ISSN 1835-9728
Environmental Economics Research Hub
Research Reports

Ordering effects and strategic response in discrete choice experiments

Gabriela Scheufele and Jeff Bennett

Research Report No. 93

March 2010

About the authors

Gabriela Scheufele is PhD student in the Crawford School of Economics and Government at the Australian National University.

Jeff Bennett is Professor at the Crawford School of Economics and Government at the Australian National University.

Environmental Economics Research Hub Research Reports are published by the Crawford School of Economics and Government, Australian National University, Canberra 0200 Australia.

These Reports present work in progress being undertaken by project teams within the Environmental Economics Research Hub (EERH). The EERH is funded by the Department of Environment and Water Heritage and the Arts under the Commonwealth Environment Research Facility.

Crawford School of Economics and Government
THE AUSTRALIAN NATIONAL UNIVERSITY
http://www.crawford.anu.edu.au

TABLE OF CONTENTS

Abstract

This study explores ordering effects and response strategies in repeated binary discrete choice experiments (DCE). Mechanism design theory and empirical evidence suggest that repeated choice tasks per respondent introduce strategic behavior. We find evidence that the order in which choice sets are presented to respondents may provide strategic opportunities that affect choice decisions ('strategic response'). The findings propose that the 'strategic response' does not follow strong cost-minimization but other strategies such as weak cost-minimization or good deal/ bad deal heuristics. Evidence further suggests that participants, as they answer more choice questions, not only make more accurate choices ('institutional learning') but may also become increasingly aware of and learn to take advantage of the order in which choice sets are presented to them ('strategic learning').

Keywords: discrete choice experiments, incentive compatibility, mixed logit models, ordering effects, repeated binary choice task, response strategies

1 Introduction

Discrete choice experiments (DCE) is a non-market valuation technique that is being increasingly used in policy analysis (Bateman et al 2006; Bennett and Blamey 2001). One advantage of DCE over other techniques (such as contingent valuation) is its potential to elicit implicit prices for individual attributes that jointly describe a particular good or service. In order to increase the statistical efficiency of DCE for a given number of respondents it is common practice to present each respondent with a sequence of choice questions rather than restricting the choice format to a single referendum. However, it is well known that all non-dictatorial mechanisms except a single binary choice format are generically incentive incompatible. Both, mechanism design theory and empirical evidence suggest that repeated choice tasks per respondent introduce strategic behavior[1].

The main objective of the study presented in this paper is to explore the effects of repeated choice questions on choice behavior. In particular, this paper investigates (1) whether the order in which choice sets are presented to respondents provides strategic opportunities that affect choice decisions ('strategic response'), (2) what response strategies respondents use to exploit these strategic opportunities, and (3) whether respondents increasingly become aware of and learn to take advantage of a particular choice set order ('strategic learning') as they answer more choice questions.

The next section reviews the literature that is concerned with strategic response in DCE. Section three provides an overview of the survey logistics, an explanation of the research design, the formulation of the hypotheses, information about the experimental design, and a discussion of the econometric framework. Results are reported in section four. In the last section, the results are discussed and conclusions drawn.

2 Literature Review

Mechanism design theory, originated by Hurwicz (1960), in particular the Gibbard-Satterhwaite theorem (Gibbard 1973; Satterthwaite 1975), provides a theoretical foundation to analyze the incentive properties of choice formats used in DCE. The theorem states that all

[1] The literature also suggests other effects caused by sequential choice formats such as institutional learning, fatigue, and value learning (e.g., Braga and Starmer 2005; Plott 1996). These impacts, however, are not in the focus of the investigation presented in this paper.

non-dictatorial mechanisms other than a single binary choice format are generically incentive incompatible[2,3,4,5]. Asking respondents to choose between more than two options and presenting respondents with more than one choice question changes the incentive properties of DCE. Hence, under such circumstances revealing preferences truthfully is not a dominant strategy for all participants. Irrespective of their problematic incentive properties, DCE using repeated multiple choice formats have been frequently conducted to inform policy decisions. Potentially biased results in this respect are thus accepted for the commonly assumed increase in statistical efficiency of the data for a given number of survey participants[6]. The extent of this bias remains unknown.

One effect of repeated choice tasks that employ a plurality vote implementation is the introduction of conditional preferences. The literature on incentive compatibility proposes that respondents may adjust their preferences on expectations about the choices of other survey participants (see, for example, Carson and Groves 2007). Accordingly, the dominant strategy for some respondents may be to choose a less preferred option across choice

---

[2] A widely cited example for an incentive compatible mechanism is a binding referendum between two candidates in an election. Carson and Groves (2007) provided evidence to suggest that replacing the binding character of the referendum by an advisory referendum does not change the incentive compatibility properties of the mechanism. Green and Laffont (1978) showed that this also holds for a sample rather than population based referenda. This is important since the majority of choice experiments use statistical samples and, when dealing with public goods, frequently simulates an advisory referendum.

[3] The Gibbard-Satterthwaite theorem also holds for Nash implementations if provision rules are required to be singleton-valued (see Maskin 1977; Muller and Satterthwaite 1985). A non-singleton provision rule may result in potentially incentive compatibility. Many policy decisions that are concerned with the provision of environmental goods and services, however, are confronted with mutually exclusive policy scenarios, that is, the choice of a single scenario is required. Therefore, using a mechanism with a Nash implementation is not a feasible alternative. Carson and Groves (2007) pointed out that in the case of private and quasi-public goods the provision of more than one good may be possible, that is, the provision rule is not singleton-valued. This provides the possibility of an incentive compatible Nash implementation, that is, respondents' incentives to untruthfully reveal their preferences may be reduced.

[4] Laboratory choice experiments frequently employ a provision rule that is based on a randomly drawn choice question to be binding, which increases the probability that respondents disclose their true preferences (see, for example, Collins and Vossler 2009). Policy decisions of public goods valued in field studies that are based on random draws, however, raise credibility concerns (Carson and Groves 2007). Hence, the results of laboratory experiments that apply a random provision rule are inapplicable to explain strategic behavior in the context of public goods.

[5] Carson and Groves (2007) add an additional aspect to the discussion of incentive compatibility in DCE. They argue that survey participants only reveal their preferences truthfully if the survey is consequential: The good or service under consideration has to be relevant to respondents, and respondents have to expect that their choices influence policy outcomes. Otherwise, respondents perceive choice options as equally non-beneficial and indistinguishable. Under such circumstances it remains unknown whether or not respondents reveal their true preferences. Associated drivers postulated to additionally influence choice behavior include the properties of the payment vehicle, plausibility of the choice questions, credibility of the policy scenario, and comprehensibility of the choice task (Carson and Groves 2007).

[6] Rose et al. (2009) used simulated data to investigate the statistical impact of panel data in discrete choice experiments. Their study provided evidence that for a given sample size increasing the number of observations per respondents yields less biased estimates and larger t-ratios. However, this advantage diminished with increasing sample size.

questions if they expect that their most preferred option has no chance of winning[7]. In contrast to this theory, Scheufele and Bennett (2010) did not find empirical evidence of such dependencies across respondents. However, their findings were based on follow-up questions with unknown incentive properties[8]. Thus, respondents' answers may be strategically biased and may therefore not reflect their actual choice behavior.

Another consequence that is expected to arise from sequential choice formats are dependencies across multiple choice questions given to each respondent. Respondents may exploit strategic opportunities by involving information about previous choice sets and choice decisions (see, for instance, Carson and Groves 2007). As a result, a dominant strategy for some respondents may be to choose a less preferred option in one or more binary choice questions.

