

Repeated Dichotomous Choice Contingent Valuation for Multi-
Attributed Environmental Resources: A Comparison between
Contingent Valuation and a Choice Experiment Format

Koichi KURIYAMA
School of Political Science and Economics
Waseda University
1-6-1 Nishi-Waseda, Shinjuku-ku
Tokyo 169-8050, JAPAN
Tel/Fax: +81 3 5286 9822
E-mail: kkuri@mn.waseda.ac.jp

Kenji TAKEUCHI
Women's College
Meiji University

Toyoaki WASHIDA
Department of Economics
Kobe University

August 1999
Draft

ABSTRACT

The purpose of this paper is to develop a new attribute-based elicitation method, a repeated dichotomous choice contingent valuation (repeated DCCV). In the field of environmental economics, contingent valuation (CV) has traditionally been used to determine the value of environmental resources. However, it is difficult to estimate preferences for attributes of environmental goods using a dichotomous choice, contingent valuation (DCCV) elicitation format. While the choice experiment (CE) technique is a type of multi-attribute preference-elicitation technique that is widely used in marketing research, there are only a few CE studies of environmental valuation. We develop a repeated DCCV format, whereby respondents are iteratively asked binary choice questions related to some offered profiles with multi-attribute bundles. Estimation using repeated DCCV is compared with that of CE using Monte Carlo simulation and with empirical survey data. The results of the simulation show that although parameters estimated by a repeated DCCV can be significant, it requires a larger sample than CE. The empirical evaluation uses survey data regarding provision of protection against oil spills in Tokyo Bay. Sixteen versions of the questionnaire were prepared, and respondents were asked DCCV questions 8 times in each version. The empirical results show that the parameters estimated by the repeated DCCV method are both significant and slightly different from those estimated by CE.

Keywords

Contingent valuation, dichotomous choice, choice experiment, conjoint analysis, environmental valuation

1. INTRODUCTION

In the field of environmental economics, contingent valuation (CV) has traditionally been used to estimate the use and non-use value of environmental resources (Carson et al. 1995). CV questions respondents regarding their willingness to pay (WTP) or willingness to accept compensation (WTA) for the protection or destruction of environmental resources. The advantages of using CV are manifold: (1) CV has been applied to environmental valuation for at least 30 years and there are many empirical studies published. (2) CV evaluates both the use value and the non-use value (passive use value) of non-market goods. (3) A single dichotomous choice CV format can be incentive compatible under some assumptions (Hoehn and Randall, 1987). (4) A respondent's task is to provide a one-time "yes" or "no" answer to a single dichotomous choice question, which is relatively easy.

CV evaluates the total value of environmental goods; however, it is difficult to distinguish the value of each attribute of multi-attribute environmental goods using CV. For example, the damage to natural resources caused by an oil spill includes direct and indirect damage to health, and the effects on coastal ecosystems, commercial fishing, recreational use and shipping. Traditional CV can estimate the total value of protection from oil spills, but it cannot identify the value of each attribute of the damage.

Some economists have recently begun to pay attention to attribute-based methods, including rating-based conjoint analysis and choice experiments, as new valuation techniques that might be able to distinguish the value of each component of a multi-attribute environmental good. Conjoint analysis and choice experiments are multi-attribute preference-elicitation techniques that are widely used in marketing research, transportation, and psychometrics (Green and Srinivasan 1978, 1990, Louviere 1988, 1994, Wittink and Cattin 1989, Wittink, Vriens, and Burhenne 1994, Green, Krieger and Schaffer 1993, Carroll and Green 1995). The main characteristics of these attribute-based methods are that they present repeated questions and profiles that are bundles of attributes. For example, when evaluating preference for cars, respondents are given several profile cards, each of which shows a unique car product that is composed of specific attributes, such as color, maximum speed, displacement volume, fuel efficiency, size, price, and so on. A rating-based conjoint (RBC) asks respondents to rate their preference among profiles on a scale, whereas choice experiments (CE) ask respondents to choose the profile they most prefer.

Previous attribute-based valuation studies in environmental economics include Viscusi et al (1991, health risk; pair-comparison), Mackenzi (1993, hunting; pair-wise RBC), Opaluch et al. (1993, hazardous waste; pair-wise RBC), Adamowicz et al. (1994, recreation; CE), Johnson and Desvousges (1997, electronic site; pair-wise RBC), Griner and Faber (1996a, b, water resource; pair-wise RBC), Boxall et al. (1996, hunting; CE), Roe et al. (1996, salmon-fishing; RBC), Adamowicz et al. (1997, hunting; CE), Kuriyama (1998, wetland ecosystem; CE) and Adamowicz et al. (1998,

habitat protection; CE). Although there have been an increasing number of attribute-based studies, there are few that estimate non-use value.

Although attribute-based methods have the potential to be powerful tools in environmental valuation, they currently present some unresolved problems. First, the elicitation format of rating-based conjoint analysis and choice experiments may not be incentive compatible: respondents may not report their true preferences. Second, the conditional logit model, which is a statistical method used in modeling choice experiments, assumes the independence of irrelevant alternatives (IIA). If IIA holds, then the choice between a subset of alternatives is independent of alternatives that are not in the subsets. When the IIA property is violated, more flexible and complex statistical methods, such as a conditional probit model, are required¹.

The purpose of this paper is to develop a new attribute-based elicitation format, a repeated dichotomous choice contingent valuation (repeated DCCV), whereby respondents are iteratively asked binary choice questions to alternative profiles with multi-attribute bundles. The repeated DCCV method can distinguish each value of a multi-attributed environmental good, and has the same advantage as a dichotomous choice CV. Table 1 provides a summary of a comparison between DCCV, CE and repeated DCCV.

