done in our study, and three or four constructs might be needed. The ICE approach would allow for this increased number of constructs—hence, one would expect that the benefits of the ICE approach over a traditional DCE would be even more evident in this case. It is worth noting that increasing the number of constructs to three or four will inevitably increase the information that respondents must consider, irrespective of whether an ICE or DCE approach is adopted. However, the complexity of the choice task—where trade-offs are made—will be reduced under the ICE approach.

Through the ICE approach we identified that the South-East Queensland community were willing to pay between AU\$1.8 and AU\$4.7 per percentage point increase in habitat protection (although see discussion below), and between AU\$19 and AU\$48 per unit increase in recreational features in Moreton Bay. Among the ecological attributes, respondents had the highest value for the protection of *hard substrate* areas (AU\$6, level 4), which include corals. There is less hard substrate habitat in Moreton Bay than the other habitat types. This means that the WTP per unit area (e.g. m²) of hard substrate is much higher than the WTP coefficient alone would suggest. Coral reefs are known to attract large visitor numbers and hence generate large tourism revenues, for example, in the Great Barrier Reef the non-market

values generated by corals have been estimated at AUS\$45 million per annum (Hundloe, Vancley, and Carter 1987). Among the recreational attributes, *beach cleanliness*, was most highly valued by respondents, at AU\$51.1 per unit decrease in litter per m².

An interesting result is the observation of plateau effects in the results for ecological attributes: *vegetated* and *outer bay* habitats. These results suggest that the public has strong preferences for the protection of these habitat types, but only up to a level of 25%: after that the value does not increase with increased protection (e.g. to 30%). Although this could be ascribed to a ‘warm glow’ for a positive change from the status quo, but no sensitivity to scope (Czajkowski and Hanley 2009), this is not present for the other two ecological attributes. Thus, we may be seeing a decreasing marginal utility for protection, or alternatively the public is conscious of the needs of other marine users, such as fisheries or the energy sector.

This research has identified a number of remaining questions that offer promising areas for future research. First, a clear approach to assess attribute non-attendance in ICE remains unidentified—beyond the use of discretionary follow-up questions eliciting stated attribute non-attendance. Future studies could provide new insight into this area by interrogating the difference in attribute non-attendance between sub-experiment and full profile-experiments, using latent class or Bayesian approaches (Kragt 2013; Scarpa et al. 2009). This additional analysis would help establish if ICE is better or worse at addressing this issue than standard DCE approaches. Second, more efficient ways of testing for process heterogeneity could be developed. In the current survey, inclusion of the training questions considerably lengthened the survey. Future researchers may find a more succinct method to evaluate respondent’s understanding of how attributes are combined to form constructs. Finally, more environmental case studies are needed to fully understand the validity of the ICE approach to

assess preferences for these goods. This replication would help explain whether respondents are able to process a full profile-experiment: 1) with more than two constructs; and 2) where both or all constructs are unfamiliar. In our case it is reasonable to assume that respondents were more familiar with the recreational-based construct than the environmental one, and thus would have had an easier time processing these additional attributes. The successful application of the current ICE further suggests that it may be possible to include a larger number of higher-order constructs to more closely approximate the true complexity of environmental systems, and we recommend this as an area of future research.

We have demonstrated how an ICE approach can improve the valuation of marine environments. This result is timely as the marine environment has never before been under greater pressure by competing user groups (Gunderson, Armstrong, and Stillman 2016). The ICE approach could be used in a variety of environmental contexts to improve our understanding of the community's preferences for complex goods. By using valuation approaches that can incorporate greater complexity, we can better encapsulate the community's value for the marine environment and thus better maximise social welfare from planning decisions.