Only a few empirical studies have investigated such lead and lag dependencies. Holmes and Boyle (2005) considered a sequence of four binary choice questions, one of which was the status quo. They found a structural influence of previous and successive choice sets on current choices. Bateman et al. (2008) explored an additional aspect of incentive properties associated with sequential elicitation formats. They found evidence that repeated choice dynamically increases awareness of strategic opportunities as progress in made through the choice task. Such strategic opportunities provide incentives to misstate rather than to disclose truthfully preferences. Previous and successive choice sets may contain alternative prices for the same or a similar level of provision of a particular good or, vice versa, the same or similar price for alternative levels of provision of a particular good. This may cause respondents either to question the credibility of the survey or learn to take advantage of this inconsistent pricing by rejecting a preferred choice option when the same or a similar level of provision was offered in a previous or successive choice question at a lower price.

The empirical evidence of Bateman et al. (2008) thus expands the well-established notion of learning in terms of 'institutional learning' (Braga and Starmer 2005) and 'value learning' (Plott 1996). 'Institutional learning' describes a process where respondents become increasingly familiar with the choice context, the offered good, and the choice task. This process of learning results in more accurate choices reflected in the scale factor[9] rather than in

[7] This is also true for a single multiple choice format. In that case, a single multiple choice format collapses to a binary choice between the two choice options that the respondent perceives to be other respondents' most preferred choice option if a plurality vote provision rule is applied. However, a single multinomial elicitation format may be potentially incentive compatible if respondents have uniform priors about other respondents' preferred choices (Moulin 1994).

[8] Follow-up question: 'When making your choices, did you consider what other respondents might choose?' (Five point Likert scale)

[9] The scale factor is inversely related to the variance of the error distribution (Swait and Louviere 1993).

a preference change. 'Value learning' suggests that respondents 'discover' their true underlying preferences through a learning process rather than possessing stable preferences. This process is expected to affect parameter estimates. In contrast, 'strategic learning' as proposed by Bateman et al. (2008) hypotheses a process where survey participants become increasingly familiar with the strategic opportunities provided by the choice task and adjust their choices without changing their preferences accordingly. Hence, the analysis of strategic response may be challenged by confounding effects of 'institutional learning' and 'value learning' and care should be taken when interpreting the results.

The findings of Bateman et al. (2008) are backed by McNair et al. (2010) who provide evidence that increasing the number of choice sets per respondent decreases estimates of WTP, and that this effect may be explained by the ordering of alternative cost levels offered across a sequence of four choice questions. The influence of ordering effects on choice experiments is further supported by findings of Day and Pinto Prades (2010). However, they found little support to explain the influence of ordering effects on choice experiments by strategic behavior in terms of Carson and Groves (2007).

Bateman et al. discuss (2008) alternative response strategies including strong and weak versions of cost-minimization and good deal/ bad deal heuristics. Respondents who follow a strong cost-minimization strategic assume that the good can be provided at the lowest cost offered. Hence, they are expected to choose never an option if a similar level of provision was offered in a previous choice set at lower cost. In contrast, respondents who employ weak cost-minimization or good deal/ bad deal heuristics are assumed to trade-off between minimizing costs and reducing risks that the provision at a low cost level might not be provided. The difference between these two strategies lies in the assumption that respondents who follow the former have stable preferences whereas those who employ the latter do not.

Using the study of Bateman et al. (2008) as a starting point, choice sets can be classified by strategic categories as follows[10]:

(1) Choice sets with a cost level that is both the minimum and the maximum presented to the respondent in the sequence to that point. Such choice sets are only positioned at the beginning of the sequence (*first*).

(2) Choice sets with a cost level that is the minimum presented to the respondent in the sequence to that point (*min*).

[10] The categorization is based on McNair et al. (2010), and was further developed in discussion with those authors.

(3) Choice sets with a cost level that is the maximum presented to the respondent in the sequence to that point (*max*).

(4) Choice sets with a cost level that is neither the minimum nor the maximum presented to the respondent in the sequence to that point (*none*).

This choice set categorization facilitates testing whether the order in which choice sets are presented to respondents provides strategic opportunities that affect choice decisions ('strategic response'). It allows further the investigation of response strategies employed by respondents. A strong cost minimizing strategy assumes that respondents always choose the options with the lowest cost, ceteris paribus. This implies that the choice categories for *max* and *none* would be empty sets. Since the *first* choice set does not provide any strategic opportunities, the choice share of a non-zero cost option of *first* category is expected to be larger than the one of the *min* category.

This review of the literature suggests that few empirical studies have investigated effects of repeated choice, and in particular strategic behavior caused by incentive incompatible elicitation formats in DCE. We are unaware of any work apart from McNair et al. (2010), Bateman et al. (2008), and Day et al. (2010) that explored ordering effects and strategic response in sequential choice experiments. The main objective of this study is to investigate further effects of multiple choice questions per respondent induced by strategic behavior. Contrarily to McNair et al. (2010) we explore these effects using a pure public good that provides use and non-use values rather than a public good with private elements. We extend the study of Bateman et al. (2008) by investigating alternative approaches such as relating choices to observed strategic categories. Finally, our study expands the research of Day et al. (2010) by employing both nonparametric statistics and parametric econometric analysis.

In particular, we explore the following hypotheses:

H_0^1: The order in which choice sets are presented to respondents does not provide strategic opportunities that affect choice decisions ('strategic response').

H_0^2; Respondents use strong cost-minimizing strategies to exploit opportunities that arise from the particular order in which choice sets are presented.

H_0^3: Respondents do not increasingly become aware of and learn to take advantage of a particular choice set order ('strategic learning') as they answer more choice questions.

3 Empirical Application

The hypotheses are tested using data from a DCE concerned with estimating use and non-use values of a public good, the preservation of a natural area, using Nadgee Nature Reserve as an example. Nadgee Nature Reserve is one of the largest coastal wilderness areas in New South Wales, Australia, and covers an area of 17,116 ha. It is pristine and has a high level of landscape diversity. The data set used in this study is derived from a random sample of the population of Sydney drawn from an internet panel[11]. The data were collected using an internet based survey[12]. The survey material was developed using expert opinions and focus groups[13]. A pilot survey was conducted to test the survey material and internet set-up, as well as to obtain parameter priors for the development of the experimental design. The final survey was structured as follows. In the first part, respondents were asked about their socio-demographic characteristics as well as their general experience of visiting protected areas in Australia or worldwide. In the second part respondents were provided with background information including photographs and explanations about the reserve and future management options. The reserve was described in term of the features of Nadgee Nature Reserve, even though it was presented as an area of land without revealing its identity. Respondents were told that funds had to be raised to enable the government to purchase the land, and thus conserve the area. A plurality vote was used as provision rule[14]. The third part of the survey asked respondents to make trade-offs between future management options including development and preservation alternatives (see Figure 1). The management options were described by three attributes with five, four, and two levels, respectively (see Table 1). In order to increase understanding of the choice task, respondents were presented with an

---

[11] Only Australian citizens or permanent residents of Australia 18 years or above qualified to participate.

[12] The overall response rate was 34%; invited but not participated (55%); participated but below five minutes completion time (2%); participated but dropped out before completion (9%).

[13] Two focus groups are conducted in Canberra. In order to ensure the applicability of the survey material for a sample of the population of Sydney the pilot survey included four follow-up questions at the end of the questionnaire. Respondents were asked if they had any concerns, comments or suggestions with any part of the questionnaire. Obtained information was used to adjust the survey material accordingly.

[14] The management option that receives the greatest support would be implemented and everyone would have to make the payment associated with that management option.'

explanation of the outcome of their first choice and given the opportunity to revise it (see Figure 2). The final part of the survey asked follow-up questions as well as additional questions about socio-economic characteristics of the respondents.