Table 1. Dichotomous Choice CV, Choice Experiments and Repeated Dichotomous Choice CV

Name	Dichotomous Choice Contingent Valuation (DCCV)	Choice Experiments (CE)	Repeated Dichotomous Choice Contingent Valuation (Repeated DCCV)
Asking	Asks respondents to answer yes or no to payment or compensation offered	Asks respondents their most preferred alternative	Asks respondents to answer yes or no to offered profiles
Attribute / Non Attribute	Non attribute-based elicitation method	Attribute-based elicitation method	Attribute-based elicitation method
Characteristics	<p>Single question about non-attributed goods</p> <p>There are many empirical studies in environmental economics</p> <p>CV does not require the assumption of IIA</p> <p>CV can estimate both the use and non-use values</p> <p>Traditional DCCV cannot distinguish the value of individual attributes</p>	<p>Multiple questions about multi-attributed profile</p> <p>There are many empirical studies in marketing research</p> <p>Most CE studies assume the IIA property</p> <p>Only a few studies estimate non-use value</p> <p>CE can distinguish the value of individual attributes</p>	<p>Multiple questions about multi-attributed profile</p> <p>There is no empirical study to date</p> <p>Same as CV</p> <p>Same as CV</p> <p>Same as CE</p>

¹ The conditional probit model assumes the error terms have a multivariate normal distribution with mean 0 and a general covariance matrix, so the IIA assumption is not required. The conditional probit is more flexible than the conditional logit; however, it needs numerical integration of its multivariate normal density. Among many simulators developed for the conditional probit model, Hajivassiliou et al. (1992) found the Geweke-Hajivassiliou-Keane (GHK) simulator to be the best for simulated maximum likelihood estimation. See also Greene (1997).

Section 2 provides economic models of repeated DCCV and analyzes their statistical properties. Section 3 shows the results of a Monte Carlo simulation that compares repeated DCCV with CE. Section 4 presents an empirical analysis of guarding against oil spills in Tokyo Bay. Finally, Section 5 provides concluding comments.

2. MODEL

A repeated DCCV questionnaire is similar to that of CE. Figure 1 shows a CE question format example that determines the value of providing protection against oil spills. In this example, three alternatives are offered to respondents. Each alternative includes five attributes: the cost, protection of recreational facilities, health effects, tidelands and fishing ports. Respondents are asked repeatedly to choose their most preferred alternative. While the attributes in the first and second alternatives are changed each time the question is repeated, the third alternative, which is no protection plan (the status quo) is held fixed

Figure 1. Example of Choice Experiment Question

Assume that the following three plans are proposed. Which alternative would you choose?

	1	2	3
Payment (tax)	30,000 yen	5,000 yen	0 yen
Recreational facilities	protect 24%	protect 93%	protect 7%
Health effects	10,000 people suffer from the smell of oil and from headaches	0 people suffer from the smell of oil and from headaches	10,000 people suffer from the smell of oil and from headaches
Tidelands	protect 90%	protect 24%	protect 24%
Fishing ports	protect 100%	protect 66%	protect 66%

Figure 2. Example of a Repeated Dichotomous Choice Contingent Valuation Question

Assume that the following plan is proposed. Would you vote for or against it?

	Protection Plan	No protection
Payment (tax)	30,000 yen	0 yen
Recreational facilities	protect 93%	protect 7%
Health effects	0 people suffer from the smell of oil and from headaches	10,000 people suffer from the smell of oil and from headaches
Tidelands	protect 79%	protect 24%
Fishing ports	protect 66%	protect 66%

Figure 2 shows an example of the repeated DCCV question format. Respondents are asked iteratively to vote for or against the protection plan offered. When the respondent chooses “for”, then she prefers the offered protection plan to no protection plan (status quo). While the attributes in the protection plan are changed each time a question is repeated, the comparison protection plan (no protection plan) is fixed².

The data from repeated DCCV and CE questions can be analyzed by a random utility model. Assume that the respondent i 's utility function (U_{ij}) of alternative j is represented by

$$U_{ij} = V_{ij} + \mathbf{e}_{ij} = V(\mathbf{x}_{ij}) + \mathbf{e}_{ij} = \mathbf{b}'\mathbf{x}_{ij} + \mathbf{e}_{ij} \quad (i = 1, 2, \dots, n) \quad (1)$$

where V_{ij} is a deterministic component, \mathbf{e}_{ij} is a stochastic component, \mathbf{x}_{ij} is a vector of the attributes of alternative j , and \mathbf{b} is a vector of parameters. In a repeated DCCV, the number of alternatives is two: a hypothetical state, U_{YES} , and the status quo, U_{NO} . Under CE, the number of alternatives is more than two. The probability of choosing alternative j can be written as follows:

$$\begin{aligned} P_{ij} &= \Pr(U_{ij} > U_{ik}, \forall k \in \mathbf{C}, k \neq j) \\ &= \Pr(V_{ij} - V_{ik} > \mathbf{e}_{ik} - \mathbf{e}_{ij}, \forall k \in \mathbf{C}, k \neq j) \\ &= \int_{-\infty}^{V_{ij} - V_{i1}} \int_{-\infty}^{V_{ij} - V_{i2}} \dots \int_{-\infty}^{V_{ij} - V_{im}} f(\tilde{\mathbf{e}}_1, \tilde{\mathbf{e}}_2, \dots, \tilde{\mathbf{e}}_m, \Omega) d\tilde{\mathbf{e}}_m d\tilde{\mathbf{e}}_{m-1} \dots d\tilde{\mathbf{e}}_1 \end{aligned} \quad (2)$$

where $\tilde{\mathbf{e}}_k = \mathbf{e}_{ik} - \mathbf{e}_{ij}$ is an error difference with covariance matrix Ω , f is the joint density of the error differences, and \mathbf{C} is a set of alternatives.