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Table 1. Attribute Levels Used in all Surveys.

| | Levels | Description |
|------------------------|-------------------------|--|
| Ecological | | |
| Vegetated habitats | 10, 18 (SQ), 25, 30% | % of ecosystem under marine protected area |
| Outer bay | 10, 16 (SQ), 25, 30% | % of ecosystem under marine protected area |
| Loose substrate | 10, 15 (SQ), 25, 30% | % of ecosystem under marine protected area |
| Hard substrate | 10, 18 (SQ), 25, 30% | % of ecosystem under marine protected area |
| Ecological condition | 2, 5, 8, 10 | Ecological rating |
| Recreational | | |
| Length of walkways | 15, 30 (SQ), 60 | Length of walkways (km): 15, 30, 60 |
| Signage | 1, 2 (SQ), 3 | Low: information about facilities, e.g. appropriateness for swimming and availability of toilets or picnicking areas. Medium: information about facilities, but also about appropriate conduct within the area for visitors' safety and for the protection of native plants and animals. High: information regarding facilities and appropriate conduct within the area, but also information on the environmental attributes of the area. |
| Beach closure | 5, 10 (SQ), 15 | Days of beach closure |
| Beach cleanliness | 1, 2 (SQ), 3 | Cleanliness of beach (metres/litter item) coded as low (1m); medium (5m); high (10m) |
| Recreational condition | 2, 5, 8, 10 | Recreation rating |
| Cost | 0 (SQ), 5, 50, 100, 150 | \$/year, for 5 years |

NOTES. SQ=Status quo levels. For the ecological and recreational condition ratings, the status quo level is set at the level reported by the individual. This means the values for the status quo level for these variables can range from 1-10.

Table 2. Sample Size and Socio-demographics for the Three Surveys and South-East Queensland Census Population.

| | Sub-experiment- rec | Sub-experiment- eco | Full profile- experiment | South-East Queensland |
|---|------------------------|------------------------|-----------------------------|--------------------------|
| Initial sample | 500 | 506 | 500 | |
| <=7 minutes | 71 | 45 | 66 | |
| Subtotal | 429 | 461 | 434 | |
| Protesters | 36 | 55 | 41 | |
| Final sample | 393 | 406 | 393 | |
| Descriptive statistics | | | | |
| % female | 54% | 57% | 56% | 51% |
| Median income (\$) | 62,400 - 88,399 | 62,400 - 88,399 | 62,400 - 88,399 | 65,000 - 77,948 |
| % university degree | 41% | 39% | 45% | 21% ¹ |
| Age distribution | | | | |
| 18-30 | 18% | 16% | 16% | 19% ² |
| 31-45 | 24% | 27% | 24% | 19% |
| 46-60 | 30% | 32% | 26% | 27% |
| 61-74 | 24% | 23% | 30% | 27% |
| 75+ | 4% | 3% | 4% | 8% |
| Undertaken water based activities in bay | 77% | 72% | 76% | |
| Undertaken foreshore based activities in bay | 87% | 82% | 86% | |
| Did you consider all of the attributes? (% Yes) | 94 | 94 | 93 | |
| Did you find the scenarios confusing or particularly difficult to answer? (% Yes) | 29 | 29 | 25 | |

¹Of those aged 15+. Note that our education age is normalised by people older than 18. The census data reports from 15+ years. Therefore, the denominators across our sample and the census population are not equivalent—the census population will deflate the final percentages reported as they include 15-19 y/o in their sample. ²Age groups are as close a match to the census data groupings as possible (one year variation at the margin).

Table 3. Mixed Logit Results for Sub-experiment-rec, Sub-experiment-eco, Concatenated Data, and Full Profile-experiment.