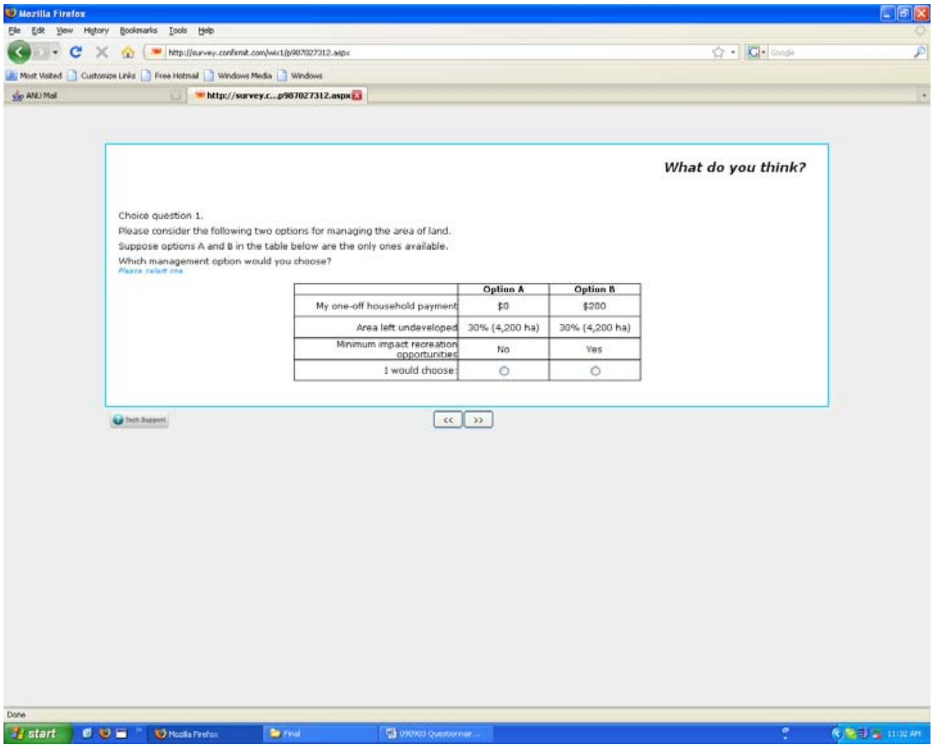

Figure 1: Example of choice set

Table 1: Attributes

Attribute	Attribute level	Coding
Cost	$0 $50 $100 $200 $300	numerical
Area of land	30% (4,200ha) 50% (7,000 ha) 70% (9,800 ha) 100% (14,000 ha)	numerical
Access for minimum impact recreation	yes no	1 -1

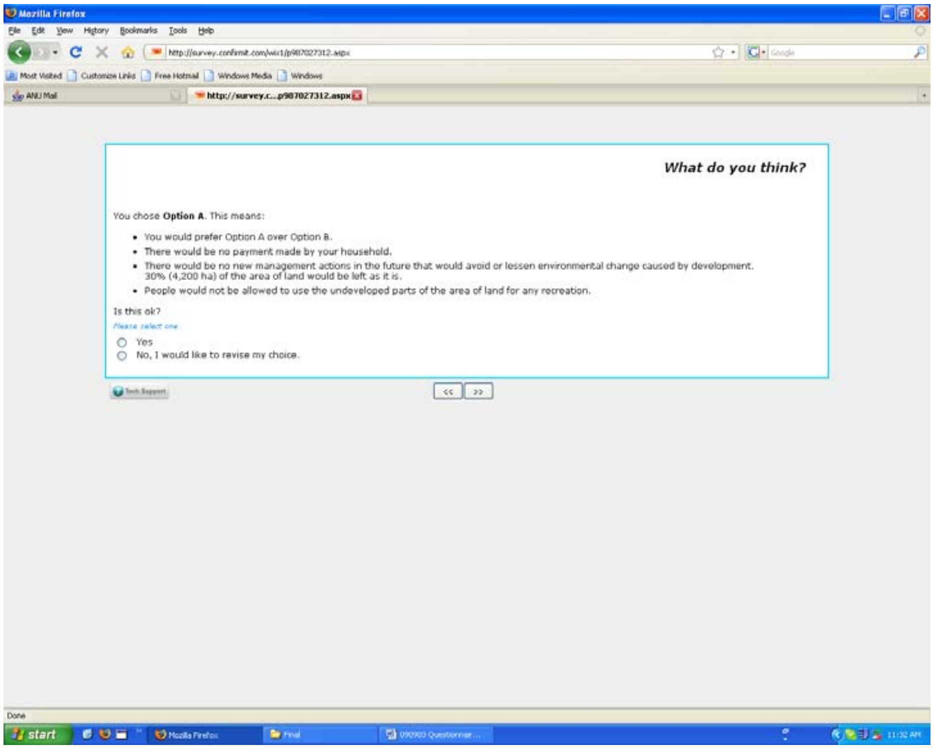

Figure 2: Example of choice set explanation

The underlying experimental design used to collect the data contained a total of 16 choice sets. Each choice set consisted of two choice options: one invariant zero cost choice option that was available in each choice set and one non-zero cost choice option that varied across choice sets. The 16 choice sets were divided into four blocks of four choice questions per respondent. The order of the four choice questions of each block was altered. The blocks were randomly assigned to respondents.

The following methods are employed to test the stated hypotheses:

Hypothesis 1 & 2

In order to test H_0^1 and H_0^2 we identify response strategies that are cable to explain ordering effects. Choice shares for the non-zero cost options of four strategic categories of choice questions (*first, min, max, none*) are identified while holding *area of land* and *cost* attribute levels constant. The choice shares of non-zero cost options are expected to differ across strategic categories of choice questions. The largest choice share is anticipated for choice sets in the *min* category, followed by the *first* category, the *none* category, and the *max* category.

In order to investigate H_0^1 and H_0^2 further effects coded variables representing the strategic category of the choice set were interacted with the constant term (*first*con, min*con, max*con, none*con*) and incorporated in a MNL and a panel MML model. The constant term was included in the utility function of the non-zero cost option. Positive parameter estimates indicate that respondents who are presented with a choice set in a particular category are more likely to choose a non-zero cost option than those in an alternative one, and vice versa. It is expected that these variables are statistically significantly different from zero with a positive sign for the *min* and *first* categories and a negative sign for the *max* and *none* categories.

Additionally, the *first, min*, *max* and *none* variables were interacted with the *cost* attribute to obtain the variables *first*cost*, *min*cost*, *max*cost* and *none*cost*. Positive parameter estimates indicate that respondents who are presented with a choice set in a particular category have a higher WTP than when presented with a choice set in an alternative category, such that

$$wtp = \frac{\beta^k}{-[\beta^m + \beta^{categeory*\cos t}]}.$$

It is expected that these variables are statistically significantly different from zero with a positive sign for the *min* and *first* categories and a negative sign for the *max* and *none* category.

Hypothesis 3

Following the approach of Bateman et al. (2008), interaction variables of the cost attribute and an effects coded variable indicating the position of the choice question in the sequence (*position-1*cost*; *position-2*cost*; *position-3*cost*; *position-4*cost*) were included in a MNL and a panel MML model to test and H_0^3[15]. A decreasing value of the *position*cost* parameters indicates that the marginal utility of income increases across the sequence of choice sets. This implies a decrease of WTP along the sequence of choice questions, such that

$$wtp = \frac{\beta^k}{-[\beta^m + \beta^{position*\cos t}]}.$$

[15] Bateman et al. (2008) used the logarithm of the position to account for the assumption that having 17 choice sets the effect will be more rapid decline within the first few choice sets. In this study, however, respondents were only given four choice sets.

The prior expectation is a decreasing WTP when moving from the first to the fourth choice question.