McFadden (1974) showed that if the error terms in equation (2) are independently and identically distributed with a type I extreme-value distribution (a Gumbel distribution), then the choice probability, P_{ij} , has the closed-form representation

$$P_{ij} = \frac{\exp(\lambda V_{ij})}{\sum_k \exp(\lambda V_{ik})} \quad (3)$$

where λ is a scale parameter, and $\mathbf{s}^2 = \mathbf{p}^2 / 6\mathbf{I}^2$, conventionally normalized to 1. McFadden's model is known as the conditional logit model. Repeated DCCV can be regarded as a two alternative case of CE (the usual logit model). The probability of accepting the offered plan is

$$P_{iYES} = \frac{\exp(V_{iYES})}{\exp(V_{iYES}) + \exp(V_{iNO})} \quad (4)$$

² Some feel that the repeated DCCV format is the same as pair-comparison rating conjoint analysis. There are, however, important differences between the two formats. Repeated DCCV asks respondents to vote for or against offered profiles, while pairwise rating asks respondents their preference on a rating scale (say, 1-9). Furthermore, the status-quo profile is fixed in repeated DCCV, but in pairwise rating the profiles are not constrained to be fixed. Because of these differences, repeated DCCV is less efficient than pairwise rating.

The log-likelihood function of CE (LL_{CE}) and repeated DCCV (LL_{RDCCV}) is as follows:

$$LL_{CE} = \sum_i \sum_j d_{ij} \ln \frac{\exp(V_{ij})}{\sum_k \exp(V_{ik})} \quad (5)$$

$$LL_{RDCCV} = \sum_i \left[d_{iYES} \ln \frac{\exp(V_{iYES})}{\exp(V_{iYES}) + \exp(V_{iNO})} + d_{iNO} \ln \frac{\exp(V_{iNO})}{\exp(V_{iYES}) + \exp(V_{iNO})} \right] \quad (6)$$

where d_{ij} is a dummy for respondent i who chooses alternative j , d_{iYES} is a dummy for a respondent who votes for the offered profile, and d_{iNO} is a dummy for the respondent who votes against the offered profile. The parameters, \mathbf{b} , are estimated by maximizing equation (5) or (6). The first and second derivatives of the log-likelihood functions are as follows:

$$\frac{\partial LL_{CE}}{\partial \mathbf{b}} = \sum_i \sum_j d_{ij} (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i) \quad (7-1)$$

$$\frac{\partial^2 LL_{CE}}{\partial \mathbf{b} \partial \mathbf{b}'} = -\sum_i \sum_j P_{ij} (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i) (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i)' \quad (7-2)$$

$$\frac{\partial LL_{RDCCV}}{\partial \mathbf{b}} = \sum_i [d_{iYES} (\mathbf{x}_{iYES} - \bar{\mathbf{x}}_i) + d_{iNO} (\mathbf{x}_{iNO} - \bar{\mathbf{x}}_i)] \quad (7-3)$$

$$\frac{\partial^2 LL_{RDCCV}}{\partial \mathbf{b} \partial \mathbf{b}'} = -\sum_i [P_{iYES} (\mathbf{x}_{iYES} - \bar{\mathbf{x}}_i) (\mathbf{x}_{iYES} - \bar{\mathbf{x}}_i)' + P_{iNO} (\mathbf{x}_{iNO} - \bar{\mathbf{x}}_i) (\mathbf{x}_{iNO} - \bar{\mathbf{x}}_i)'] \quad (7-4)$$

where $\bar{\mathbf{x}}_i = \sum_j P_{ij} \mathbf{x}_{ij}$. From (7-2) and (7-3), the log-likelihood functions (5) and (6) are globally

concave in \mathbf{b} . Under general conditions, the maximum likelihood estimators are consistent and asymptotically normal with the following covariance matrices.

$$\text{Asymptotic covariance matrix of CE: } \Omega_{CE} = \left[-E \left[\frac{\partial^2 LL_{CE}}{\partial \mathbf{b} \partial \mathbf{b}'} \right] \right]^{-1} \quad (8-1)$$

$$\text{Asymptotic covariance matrix of repeated DCCVCE: } \Omega_{RDCCV} = \left[-E \left[\frac{\partial^2 LL_{RDCCV}}{\partial \mathbf{b} \partial \mathbf{b}'} \right] \right]^{-1} \quad (8-2)$$

From (8-1) and (8-2), the asymptotic variances of the estimated parameters depend on the number of alternatives (j), the sample size (n), and the profile design (\mathbf{x}_{ij}). Repeated DCCV is constrained to only two alternatives with a fixed status-quo profile, and thus it may be statistically less efficient than CE. In other words, to achieve the same significance level as CE, repeated DCCV might need a

larger sample than CE, along with a more efficient profile design.

One solution to the poor efficiency of repeated DCCV is to use an efficient profile design such as D-efficiency (Huber and Zwerina, 1996; Zwerina et al., 1996). D-efficiency, which minimizes $|\Omega|^{1/K}$ where K is the number of parameters, is the most common criterion for efficient profile design. A profile design based on D-efficiency is more efficient than the usual orthogonal design, in which attribute levels across alternatives are uncorrelated. Another solution is to use large choice sets, increasing the number of iterations of questions. Traditional DCCV uses the data from a one-time dichotomous choice question format; it is therefore too costly to estimate multi-attribute goods, because they require a large amount of survey data. Repeated DCCV asks respondents questions iteratively, and therefore more data can easily be collected than with traditional DCCV. However, increasing the number of iterations of the DC question asked of each respondent requires a longer interview time, an increased burden on the respondents, and possibly more item non-responses. While the range of choice sets used by CE studies is between one and thirty two (Carson et al., 1994), it is not clear whether this size of choice set is sufficient in repeated DCCV. It is important to decide the optimal sample size and choice sets for repeated DCCV. We analyze this problem next, using a Monte Carlo simulation.

3. A MONTE CARLO SIMULATION

This section analyzes how large a sample is required in a survey with repeated DCCV format, using Monte Carlo simulation. Monte Carlo simulation uses simulated data that is generated using a utility function and simulated random terms. Figure 3 illustrates the procedure behind the Monte Carlo simulations of this section. The procedure was as follows:

(1) Set the parameters. The parameters were set to the estimates from a prior survey. We conducted four pilot surveys (pilot 1-4) and two main surveys (main 1 and 2). The parameters of main 1, which were used for this simulation, are shown in Table 2. Note that REC was not significant in the main 1 data.