| Attribute (level) | Coef.# | 95%CI | Coef.# | 95%CI | Coef.# | 95%CI | Coef.# | 95%CI |
|-------------------------|--------------------|------------------|--------------------|-------------------|-------------------|-------------------|--------------|------------------|
| | Sub-experiment-rec | | Sub-experiment-eco | | Concatenated data | | Full-profile | |
| Cost | -1 | NA | -1 | NA | -1 | NA | -1 | NA |
| Beach closure | | | -8.7 ** | [-15.5, -1.8] | -8.9 *** | [-15.2, -2.7] | 7 * | [-1.0, 15.1] |
| Beach cleanliness | | | 51.1 *** | [42.9, 59.3] | 47.9 *** | [41.2, 54.6] | 43.2 *** | [36.1, 50.3] |
| Length of walkways (2) | | | 22.4 *** | [8.7, 36.2] | 19.0 *** | [6.8, 30.9] | 20.5 *** | [10.2, 30.7] |
| Length of walkways (3) | | | 38.5 *** | [25.5, 51.4] | 36.5 *** | [24.9, 48.1] | 14.1 ** | [2.3, 26.0] |
| Signage (2) | | | 24.3 *** | [12.1, 36.6] | 24.2 *** | [13.1, 35.4] | 13.5 ** | [1.8, 25.1] |
| Signage (3) | | | 32.4 *** | [18.5, 46.2] | 32.7 *** | [20.0, 45.3] | 28.6 *** | [17.6, 39.7] |
| Ecological condition | | | 16.0 *** | [13.4, 18.5] | 15.1 *** | [13.0, 17.3] | | |
| Loose substrate | 2.0 *** | [1.1, 2.9] | | | 1.8 *** | [0.9, 2.8] | 1.8 *** | [1.0, 2.5] |
| Loose substrate (30) | -4.7 | [-21.2, 11.7] | | | -3.6 | [-21.3, 14.1] | 7.3 | [-7.5, 22.0] |
| Hard substrate | 2.0 *** | [1.1, 2.8] | | | 2.1 *** | [1.2, 3.0] | 2.3 *** | [1.5, 3.2] |
| Hard substrate (30) | 6.0 | [-7.5, 19.5] | | | 4.7 | [-9.9, 19.2] | -34.4 *** | [-50.9, -17.8] |
| Outer bay | 3.8 *** | [2.9, 4.6] | | | 4.0 *** | [3.1, 4.9] | 3.4 *** | [2.5, 4.3] |
| Outer bay (30) | -18.7 ** | [-33.8, -3.9] | | | -20 ** | [-35.9, -4.0] | -15.9 * | [-32.9, 1.1] |
| Vegetated habitats | 4.3 *** | [3.4, 5.2] | | | 4.5 *** | [3.6, 5.5] | 3.9 *** | [3.1, 4.8] |
| Vegetated habitats (30) | -19.7 *** | [-34.0, -5.3] | | | -20.3 *** | [-35.8, -4.9] | -29.2 *** | [-44.6, -13.8] |
| Recreational condition | 6.1 *** | [4.5, 7.7] | | | 5.9 *** | [4.2, 7.7] | | |
| Status quo v2 | | | | | 32.9 *** | [7.9, 57.9] | | |
| Status quo | -12.2 | [-28.8, 4.3] | 30.2 *** | [8.5, 51.9] | -9.5 | [-26.3, 7.2] | -8.8 | [-27.9, 10.3] |
| Status quo (SD) | 143.0 *** | [122.0, 164.0] | 142.1 *** | [119.2, 165.1] | 141.9 *** | [126.6, 157.1] | 140.9 *** | [-162.7, -119.1] |
| Scale coefficient | 0.0153 *** | [0.0137, 0.0139] | 0.0126 *** | [0.0110, 0.01443] | 0.0111 *** | [0.0129, 0.01519] | 0.0149 *** | [0.0130, 0.0168] |
| No of observations | 3144 | | 3241 | | 6385 | | 3144 | |
| No of respondents | 393 | | 406 | | 799 | | 393 | |
| Log likelihood | -2723.81 | | -2504.52 | | -5232.1 | | -2661.2 | |

[#]Estimates in WTP space, and represent WTP in \$'s per unit change in attribute, per year for 5 years. Note that each respondent saw eight choice questions.