In order to investigate H_0^3 further, we divided the data set by choice set position (P1, P2, P3, P4) and compared the DCE outcomes of the choice questions related to the first, second, third, and fourth choice set position. The prior expectation is that the bid acceptance curve of P1 lies above those of the other P2, P3, and P4. We anticipate a difference in the acceptance rates of non-zero cost options, decreasing magnitude of the parameter vector, increasing scale factors, and decreasing WTP from the first choice question along the sequence.

The complete research design is summarized in Table 2.

Table 2: Research design

H_0^1, H_0^2	
Test method 1	Comparisons of choice shares across strategic categories
Test method 2	Inclusion of effects coded variables in econometric models representing strategic categories (*category*con*; *category*cost*)[16]. Coding: First: 1,0,0 (1,0,0) Min: 0,1,0 (-1,-1,-1) Max: 0,0,1 (0,0,1) None: -1,-1,-1 (0,1,0)
H_0^3	
Test method 1	Inclusion of interaction variables in econometric models representing the position of the choice question (*position*cost*)[17] Coding: First: 1,0,0 (1,0,0) Third: 0,1,0 (-1,-1,-1) Fourth: 0,0,1 (0,0,1) Second: -1,-1,-1 (0,1,0)
Test method 2	Comparison of choice shares, did acceptance curves, parameter vectors, scale factors, WTP across P1, P2, P3, P4

All choice sets were created using a Bayesian D-efficient design (Bliemer et al 2008). Bayesian D-efficient designs are statistically efficient designs (see, for example, Ferrini and Scarpa 2007; Rose and Bliemer 2008; Rose et al 2008). Statistically efficient designs aim to maximize the amount of obtained information. A commonly used measure to express the global level of efficiency is the D-error, which minimizes the determinant of variance-covariance matrix. The smaller the D-error, the more statistically efficient is the design. Therefore, a statistically efficient design can be used to increase efficiency while holding the sample size fixed. The Bayesian D-efficient designs (100 Halton draws) used in this study are

[16] One of the four category*cost variables (*none*cost*) was omitted from the model estimation. However, it was estimated in separate MNL and panel MML models with changed underlying coding (in parentheses).
[17] One of the four position*cost variables (*position-2*cost*) was omitted from the model estimation. However, it was estimated in a separate MNL and panel MML model with changed underlying coding (in parentheses).

developed based on the calculation of the Db-error of randomly selected designs (10,000 iterations). Attribute levels are randomly assigned to each attribute in each choice set of the change options while accounting for attribute balance. The base level (zero cost option) is held constant but included in the design process. Priors ware obtained from pilot studies targeting the population of Sydney and Canberra[18]. Following a suggestion of Rose and Bliemer (2005), the rows and columns related to the constant term are excluded from the calculation of the Db-error in order to avoid the dominance of the unproportionally large standard errors of the constant. Dominant and redundant choice sets are removed through restrictions and swapping of attribute levels marginally reducing the Db-efficiency (3%). The Bayesian D-efficient designs are developed for multinominal logit (MNL) models without accounting for covariate effects. Estimating different models may alter the design efficiency (Rose and Bliemer 2005).

There is a range of models motivated by random utility theory (McFadden 1974; 1980) that can be used to analyze discrete choices. In this study, we used multinomial logit (MNL) and panel mixed multinomial logit (MML) models to analyze the collected data. The MNL model, introduced by McFadden (1974), is restrictive in that is assumes parameter vectors to be fixed across respondents and choice tasks, and the error terms to be independently and identically (IID) extreme value type 1 (EV1) distributed. MML models (see, for example, Brownstone and Train 1999; Greene and Hensher 2006; 2007; Greene 2008; Hensher et al 2005; Hensher and Greene 2003; Louviere et al 2000; McFadden and Train 2000) allow for a complete relaxation of these assumptions by disaggregating the error component in a stochastic IID-EV1 error term and error terms that are based on underlying parameter vectors and observed data associated with choice options and respondents.

This relaxation provides the opportunity to model preference heterogeneity associated with preference parameters that are assumed to be distributed continuously over respondents around a fixed or heterogeneous mean, where the assumed distributions may be specified as heteroscedastic across respondents. In a random parameter specification, preference parameters can be assumed to be random across both respondents and choice tasks (cross-sectional) or across respondents but not choice tasks (panel). Cross sectional data assume a single choice task per respondent whereas panel data assumes repeated choices per respondent. MML models allow accommodating correlated choice tasks within respondents for panel data in two ways. One way is to change the log-likelihood function, presuming that

[18] The choice sets of the pilot study were created using a Bayesian D-efficient design. Priors were obtained from the focus group choice experiment.

the random effects are the same across choice tasks (Revelt and Train 1998). As such, the log-likelihood function of a cross-sectional specification is replaced by a log-likelihood function that accounts for dependencies across choice options and choice tasks[19].

In all MML models used in this study, all choice attributes were defined as random parameters to account for preference heterogeneity. If not stated otherwise, all econometric models were estimated using Nlogit 4.1. Following Greene and Hensher (2006; 2006), a constrained triangular distribution was used for the *cost* parameter to ensure a negative sign. The distributions on the *access* and the *area of land* attributes were not constrained to allow for both positive and negative preferences towards the attributes. A normal distribution was assumed for these attribute parameters. The WTP for all attribute parameters[20] were estimated using a bootstrapping procedure with 1000 draws (Krinsky and Robb 1986).

4 Results

Sample characteristics

A series of chi-square tests was conducted to test for equivalence between the population statistics using the 2006 census data (ABS 2009) and the sample. No statistically significant differences at the 5% level with respect to *sex* and *age* were discovered. However, *individual gross income*, *household gross income*, *level of non-school education*, and *highest year of school completed* of the population and the sample were statistically significantly different at the 5% level. The sample is therefore not representative of the households of Sydney and care should be taken when interpreting the results on a population level.

Ordering effects and response strategies in repeated choice tasks: H_0^1 and H_0^2

Choice shares of non-zero cost options of the four strategic categories were investigated while holding the *area of land* and *access* attribute levels constant. The percentages of choice sets within each category are 25% (*first*), 23% (*min*), 28% (*max*), and 24% (*none*). The choice shares of non-zero cost options for particular bundles of attribute levels are plotted in Figure 3. Figure 4 displays these choice shares relative to the *first* category that is assumed to be

[19] A second way to incorporate correlations across choice tasks is to include a first order autoregressive (AR1) error term, assuming that previous choices influence latter choices (see, for example, Greene 2007).

[20] Implicit prices

incentive compatible[21]. In both figures, the cost share curves of all attribute bundles follow the same pattern. Table 3 summarizes choice shares of non-zero cost options across categories and attribute bundles[22]. As expected, the choice shares of the *min* category are statistically significantly larger at the 1% level across all attribute bundles than those of the *max* category using a chi-square test. This clearly indicates the presence of ordering effects that may be explained by strategic response in form of lag effects.

The differences between the *first* and the *min* category are heterogeneous across attribute bundles and statistically significantly different for *no50* at the 1% level. Inspecting the choice shares of the *max* and *none* category shows statistically significantly different choice shares for the *no access* but not for the *access* attribute bundles.

Choice shares of non-zero cost options for choice sets in the *max* and *none* categories lay between 20% - 51% and 26% - 59% across attribute bundles, respectively. However, a chi-square test to examine if the choice shares of non-zero cost options in each of the two categories are statistically significantly different from zero implies a division by zero. A less rigorous test is the comparison of both choice shares with a choice share of 1% (p-value for both categories evaluated at each attribute bundle is 0.0000). This indicates that the *max* and *none* categories are not an empty set, suggesting that respondents do not employ a strong cost-minimizing strategy. However, more rigorous testing is required to confirm these results.