Table 2. Assumed Values of Parameters

TAX	-0.2876
REC	0.0795
HEL	0.4364
TIDE	0.5403
FISH	1.0322

Note: These parameters were estimated using the conditional logit model and data from a CE format survey in main 1. REC was not significant in this survey.

(2) **Select attribute levels and profile design.** Table 3 shows a list of the attributes used in the simulation. 128 profiles were designed for repeated DCCV by the D-efficiency criterion using the parameters of a pilot study. For comparison, 64 profiles were designed for CE by the same procedure.

Table 3. List of Attributes

TAX (unit 10,000 yen)	0.5	1	3	9
REC (protection ratio of recreational facilities)	7%	24%	69%	93%
HEL (the number of people protected from smell and headaches. Unit 10,000 people)	0	1		
TIDE (protection ratio of tidelands)	24%	48%	79%	90%
FISH (protection ratio of fishing ports)	63%	100%		

(3) **Set sample size.** To analyze the effects of sample size, different sample sizes were tested. The sample sizes tested were 50, 100, 200,300, 500, 800, 1000, 1500, and 2000.

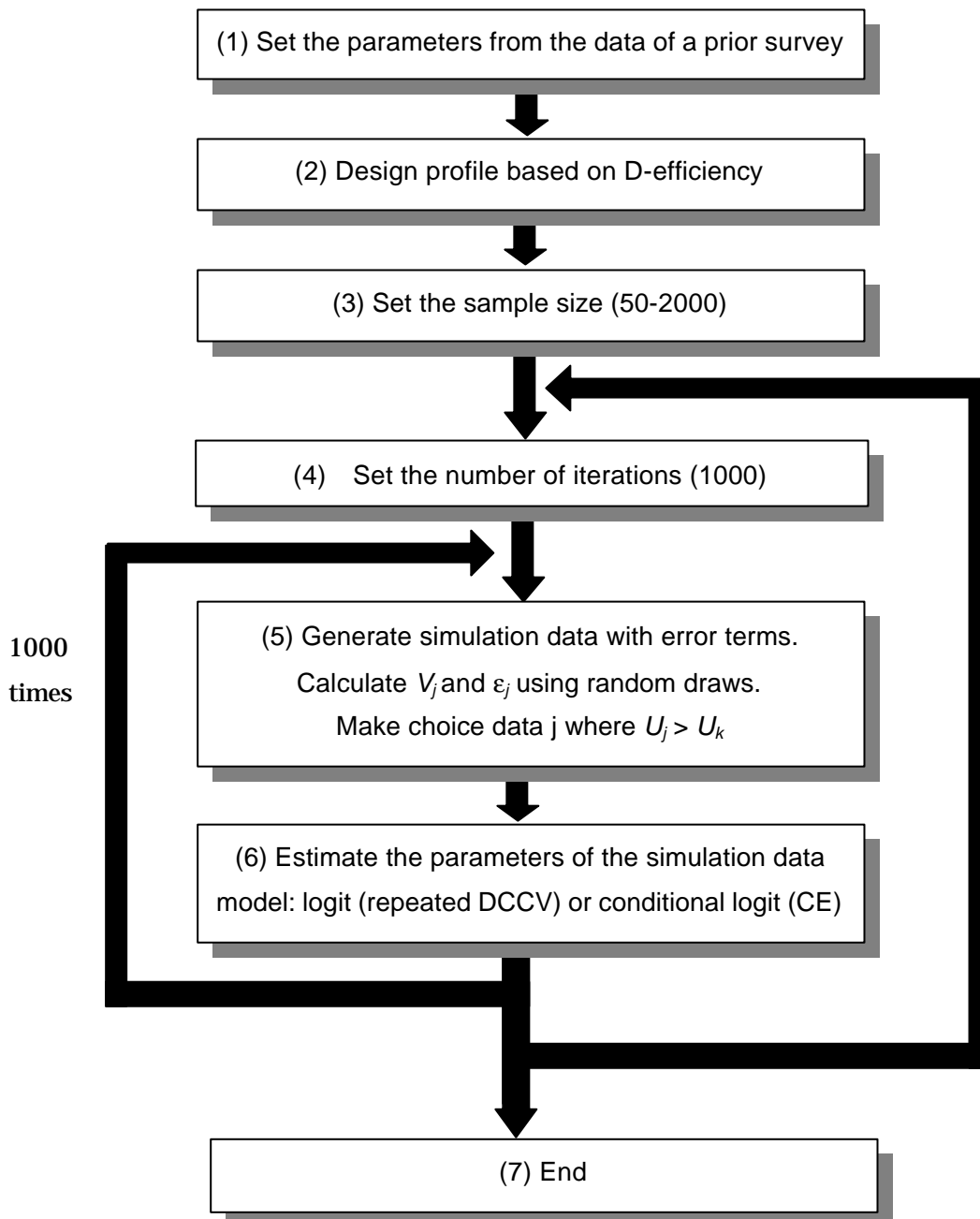
(4) **Set iteration.** Set the number of iterations for the Monte Carlo simulation. We used 1000 as the number of iterations.

(5) **Generate simulation data with error terms.** The deterministic component of utility V_j of profile j is calculated using given parameters, while error terms are generated using random draws from a type I extreme-value distribution (a Gumbel distribution). When the distribution of the random draws is standard normal, the estimated parameters need to be scaled by $\mathbf{p}/\sqrt{6}$.

(6) **Estimate parameters.** The simulation data for repeated DCCV are estimated using a logit model, and the CE data are estimated by a conditional logit model.