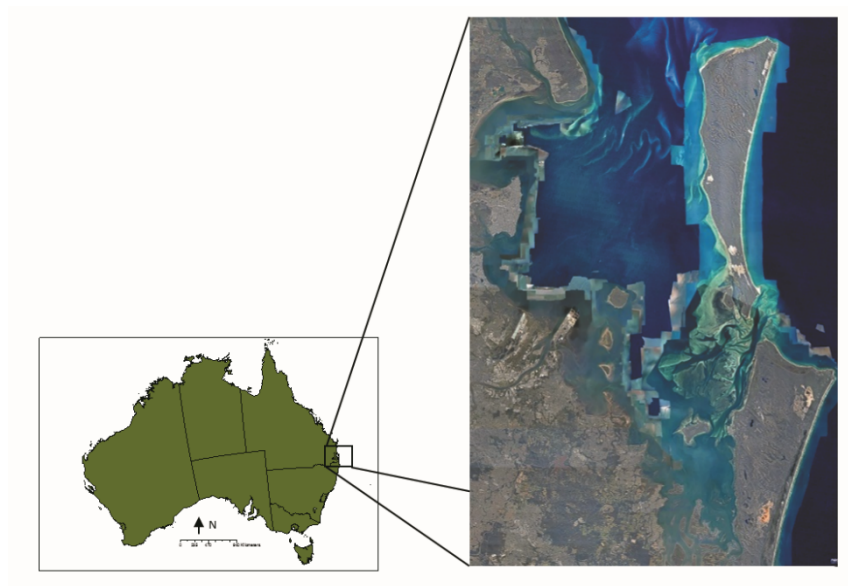


Figure 1. Moreton Bay in South-East Queensland, Australia.

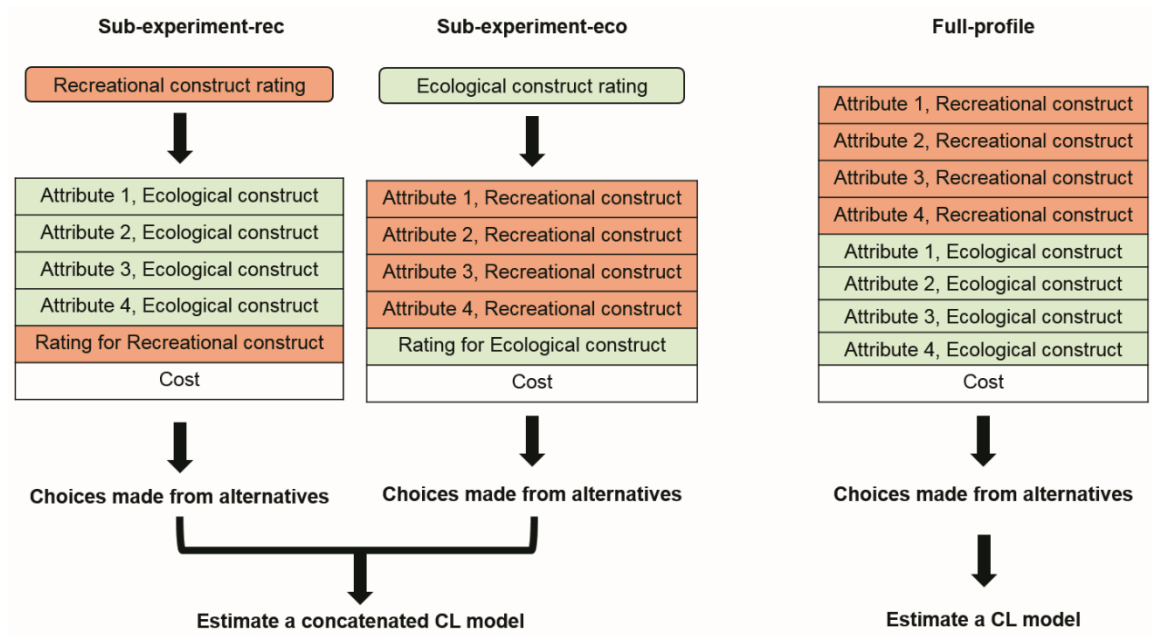



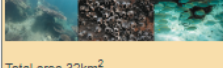


Figure 2. Stylised Representation of the Two Sub-experiment Profiles in the Integrated Choice Experiment, and the Full Profile-experiment. CL=Conditional Logit.