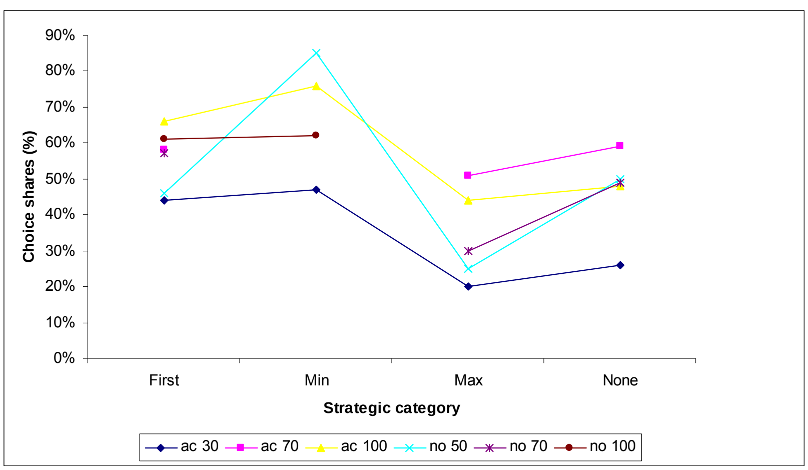

Figure 3: Choice shares of non-zero cost options by strategic category

---

[21] Scheufele and Bennett (2010) found evidence that the knowledge of the prospect of multiple choices does not effect choices if no information about possible attribute levels is given to respondents in the data used in the study presented in this paper.

[22] No access allowed (no); access allowed (ac); 30,50,70, and 100 denote the area of land in percentage.

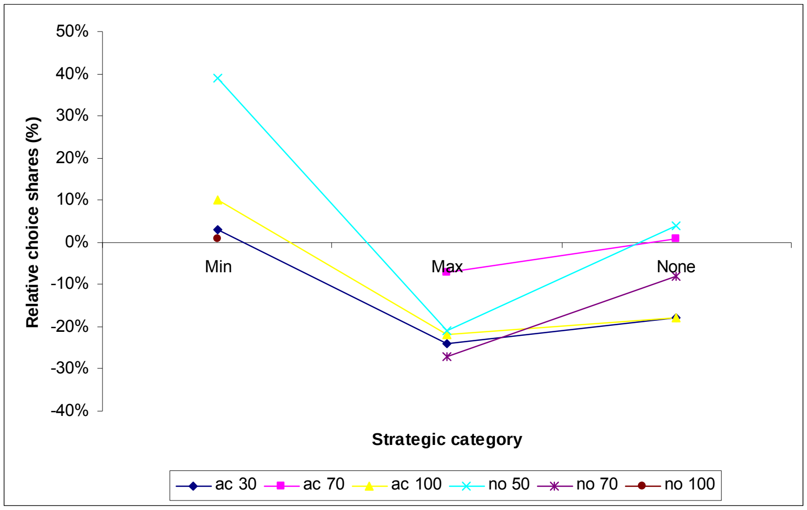

Figure 4: Relative choice shares of non-zero cost options by strategic category using the potentially incentive compatible *first* category as the baseline

Table 3: Choice shares of non-zero cost options across strategic category and attribute bundles[23]

Attribute bundle	First	Min	Max	None	First-Min (p-value)	Max-None (p-value)	Min-Max (p-value)
ac 30	44%	47%	20%	26%	0.6511	0.1797	0.0000
ac 70	58%	-	51%	59%	-	0.2626	0.0000
ac 100	66%	76%	44%	48%	0.2184	0.5465	0.0000
no 50	46%	85%	25%	50%	0.0000	0.0000	0.0000
no 70	57%	-	30%	49%	-	0.0005	0.0000
no 100	61%	62%	-	-	0.8981	-	0.0000

Additionally, *category*con* variables were incorporated in a MNL and a panel MML estimation (Table 4). The model fit of both models statically significantly improved after the inclusion of these variables (p=0.0000; p=0.0000). The parameter estimate *first*con* was statistically different from zero at the 1% level and positive as expected in both models, indicating that the probability of respondents to choose a non-zero cost options is higher in the first choice question than in the following ones. The parameter estimate *min*con* was statistically different from zero at the 1% level and 10% level, respectively, and positive as anticipated in both models. This result suggests that respondents being presented with a choice set in the *min* category are more likely to choose non-zero cost option than those who are presented with a choice set in any other category. The parameter estimate of *max*con* was statistically significantly different from zero at the 1% level and negative as expected in both model specification. These results are evidence that respondents being asked a choice question in the *max* category are less likely to choose a non-zero cost option than those being

[23] The attribute bundle *ac 50* at any cost level was not included in the DCE design; *no 30* was not available at zero cost; other missing values in this table represent attribute bundles not represented by the particular category.

offered a choice set in any other category. The *none*con* parameter estimate is negative and statistically significantly different from zero at the 5% level in the MNL but only at the 13% level in the panel MML model specification. However, both results suggest that respondents being offered a choice in the *none* category are more (less) likely to choose a non-zero cost option than those being asked a choice question in the *max* (*first*, *min*) category.

Finally, *category*cost* variables were included in a MNL and a panel MML model specifications (Table 5). The model fit of both models statistically significantly improved after the inclusion of the interaction variables (p=0.0000 and p=0.0000, respectively)[24]. The *first*cost* parameter estimates was statistically significantly different from zero at the 1% level and positive as expected in both model specifications. This indicates that WTP is higher if respondents have not seen higher or lower cost levels, ceteris paribus. The *max*cost* parameter estimate was statistically significantly different from zero at the 1% level for both model specifications. A negative *max*cost* parameter estimate provides evidence that WTP is lower if respondents saw a lower cost option in previous choice sets, ceteris paribus. The *min*cost* parameter was not statistically significantly different from zero in neither model (p=0.2257 and p=0.3387, respectively). The *none*cost* parameter estimate was statistically significantly different from zero and negative as expected in both models. Again, this indicates that WTP is lower if respondents were offered an option that was neither lower nor higher in previous choice questions, ceteris paribus. The smaller magnitude of the *none*cost* in comparison to the *max*cost* parameter estimate suggests, however, a weaker impact on WTP.

Overall, these results provide evidence to justify the rejection of H_0^1 and H_0^2.

[24] Log-likelihood ratio test (-2[LLr-LLur])

Table 4: Model results for panel MML model specifications including variables reflecting strategic categories of choice sets interacted with the constant term[25]

	MNL		Panel MML	
Variable	Coefficient	Standard error	Coefficient	Standard error
Nonrandom parameters				
constant	-0.06501 (0.4241)	0.08133	0.31738* (0.0900)	0.18720
cost	-0.00342*** (0.0000)	0.00040		
area	0.01366*** (0.0000)	0.00107		
access	0.02477 (0.3651)	0.02735		
first*con	0.27339*** (0.0000)	0.04676	0.85385*** (0.0000)	0.12337
min*con	0.20165*** (0.0008)	0.06036	0.24397* (0.0829)	0.14069
max*con	-0.37382*** (0.0000)	0.06034	-0.92041*** (0.0000)	0.19673
Random parameters				
cost			-0.01813*** (0.0000)	0.00178
area of land			0.05414*** (0.0000)	0.00547
access			0.19532*** (0.0046)	0.06889
Standard deviations/spread of triangular distribution				
Cost (t,1)			0.05022*** (0.0000)	0.00438
area of land (n)			0.09434*** (0.0000)	0.00826
access (n)			1.28098*** (0.0000)	0.17405
Model statistics				
N (observations)	5932		5932	
LLβ	-3828.638		-3195.250	
$\chi^2_{,3}$ (inclusion vs. exclusion of category*cost)	66.488*** (0.0000)		66.022*** (0.0000)	
AIC	1.29320		1.08066	
BIC	1.30109		1.09194	

***=significant at 1% level, **=significant at 5% level, *=significant at 10% level; p-values in parentheses;

[25] One of the four category*con variables (*none*con*) was omitted from the model estimation. However, it was estimated in separate MNL and panel MML models with changed underlying coding. MNL model specification: coefficient (-0.10122), p-value (0.0333), standard error (0.04755); panel MML model specification: coefficient (-0.17741), p-value (0.1326), standard error (0.11796).