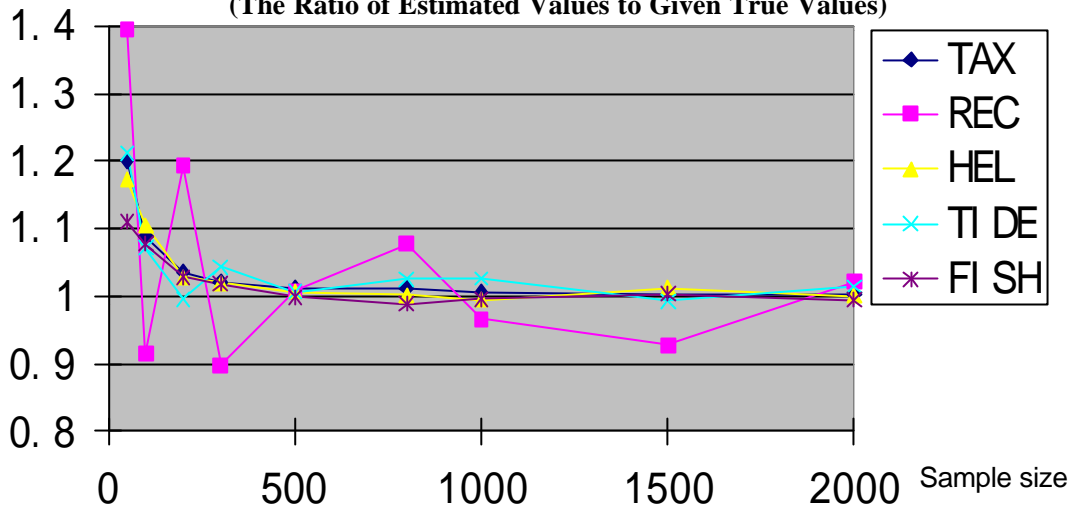
(7) **End after iteration**

Figure 3. Monte Carlo Simulation Procedure



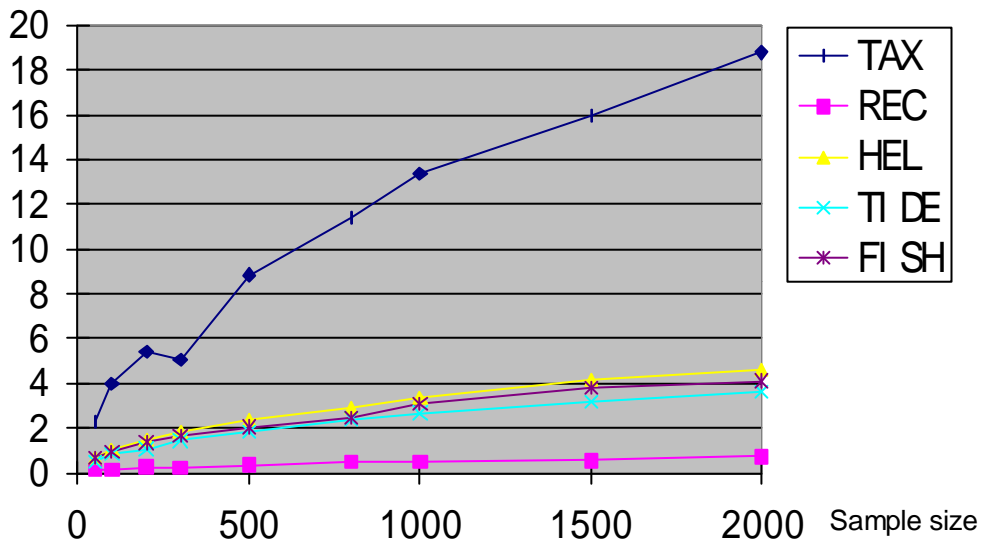
Figures 4 and 5 show the results of a Monte Carlo simulation of the repeated DCCV format. Figure 4 illustrates the ratio of the parameters estimated by simulation compared with the true parameters. Ideally, the estimated parameters should equal the true parameters, thus this ratio should be one. This figure suggests that all the parameters converge to the true parameters as the sample increases. Except for REC, the error of the estimated parameters is less than 3% when the sample size is over 500.

Figure 4. The Estimated Parameters of a Monte Carlo Simulation (Repeated DCCV)
 (The Ratio of Estimated Values to Given True Values)



Note: Estimated by a Monte Carlo simulation based on 1000 iterations.

Figure 5. The Asymptotic T Values of Estimated Parameters (Repeated DCCV)

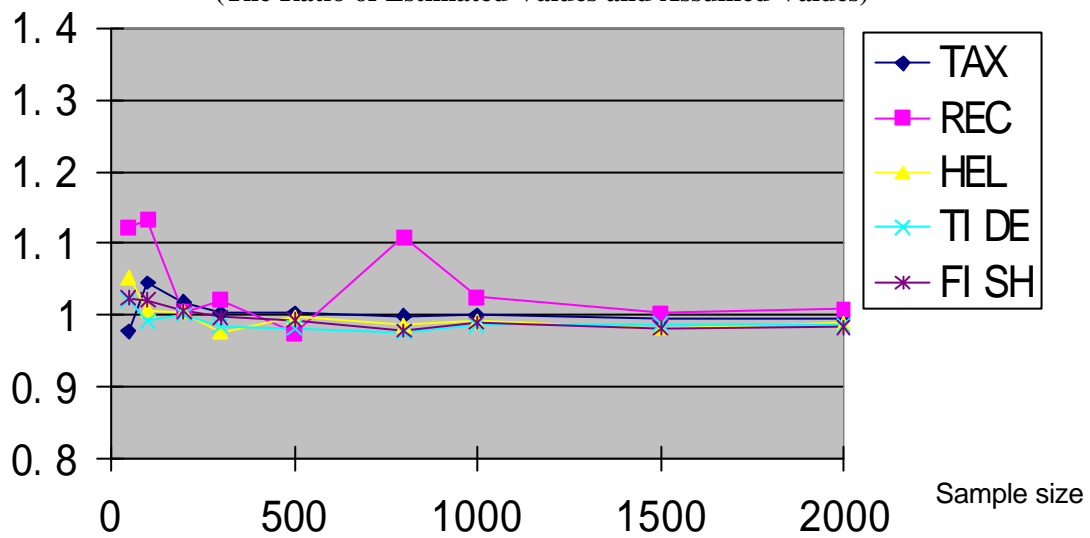


Note: Estimated by a Monte Carlo simulation based on 1000 iterations. Absolute values of asymptotic t values.