| Habitat type | | Option 1 | Option 2 | Your best possible combination |
|---|--------------------------------------|----------|----------|--------------------------------|
|  Total area 550km ² | Percent of vegetated habitats | 25% | 30% | 30% |
|  Total area 1262km ² | Percent of outer bay | 25% | 10% | 25% |
|  Total area 1620km ² | Percent of loose substrate | 10% | 15% | 30% |
|  Total area 32km ² | Percent of hard substrate | 10% | 25% | 18% |

For Options 1 and 2, score the quality of the environmental condition from 1 (worst possible condition) to 10 (best possible condition):


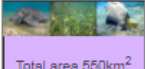

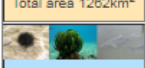
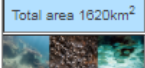


Figure 3. Example ecological construct rating question, sub-experiment-eco. ‘Your best possible combination’ is based on prior response by respondent. In this example, the respondent had indicated in the ‘build your own’ task that protection for *hard substrate* was not important to them.

Management scenario 1: Consider the following options.

Assuming these are the only options available to you, which one would you choose?

Keep in mind what you can afford when weighing up the cost of each option.

| | | Option 1 | Option 2 | Option 3 (Current situation) | |
|---|---|----------|----------|---------------------------------|--|
|  | Recreational experience | 5 | 5 | 6 | Score out of 10 |
|  Total area 550km ² | Percent of vegetated habitats | 30% | 30% | 18% | Percentage protected as Marine National Park |
|  Total area 1262km ² | Percent of outer bay | 25% | 10% | 16% | |
|  Total area 1620km ² | Percent of loose substrate | 30% | 10% | 15% | |
|  Total area 32km ² | Percent of hard substrate | 10% | 18% | 18% | |
| | Cost to you, \$/year for the next 5 years | \$5 | \$5 | \$0 | |

Which one would you choose?

Option 1

Option 2

Option 3

Figure 4. Example valuation question, sub-experiment-rec. Respondents were asked to select their preferred option. In this example, the respondent had given the current recreational experience of Moreton Bay a ‘6’.

Management scenario 1: Consider the following options.

Assuming these are the only options available to you, which one would you choose?

Keep in mind what you can afford when weighing up the cost of each option.

| | | Option 1 | Option 2 | Option 3 (Current situation) | |
|---|--|-------------------|------------------|---------------------------------|---|
|  | Beach closure | 15 days per annum | 5 days per annum | 10 days per annum | Levels |
|  | Beach cleanliness | Medium | High | Medium | |
|  | Walking trails | 15 km | 30 km | 30 km | |
|  | Signage | Low | Medium | Medium | |
|  | Vegetated habitats | 25% | 10% | 18% | Percentage protected as Marine National Park |
|  | Outer bay | 10% | 10% | 16% | |
|  | Loose substrate | 10% | 15% | 15% | |
|  | Hard substrate | 18% | 10% | 18% | |
| | Cost to you, \$/year for the next 5 years | \$5 | \$5 | \$0 | |

Which one would you choose?

Option 1

Option 2

Option 3

Figure 5. Example valuation question, full profile-experiment.