Table 5: Model results for panel MML model specifications including variables reflecting strategic categories of choice sets interacted with the cost attribute[26]

	MNL		Panel MML	
Variable	Coefficient	Standard error	Coefficient	Standard error
Nonrandom parameters				
constant	0.08689 (0.2783)	0.08014	0.49943*** (0.0053)	0.17917
cost	-0.00417*** (0.0000)	0.00048		
area of land	0.01368*** (0.0000)	0.00108		
access	0.02991 (0.2756)	0.02743		
first*cost	0.00158*** (0.0000)	0.00032	0.00596*** (0.0000)	0.00091
min*cost	0.00086 (0.1904)	0.00066	0.00192 (0.2257)	0.00158
max*cost	-0.00123*** (0.0002)	0.00033	-0.00523*** (0.0000)	0.00112
Random parameters				
cost			-0.01910*** (0.0000)	0.00194
area of land			0.05542*** (0.0000)	0.00558
access			0.20075*** (0.0040)	0.06970
Standard deviations/spread of triangular distribution				
Cost (t,1)			0.05340*** (0.0000)	0.00466
area of land (n)			0.09465*** (0.0000)	0.00845
Access (n)			1.27558*** (0.0000)	0.17459
Model statistics				
N (observations)	5932		5932	
LLβ	-3826.311		-3180.259	
$\chi^2_{,3}$ (inclusion vs. exclusion of category*cost)	71.142*** (0.0000)		96.004*** (0.0000)	
AIC	1.29242		1.07562	
BIC	1.30031		1.08688	

***=significant at 1% level, **=significant at 5% level, *=significant at 10% level; p-values in parentheses;

Strategic learning: H_0^3

In order to test H_0^3 MNL and a panel MML models were estimated. The results are presented in Table 6. The fit of both estimated model specifications increased statistically significantly after including the *position*cost* variables (p=0.0000, p=0.0000, respectively)[27]. In both

[26] One of the four category*cost variables (*none*cost*) was omitted from the model estimation. However, it was estimated in separate MNL and panel MML models with changed underlying coding. MNL model specification: coefficient (-0.00122), p-value (0.0003), standard error (0.00034); panel MML model specification: coefficient (-0.00265), p-value (0.0024), standard error (0.00087).

[27] Log-likelihood ratio test (-2[LLr-LLur])

models the *cost* and *access* parameter estimates are statistically significantly different from zero at the 1% level and have the expected signs, whereas the *area of land* parameter estimate is only statistically significantly different from zero at the 1% level in the panel MML model specification. The *position*cost* parameter estimates are statistically significantly different from zero for the first, the third and the fourth choice question. The magnitudes of the parameter estimates decrease along the sequence of choice questions in both model specifications. Hence, WTP diminishes along the sequence of choice questions. This suggests that respondents who are presented with repeated choices may learn to exploit strategic opportunities and thus become more cost sensitive towards higher cost levels when progressing through the choice task.

Table 6: MNL and panel MML model results after including the *position*cost* variables[28]

	MNL		Panel MML	
Variable	Coefficient	Standard error	Coefficient	Standard error
Nonrandom parameters				
constant	0.16646** (0.0151)	0.06847	0.82741*** (0.0000)	0.14509
cost	-0.00495*** (0.0000)	0.00029		
area of land	0.01331*** (0.0000)	0.00107		
access	0.03523 (0.1963)	0.02726		
position-1*cost	0.00203*** (0.0000)	0.00025	0.00686*** (0.0000)	0.00087
position-3*cost	-0.00095*** (0.0003)	0.00026	-0.00373*** (0.0000)	0.00080
position-4*cost	-0.00075*** (0.0041)	0.00026	-0.00212*** (0.0065)	0.00078
Random parameters				
cost			-0.02195*** (0.0000)	0.00179
area of land			0.05388*** (0.0000)	0.00544
access			0.21578*** (0.0020)	0.06998
Standard deviations/ spread of triangular distribution				
cost (t,1)			0.05293*** (0.0000)	0.00461
area of land (n)			0.09475*** (0.0000)	0.00841
access (n)			1.30566*** (0.0000)	0.17591
Model statistics				
N (observations)	5932		5932	
LLβ	-3827.989		-3182.229	
$\chi^2_{,3}$ (Inclusion vs. exclusion of position*cost)	67.784*** (0.0000)		92.064*** (0.0000)	
AIC	1.29298		1.07627	
BIC	1.30088		1.08755	

***=significant at 1% level, **=significant at 5% level, *=significant at 10% level; p-values in parentheses;

In order to test H_0^3 further we investigated choice shares of non-zero cost options of P1, P2, P3, and P4 (choices related to choice questions in the first, second, third, and fourth choice set position) (see Figure 5). The percentage choosing a non-zero cost option is 53% for P1, 46% for P2, 42% for P3, and 44% for P4. A statistically significantly difference is observed between P1 and P3 (p=0.1085) but not between P1 and P2 (p=0.1585) and between P1 and P4 (p=0.30004). We further explored choice shares by analyzing bid acceptance curves. The

[28] One of the four position*cost variables (*position-2*cost*) was omitted from the model estimation. However, it was estimated in separate MNL and panel MML models with changed underlying coding. MNL model: coefficient (-0.00033), p-value (0.2019), standard error (0.00025); panel MML model: coefficient (-0.00101), p-value (0.1852), standard error (0.00076).

research design ensures that the choice sets presented in P1, P2, P3, and P4 are the same. Hence, there is no confounding influence of varying attribute levels. Bid acceptance curves for P1, P2, P3 and P4 are displayed in Figure 6. This figure shows choice sensitivity to the relative cost levels within P1, P2, P3, and P4, with acceptance rates declining with increasing cost levels. As expected, the bid acceptance curve of P1 lies above those of P2, P3, and P4. Statistically significantly differences are observed between P1 and P2, P3, and P4 at the $200 and $300 cost levels. Hence, non-zero cost options, especially the one with higher cost levels, were chosen more often in the first choice than in the following ones. This indicates that respondents become more cost sensitive towards higher cost levels when progressing through the choice task, that is, respondents may learn to exploit strategic opportunities while progress is made in the choice task, especially after they gained experienced in making their first choice.