Figure 5 provides the absolute values of the asymptotic t statistics of the parameters estimated by simulation. The t values of all variables increase as the sample size increases. While REC is not significant, other variables are significant at the 5% level when the sample is larger than 800. Note that REC was not significant in the survey data. These results suggest that we need a sample size of at least 800 usable data to estimate the value of each attribute using the DCCV format. Usually, CV

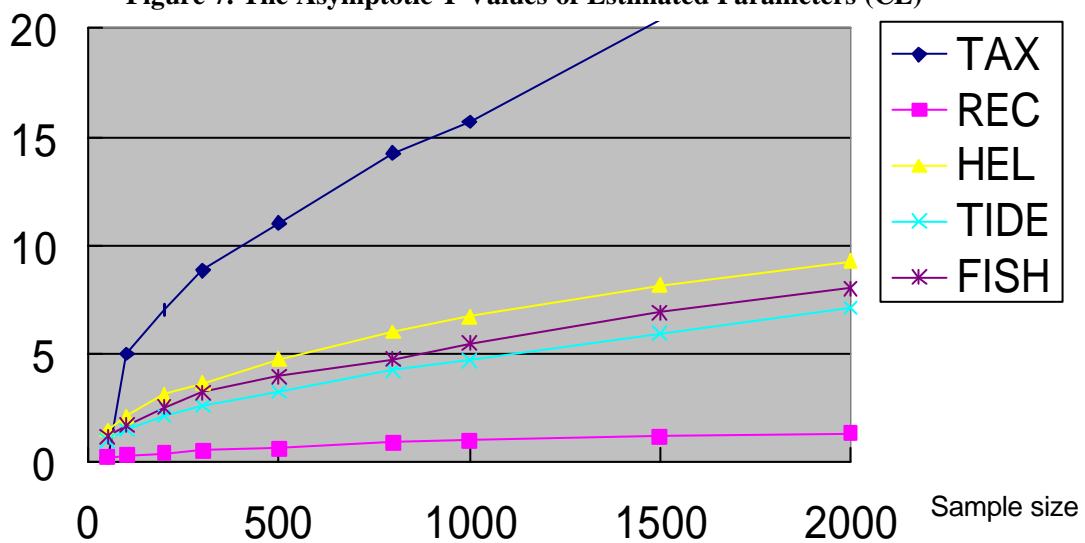
researchers have to remove some survey responses, such as protest responses, “don’t know” responses, and outliers, and consequently, more than 1000 samples may be required. This means that it is difficult to adopt a single question, as the traditional DC format does, for attribute-based valuation, because the cost would be too high. While traditional DCCV asks respondents a single binary question, repeated DCCV asks for responses to multiple binary questions. For example, when the choice set is eight, which is the usual choice set scenario in CE, repeated DCCV asks binary questions eight times, and therefore the minimum number of respondents required is $800 / 8 = 100$.

Figure 6. The Estimated Parameters of a Monte Carlo Simulation (CE)
(The Ratio of Estimated Values and Assumed Values)



Note: Estimated by a Monte Carlo simulation based on 1000 iterations.

Figure 7. The Asymptotic T Values of Estimated Parameters (CE)



Note: Estimated by a Monte Carlo simulation based on 1000 iterations. Absolute values of asymptotic t values.

Figures 6 and 7 show the results of a Monte Carlo simulation using a CE format. The error of estimation of CE is relatively small and asymptotic t values tend to be higher than those for repeated DCCV. Figure 7 suggests that all variables except REC are significant at the 5% level when the sample is larger than 200. These results show that repeated DCCV is less efficient than the CE format, and requires a larger sample.

To summarize our Monte Carlo simulation results: it is possible to distinguish the value of each attribute of a multi-attribute environmental good using the DC format, but the questions are less efficient than those of CE, and more than 800 usable survey responses are required. It is therefore difficult to estimate the value of multi-attributed goods using traditional DCCV. Therefore, repeated DCCV is necessary to analyze attribute-based data at reasonable cost.

4. EMPIRICAL RESULTS

This empirical study uses survey data concerning the provision of protection from oil spills in Tokyo Bay. Japan depends on imports for most of its petroleum resources; transportation of petroleum resources by tanker vessels is therefore indispensable. Each year, there are about 200-300 accidents involving oil spills in Japanese or nearby waters, and 10% of these accidents involve the possibility of large spills. Recent examples include the Russian tanker *Nakhodka* (13,157t), which broke up in the Sea of Japan on January 2, 1997, polluting the coastline, and the tanker *Diamond Grace* (257,000t), which ran aground in Tokyo Bay on July 2, 1997. Damage from oil spills includes direct and indirect damage to health, coastal ecosystems, commercial fishing, recreational use and shipping. Thus, an attribute-based valuation method should be adopted, to estimate the value of each attribute of the benefit derived from guarding against oil spills.

After two focus group interviews and four pilot surveys, two main surveys were developed. The first section of the survey described the damage caused by oil spills, including the damage to recreational sites, health, tidelands, and fishing ports. Some panels describing these attributes in detail were shown to respondents. The second section provided hypothetical plans to provide protection against damage from oil spills. These plans were the profiles: they are bundles of attributes. Some plans offer complete protection from oil spills, but they are expensive. Other plans cannot prevent all of the damage, but they are inexpensive. Respondents must prioritize the damage and choose what they most want to guard against. The payment vehicle is a one-time special tax. While the elicitation methods in the first main survey were a pair-wise rating, CE, and single DCCV, the second main survey used a CE and repeated DCCV format. Each format asked questions sequentially, and the order of the sequence was randomized to avoid order effects. While split sample comparisons between WTP, WTA, and the resource compensation format were made in the second main survey, this paper uses data only from the WTP format. The results of the other formats

are described in Takeuchi et al. (1999).