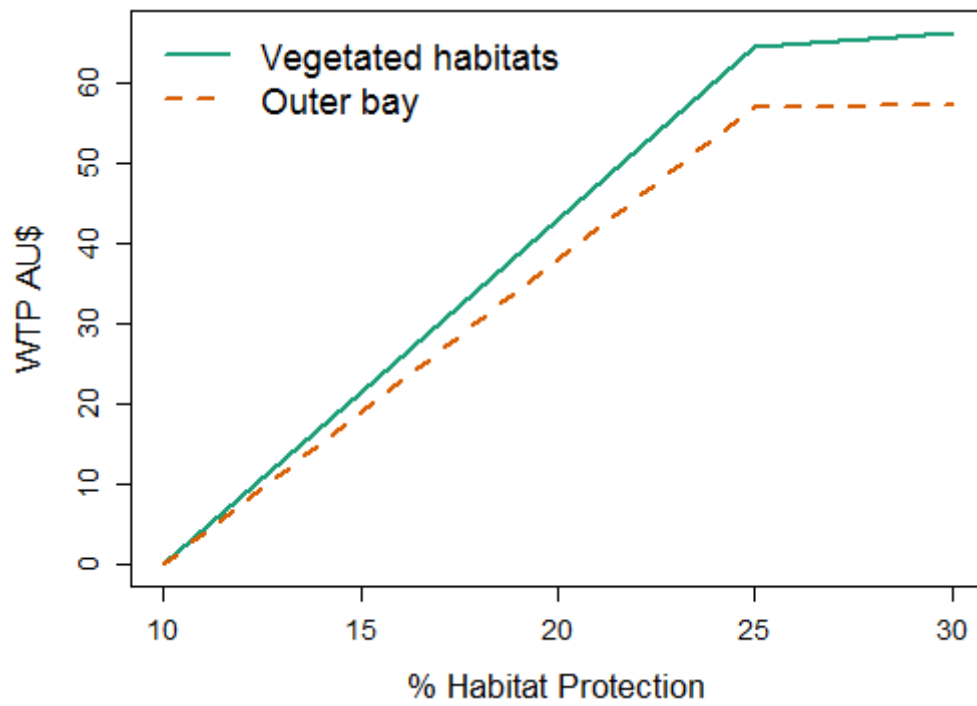


Figure 6. Willingness to pay for different levels of *outer bay* and *vegetated habitat* protection: sub-experiment-rec.

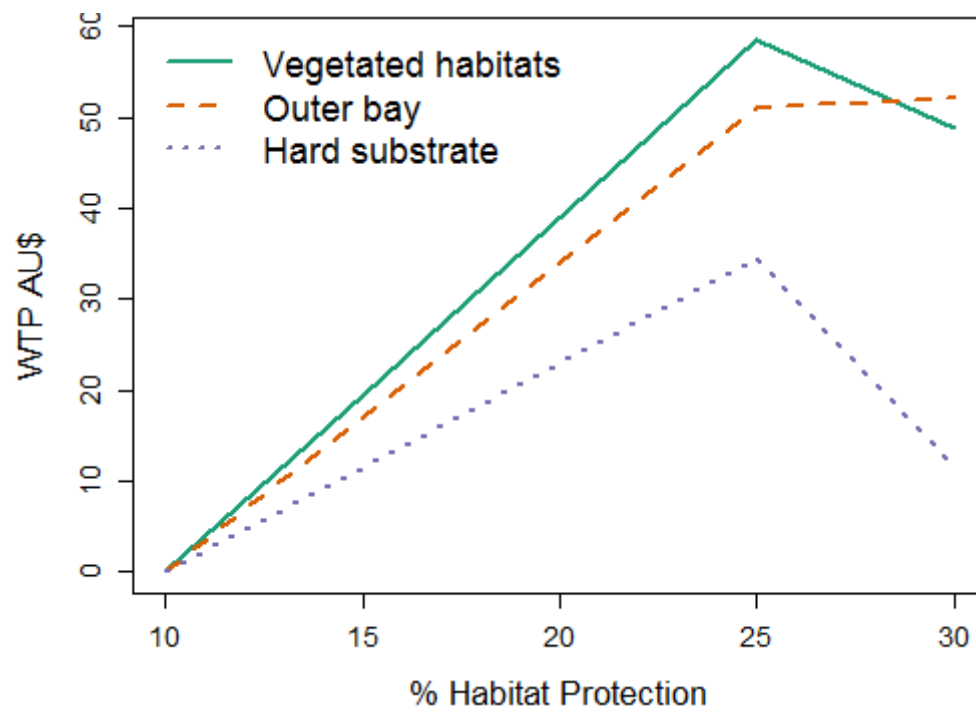


Figure 7. Willingness to pay for changes in area protected for *hard substrate*, *vegetated* and *outer bay*: full profile-experiment.

¹ We note that there could be differences between stated and inferred attribute non-attendance (Kragt 2013), and that investigation of the latter could reveal a different result.