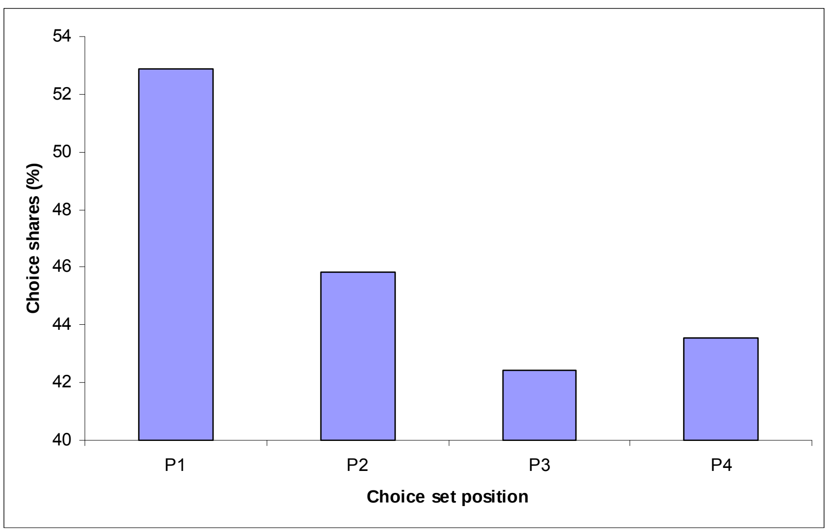

Figure 5: Choice shares of non-zero cost options for P1, P2, P3, and P4

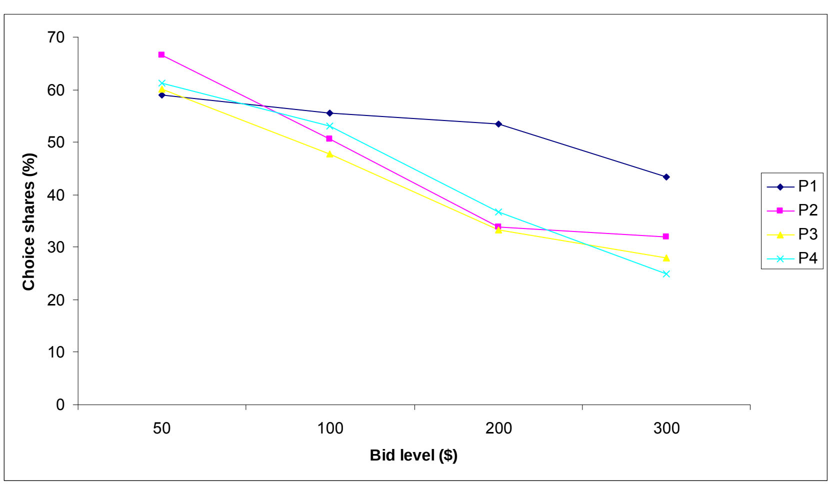

Figure 6: Bid acceptance curves for P1, P2, P3, and P4

Additionally, MNL models were estimated for P1, P2, P3, and P4[29]. The *cost* parameter estimates are statistically significant and have the expected negative signs. The *area of land* parameter estimates are statistically significant and positive as expected in P1, P2, P3, and P4. The *access* parameter estimates, however, are statistically insignificant in P1, P3, and P4 but statistically significant in P2. Differences in parameter estimates and scale factors of P1, P2, P3, and P4 are explored using the Swait-Louviere test (1993). The test results are reported in Table 7.

A comparison of P1 with P2, P3, and P4 reveals a statically significantly difference in the parameter estimates after having made the first choice. Possible explanations are 'strategic learning' or 'value learning'. A statistically significant difference in a parameter estimate prevents a test for scale factor equality[30]. Scale factors of 1.8278, 2.2491, and 2.2928, respectively, weakly indicate a difference. A possible explanation is 'institutional learning'. A comparison of P2 with P3, P3 with P4, and P2 with P4 reveals no statically significantly difference neither in the parameter estimates or the scale factors.

Table 7: Test results for equality for attribute and scale factors between P1, P2, P3 and P4

Position P	LL 1^{st} split	LL 2^{nd} split	LL Pooled[a]	LR-test[b] (5d.f.)	Reject $H_0:\beta_i \neq \beta_j$	Scale ratio λ_i/λ_j	LL Pooled[c]	LR-test[d] (1 d.f.)	Reject $H_0:\lambda_i \neq \lambda_j$
1 vs. 2	-995.738	-955.834	-1958.804	0.0129	yes	1.8278	NA	NA	NA
1 vs. 3	-995.738	-939.124	-1944.068	0.0025	yes	2.2491	NA	NA	NA
1 vs. 4	-995.738	-929.612	-1931.596	0.0286	yes	2.2928	NA	NA	NA
2 vs. 3	-955.834	-939.124	-1897.95	0.3078	no	1.0134	-1898.107	0.5752	no
3 vs. 4	-939.124	-929.612	-1871.819	0.2905	no	1.0277	-1871.763	0.7379	no
2 vs. 4	-955.834	-929.612	-1889.235	0.1811	no	1.1770	-1890.164	0.1729	no

[a] Pooled MNL model allowing varying scale factors;
[b] Log-likelihood ratio test, test statistics $-2(LL_{pool}-\ (LL_1+LL_2))$ with d.f. k+1, where k is the number of parameters including the constant is asymptotically chi-square distributed;
[c] Pooled MNL model assuming equal scale factors in both split samples;
[d] Log-likelihood ratio test, test statistics $-2(LL_{equalscale}-\ (LL_{varyingscale}))$ with 1 d.f. is asymptotically chi-square distributed

The WTP estimates for P1, P2, P3, and P4 are displayed in Table 8. A Poe test (2005) was conducted to test for equivalence of WTP estimates. The WTP for P1 was statistically significantly different from P2 (p=0.0000). The confidence interval of P1 is wider than the one for P2. A comparison of the WTP estimates of P2 with P3 and P3 with P4 reveals no

[29] Using a MML model specification instead of a MNL model specification did not improve the model fit of P1, P2, P3, and P4. The *cost* parameter was the only attribute parameter that was statistically significantly different from zero at the 5% level. Rose et al. (2009) using simulated data suggested that obtaining only a single choice observation per respondent may not allow the discovery of random parameters that are statistically significantly different from zero. A possible explanation is that in the absence of a very large sample it is impossible to disentangle the assumed distribution of random terms associated with preference parameters or alternatives from the assumed EV1 distribution of the remaining random term that is assumed to be IID across alternatives and individuals. This implies that the MML model specification cannot be used to compare the P1, P2, P3, and P4.

[30] Parameter vector and scale factor are confounded in MNL models. Hence, having a varying scale factor prevents testing for parameter vector equality.

statistically significant differences at the 5% level. The confidence intervals are similar for P2, P3, and P4. The differences in confidence intervals and the relative scale factors between P1 and P2 are indications that respondents may use the first choice question to learn about the choice task.

The overall results lead to the rejection of H_0^3. However, the tests employed in this study were not capable to separate potential 'value learning' from 'strategic learning'. Therefore, it cannot be ruled out that 'value learning' is at least partially responsible for the observed effects.

Table 8: WTP in P1, P2, P3 and P4

Position P	WTP	Confidence interval WTP
1	\$6.20*** (0.0075)	\$3.36-\$11.56
2	\$1.87*** (0.0000)	\$1.12-\$2.72
3	\$2.75*** (0.0000)	\$1.92-\$3.73
4	\$2.28*** (0.0000)	\$1.55-\$3.09
Poe tests	p-value	
1 vs. 2	0.00	
2 vs. 3	0.16	
3 vs. 4	1.56	

*p-values in parentheses; 95% confidence intervals in parentheses based on the 2.5th and 97.5th percentile of the simulated WTP distribution. In comparison to the delta method, this method does not imply a normal distribution.

5 Conclusion

The main objective of this study was to explore the effects of repeated choice questions. In particular, this paper investigated (1) whether the order in which choice sets are presented to respondents provides strategic opportunities that affect choice decisions ('strategic response'), (2) what response strategies respondents use to exploit these strategic opportunities, and (3) whether respondents increasingly become aware of and learn to take advantage of a particular choice set order ('strategic learning') as they answer more choice questions.

The results show that the order in which choice sets are presented to respondents affects choice decisions. A possible explanation for this effect is that a particular choice set order provides strategic opportunities that are exploited by respondents ('strategic response'). We find evidence that the response strategies do not follow strong cost-minimization but other strategies such as weak cost-minimization or good deal/ bad deal heuristics. Our findings further suggest that participants of sequential binary DCE not only make more accurate choices but also become increasingly aware of and learn to take advantage of a particular choice set order ('strategic learning') as they progress through the choice questions. However, the tests employed in this study were not capable to separate potential ‘value learning’ from ‘strategic learning’. Therefore, it cannot be ruled out that ‘value learning’ is at least partially responsible for the observed effects.