We focus on the WTP format of repeated DCCV and CE questions in the second main survey. The attributes and levels in Table 3 were used. See Figure 1 and Figure 2 for the questionnaire that was used in the survey. The “don’t know” option was explicitly offered to respondents in the repeated DCCV format. 128 profiles were designed for repeated DCCV and 64 for CE, using the Defficiency criterion, with the parameters estimated from the first main survey data. There were eight choice sets of repeated DCCV and CE. The version of repeated DCCV was $16 = 128 / 8$; and CE was $8 = 64 / 8$. Residents around Tokyo Bay were interviewed in-person in January 1999. There were 500 responses completed for the second main survey (a response rate of 58.8%). Usable samples for the repeated DCCV and CE formats (WTP version) were 1024 (=128 respondents * 8 choice sets) and there were 113 (11%) “don’t know” repeated DCCV format responses. For more details of this survey, see Takeuchi et al. (1999).

Table 4 shows the estimated parameters of the repeated DCCV question, which were estimated using a logit model. While “don’t know” responses were treated as “no” in Model 1, they were removed from Model 2³. REC is not significant in Model 1, but all variables are significant at the 5% level in Model 2. This table suggests that repeated DCCV can determine the significant parameters of attribute-based valuation when the sample size is more than 1000.

Table 4. Logit Estimation of Repeated DCCV model

	Model 1	Model 2
	RDCCV1 ^{*1}	RDCCV 2 ^{*2}
TAX	-0.24375 *** (-11.931)	-0.23865 *** (-11.326)
REC	0.21379 (1.439)	0.37092 ** (2.278)
HEL	0.43082 *** (3.478)	0.50283 *** (3.786)
TIDE	0.38370 * (1.873)	0.64488 *** (2.983)
FISH	1.64819 *** (5.176)	1.66041 *** (4.944)
N	1024	911
LogL	-616.296	-542.063

^{*1} “don’t know” response was coded to “no”

^{*2} “don’t know” response was removed

A comparison between repeated DCCV and CE is shown in Table 5. Model 1 is the same

³ Carson et al. (1995) treated a “don’t know” response simply as “no” and found that offering the “don’t know” option did not change the estimate of WTP. However, to drop the “don’t know” respondents not only results in lost information of choice preferences, but may also cause a sample selection bias if the “don’t know” respondents’ preferences are not the same as those of the other respondents.

as in Table 4. Model 3 is the CE parameters estimated using conditional logit. The asymptotic t values of Model 3 tend to be higher than those of Model 1, showing that CE is more efficient than repeated DCCV. The likelihood ratio statistic is 11.61, and is significant at the 5% level. Therefore, the parameters in the repeated DCCV and CE models are significantly different. Models 5 and 6 are joint estimates of repeated DCCV and CE data sets (Adamowicz et al., 1998). The likelihood function of the joint model is as follows:

$$LL_{CV+CE} = LL_{RDCCV}(\mathbf{Ib}) + LL_{CE}(\mathbf{b}) \quad (9)$$

where λ is a scale parameter. While Model 5 assumes that λ is equal to 1, Model 6 does not. The estimated scale parameter ($\hat{\lambda}$) of Model 6 is 1.057, and this is not significantly different from unity. This means that there is no significant difference in the error variance of repeated DCCV and CE.

Table 5. Estimated parameters of repeated DCCV and CE models

	Model 1	Model 3	Model 5	Model 6
	RDCCV 1	CE	RDCCV 1 & CE	RDCCV 1 & CE with λ
TAX	-0.24375*** (-11.931)	-0.21596*** (-12.348)	-0.23020*** (-17.420)	-0.22487*** (-13.328)
REC	0.21379 (1.439)	-0.22652** (-2.131)	-0.07713 (-0.893)	-0.07387 (-0.757)
HEL	0.43082*** (3.478)	0.69225*** (8.913)	0.62988*** (9.647)	0.61485*** (8.581)
TIDE	0.38370* (1.873)	0.54331*** (4.046)	0.51398*** (4.631)	0.49947*** (4.438)
FISH	1.64819*** (5.176)	1.06343*** (4.767)	1.27160*** (7.100)	1.24459*** (6.708)
λ				1.05694*** (9.081)
N	1024	1024	1024	1024
LogL	-616.296	-1022.54	-1644.64	-1644.51

Next, consider the estimation of the welfare from the protection against damage from oil spills. When the utility function is linear in the attributes, the total differential of the utility function is

$$dV_{ij} = \mathbf{b}_{TAX} dTAX_{ij} + \mathbf{b}_{REC} dREC_j + \mathbf{b}_{HEL} dHEL_j + \mathbf{b}_{TIDE} dTIDE_j + \mathbf{b}_{FISH} dFISH_j \quad (10)$$

where utility is assumed to be held constant ($dV_{ij}=0$). The monetary measure for 1 unit change of

protecting the recreation sites is

$$MWTP_{RECj} = \frac{dTAX_{ij}}{dREC_j} = -\frac{\mathbf{b}_{REC}}{\mathbf{b}_{TAX}} \quad (11)$$

The marginal WTPs of other attributes can be estimated similarly. Table 6 shows marginal WTPs estimated by repeated DCCV and CE using equation (11). The numbers in brackets are 95% confidence intervals that are obtained using the method of Krinsky and Robb (1986), and are based on 4000 random draws. When comparing Model 1 (repeated DCCV) and Model 3 (CE), there are some differences between marginal WTPs: While FISH of Model 1 (676) is higher than that of Model 3 (492), HEL and TIDE of Model 1 (177, 157) are lower than those of Model 3 (321, 252). However, the order of marginal WTPs is the same for repeated DCCV and CE: FISH > HEL > TIDE > REC. This result suggests that repeated DCCV can at least get the same preference order as CE.