The conclusions discussed above are based on the assumption that potential impacts of strategic behavior associated with respondents’ expectations about the choices of other survey participants did not confound the results. More research is needed to explore the influence of dependencies across respondents on choice behavior.

Topics for future research should include investigations of the magnitude of ordering effects and the exploration of relations between socio-demographic characteristics and strategic response. Both might support the development of tools to adjust WTP estimates accordingly. Finally, this study examined ordering effects of sequential rather than multiple binary DCE formats. Further research is needed to investigate if similar effects are present in sequential multiple elicitation formats.

REFERENCES

ABS, 2006. 'Census data', Australian Bureau of Statistics.

Bateman, I.J., Carson, R.T., Day, B., Dupont, D., Louviere, J.J., Morimoto, S., Scarpa, R. and Wang, P., 2008. *Choice set awareness and ordering effects in discrete choice experiments,* Research Centre for Social and Economic Research on the Global Environment

Bateman, I.J., Day, B., Georgiou, S. and Lake, I., 2006. 'The aggregation of environmental benefit values: welfare measures, distance decay and total WTP', *Ecological Economics,* 60:450-460.

Bennett, J. and Blamey, R., 2001. *The choice modelling approach to environmental valuation*Edward Elgar Publishing Limited, Massachusetts.

Bliemer, M.C.J., Rose, J.M. and Hess, S., 2008. 'Approximation of Bayesian efficiency in experimental choice designs', *Journal of Choice Modelling,* 1(1):98-127.

Braga, J. and Starmer, C., 2005. 'Preference anomalies, preference elicitation and the discovered preference hypothesis', *Environmental and Resource Economics,* 32(1):55-89.

Brownstone, D. and Train, K., 1999. 'Forecasting new product penetration with flexible substitution patterns', *Journal of Econometrics,* 89(1):109-129.

Carson, R.T. and Groves, T., 2007. 'Incentive and informational properties of preference questions', *Environmental and Resource Economics,* 37(1):181-210.

Collins, J.P. and Vossler, C.A., 2009. 'Incentive compatibility tests of choice experiment value elicitation questions', *Journal of Environmental Economics and Management,* 58:226-235.

Ferrini, S. and Scarpa, R., 2007. 'Designs with a priori information for nonmarket valuation with choice experiments: A Monte Carlo study', *Journal of Environmental Economics and Management,* 53:343-362.

Gibbard, A., 1973. 'Manipulation of voting schemes', *Econometrica,* 41:587-601.

Green, J.R. and Laffont, J.J., 1978. 'A sampling approach to the free rider problem', in A. Sandmo (ed.), *Essays in public economics*, Lexington Books

Greene, W. and Hensher, D., 2006. 'Accounting for heterogeneity in the variance of unobserved effects in mixed logit models.', *Transportation Research Part B: Methodological,* 40:75-92.

Greene, W. and Hensher, D., 2007. 'Heteroscedastic control for random coefficients and error components in mixed logit', *Transportation Research Part E: Logistics and Transportation Review,* 43:610-623.

Greene, W.H., 2007. *Nlogit version 4.0 reference guide*Econometric Software, Inc., Castle Hill.

Greene, W.H., 2008. *Econometric analysis*Pearson/Prentice Hall, Upper Saddle River, N.J.

Greene, W.H., Hensher, D.A. and Rose, J., 2006. 'Accounting for heterogeneity in the variance of unobserved effects in mixed logit models', *Transportation Research Part B: Methodological,* 40(1):75-92.

Hensher, D., Rose, J.M. and Greene, W.H., 2005. *Applied choice analysis : a primer* Cambridge University Press, Cambridge.

Hensher, D.A. and Greene, W.H., 2003. 'The Mixed Logit model: The state of practice', *Transportation,* 30:133-176.

Holmes, T.P. and Boyle, K.J., 2005. 'Dynamic learning and context-dependence in sequential, attribute-based, stated preference valuation questions', *Land Economics,* 81(1):114-126.

Hurwicz, L., 1960. 'Optimality and informational efficiency in resource allocation processes', in K. Arrow, S. Karlin and P. Suppes (eds), *Mathematical Methods in the Social Sciences*, Stanford University Press

Krinsky, I. and Robb, A.L., 1986. 'On approximating the statistical properties of elasticities', *Review of Economics and Statistics,* 68:715-719.

Louviere, J., Hensher, D. and Swait, J., 2000. *Sated choice methods: analysis and applications*Cambridge University Press, Cambridge, UK ; New York, NY, USA.

Maskin, E., 1977. 'Nash equilibrium and welfare optimality', *Summer workshop of the Econometric Society* Published 1999 in the Review of Economic Studies 66, 23-38, Paris.

McFadden, D., 1974. 'Conditional logit analysis of qualitative choice behaviour', in P. Zarembka (ed.), *Frontiers in econometrics*, Academic Press, New York

McFadden, D., 1980. 'Econometric models for probabilistic choice among products', *Journal of Business,* 53:13-29.

McFadden, D. and Train, K., 2000. 'Mixed MNL models for discrete response', *Journal of Applied Econometrics,* 15:447-470.

McNair, B., Bennett, J. and Hensher, D., 2010. 'Strategic response to a sequence of discrete choice questions', *54th Annual conferences of the Australian Agricultural and Resource Economics Society*, Adelaide.

Moulin, H., 1994. 'Social choice', in R.J. Aumann and H. S. (eds), *Handbook of game theory with economic applications*, Amsterdam

Muller, E. and Satterthwaite, M.A., 1985. 'Strategy-proofness: the existence of dominant-strategy mechanisms', in L. Hurwicz, D. Schmiedler and H. Sonnenschein (eds), *Social Goals and Social Organization*, Cambridge University Press, Cambridge

Plott, C.R., 1996. 'Rational individual behavior in markets and social choice processes: the discovered preference hypothesis', in K. Arrow, E. Colombatto, M. Perleman and C. Schmidt (eds), *Rational foundations of economic behavior*, Macmillan, London

Poe, G.L., Giraud, K.L. and Loomis, J.B., 2005. 'Computational methods for measuring the difference of empirical distributions', *American Journal of Agricultural Economics,* 87(2).

Revelt, D. and Train, K., 1998. 'Mixed logit with repeated choices: households' choices of appliance efficiency level', *Review of Economics and Statistics,* 80(4):647-657.

Rose, J.M. and Bliemer, M.C.J., 2005. 'Designing efficient data for stated choice experiments: accounting for socio-dempgraphic and contextual effects in designing stated choice experiments', *11th International Conference on Travel Behaviour Research*, Kyoto, Japan.

Rose, J.M. and Bliemer, M.C.J., 2008. 'Stated preference experimental design strategies', in D.A. Hensher and K.J. Button (eds), *Handbook of transport modelling*, Pergamon

Rose, J.M., Bliemer, M.C.J., Hensher, D.A. and A., C., 2008. 'Designing efficient stated choice experiments in the present of reference alternatives', *Transportation Research Part B,* 42 395–406.

Rose, J.M., Hess, S., Bliemer, M.C.J. and Daly, A., 2009. 'The impact of varying the number of repeated choice observations on mixed multinomial logit models'.

Satterthwaite, M.A., 1975. 'Strategy-proofness and Arrow's conditions: Existence and correspondence theorems for voting procedures and social welfare functions', *Journal of Economic Theory,* 10:187-217.

Scheufele, G. and Bennett, J., 2010. 'Effects of alternative elicitation formats in discrete choice experiments', *54th Annual Conference of the Australian Agricultural and Resource Economics Society*, Adelaide, SA.

Swait, J. and Louviere, J., 1993. 'The role of the scale parameter in the estimation and comparison of multinominal logit models', *Journal of Marketing Research,* 30(3):305-314.