Table 6. Estimated Marginal Willingness to Pay of the Attributes

model 1 (RDCCV1)	REC	88 yen / %	[-33 - 210]
	HEL	177 yen / 100 person	[78 - 273]
	TIDE	157 yen / %	[-8 - 312]
	FISH	676 yen / %	[427 - 947]
model 2 (RDCCV2)	REC	155 yen / %	[19 - 290]
	HEL	211 yen / 100 person	[104 - 315]
	TIDE	270 yen / %	[99 - 443]
	FISH	696 yen / %	[424 - 1,001]
model 3 (CE)	REC	-105 yen / %	[-209 - -8]
	HEL	321 yen / 100 person	[254 - 397]
	TIDE	252 yen / %	[132 - 371]
	FISH	492 yen / %	[307 - 693]
model 4 (RDCCV1 & CE)	REC	-34 yen / %	[-109 - 40]
	HEL	274 yen / 100 person	[220 - 330]
	TIDE	223 yen / %	[131 - 316]
	FISH	552 yen / %	[403 - 699]
model 5 (RDCCV1 & CE with λ)	REC	-33 yen / %	[-122 - 52]
	HEL	273 yen / 100 person	[219 - 330]
	TIDE	222 yen / %	[129 - 314]
	FISH	553 yen / %	[402 - 712]

The numbers in brackets are 95% confidence intervals which are obtained by the method of Krinsky and Robb (1986) and based on 4000 random draws.

5. DISCUSSION

We developed a repeated DCCV format whereby respondents were iteratively asked binary choice questions related to some offered profiles with multi-attribute bundles. Estimation by repeated DCCV was compared with that by CE in a Monte Carlo simulation and by using empirical survey data. The results of the simulation show that the parameters estimated by repeated DCCV with efficiently designed profiles can be significant, although repeated DCCV is less efficient than CE and requires more than 800 usable survey responses. Empirical results show that the parameters estimated by repeated DCCV are significant when the sample is more than 1000, however, and that estimated marginal WTPs from repeated DCCV responses are slightly different to those from CE. One possible reason for this difference is the difficulty of the CE question: respondents must compare three or more alternatives to decide their most preferred profile in CE format, which some respondents might find confusing. Another possible problem is the “yes-saying” bias of the repeated DCCV format. Further study is required to detect the biases in repeated DCCV and CE methods.

1. Adamowicz, W.L., J. Louviere, and M. Williams, *Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities*. Journal of Environmental Economics and Management, 1994. **26**(3): p. 271-292.
2. Adamowicz, W.L., *et al.*, *Perception versus Objective Measures of Environmental Quality in Combined Revealed and Stated Preference Models of Environmental Valuation*. Journal of Environmental Economics and Management, 1997. **32**(1): p. 65-84.
3. Adamowicz, W.L., *et al.*, *Stated Preference Approaches for Measuring Passive Use Values: Choice Experiment and Contingent Valuation*. American Journal of Agricultural Economics, 1998. **80**(1): p. 64-75.
4. Boxall, P., *et al.*, *A comparison of stated preference approaches to the measurement of environmental values*. Ecological Economics, 1996. **18**: p. 243-253.
5. Carroll, J.D. and P.E. Green, *Psychometric Methods in Marketing Research: Part I, Conjoint Analysis*. Journal of Marketing Research, 1995. **32**(4): p. 385-391.
6. Carson, R.T., *et al.*, *A Bibliography of Contingent Valuation Studies and Papers*. 1995, CA. San Diego.: Natural Resource Damage Assessment, Inc.
7. Carson, R.T., *et al.*, *Referendum Design and Contingent Valuation: The NOAA Panel's No-Vote Recommendation*. Review of Economics and Statistics, 1998. **80**(3): p. 484-487.
8. Green, P.E. and V. Srinivasan, *Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice*. Journal of Marketing, 1990. **54**: p. 3-19.
9. Greene, W.H., *Econometric Analysis*. 3rd E. 1997, New Jersey: Prentice Hall. 1075.
10. Hajivassiliou, V.A., D.L. McFadden, and P.A. Ruud, *Simulation of Multivariate Normal Orthant Probabilities: Method and Programs*. 1992: mimeo, Cowles Foundation for Research in Economics, Yale University.
11. Hoehn, J.P. and A. Randall, *A Satisfactory Benefit Cost Indicator from Contingent Valuation*.

- Journal of Environmental Economics and Management, 1987. **14**(3): p. 226-47.
12. Huber, J. and K. Zwerina, *The Importance of Utility Balance in Efficient Choice Designs*. Journal of Marketing Research, 1996. **33**: p. 307-317.
 13. Johnson, F.R. and W.H. Desvousges, *Estimating Stated Preferences with Rated-Pair Data: Environmental, Health, and Employment Effects of Energy Programs*. Journal of Environmental Economics and Management, 1997. **34**(1): p. 79-97.
 14. Krinsky, I. and A.L. Robb, *Approximating the Statistical Properties of Elasticities*. Review of Economics and Statistics, 1986. **68**: p. 715-719.
 15. Louviere, J., *Conjoint Analysis*, in *Advanced Method of Marketing Research*, R.P. Bagozzi, Editor. 1994, Blackwell. p. 223-259.
 16. Louviere, J., *Analyzing Decision Making: Metric Conjoint Analysis*. Series: Quantitative Applications in the Social Sciences. Vol. 67. 1998: SAGA Publications. 95.
 17. Mackenzie, J., *A Comparison of Contingent Preference Models*. American Journal of Agricultural Economics, 1993. **75**(3): p. 593-603.
 18. McFadden, D., *Conditional Logit Analysis of Qualitative Choice Behavior*, in *Frontiers in Econometrics*, P. Zarembka, Editor. 1973, Academic Press: New York. p. 105-142.
 19. Opaluch, J.J., *et al.*, *Evaluating Impacts from Noxious Facilities: Including Public Preferences in Current Siting Mechanisms*. Journal of Environmental Economics and Management, 1993. **24**(1): p. 41-59.
 20. Roe, B., K.J. Boyle, and M.F. Teisl, *Using Conjoint Analysis to Derive Estimates of Compensating Variation*. Journal of Environmental Economics and Management, 1997. **31**(2): p. 145-159.
 21. Viscusi, W.K., W.A. Magat, and J. Huber, *Pricing Environmental Health Risks: Survey Assessments of Risk-Risk and Risk-Dollar Trade-Offs for Chronic Bronchitis*. Journal of Environmental Economics and Management, 1991. **21**(1): p. 91-96.
 22. Zwerina, K., J. Huber, and W.F. Kuhfeld, *A General Method for Constructing Efficient Choice Designs*. mimeo, 1996.