ASSESSING DOUBLE-SCENARIO CV RESPONSES IN VALUING ENVIRONMENTAL IMPACT OF ROAD PROJECTS*

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1. Introduction

Common thinking that road equates to economic development pave ways for more and more roads to be built, and cause impacts to the natural, human and social environments. In aid of sustainability, environmental assessment (EA) is one of the mechanisms for internalizing this kind of impacts. Alternative solutions or designs to mitigating significant impact are considered for a more sustainable road planning[1]. Evaluation of these alternatives involves comparison of values (i.e. use and non-use) measured against particular criteria. Contingent Valuation (CV) is among the popular methodologies on the valuation of non-use values. This survey-based methodology involves eliciting respondents willingness to pay (WTP) to maintain or attain a certain level of environmental quality.

Current CV surveys favour close-ended or dichotomous choice (DC) valuation format over open ended elicitation format. Moreover, inclusion of a follow-up question to asymptotically increase the significance of the WTP estimates has been progressively employed[2]. This is commonly called double-bounded dichotomous choice (DBDC). However, though this elicitation procedure provides more information about underlying WTP distribution, it also presents windows for inconsistencies arising from the repetitive bidding process. This confusion may be aggravated when the respondents are presented different scenarios offering various quality or quantity of the environmental good under consideration. In this situation, it is very hard to comprehend and compare the different attributes of the goods possibly causing the respondent to make preference out of rational tendencies.

Multiple-scenario CV surveys commonly employed in recent CV surveys. Scenarios may vary according to the quantity or quality of environmental good[3) 4)], or according to comparative goods[5]. These surveys are usually done to economize on cost associated with separate surveys. There is always a need to do EA and valuation of impacts of alternative solutions/designs to facilitate sound decision-making, particularly in the planning stage of a program or project to consider possible trade-offs.

This study aims to investigate these biases on a two-scenario context. Particular points for investigation are: (1) effects of scenario responses correlation to characteristics of WTP distributions; (2) further effect of response bias, anchoring in particular, in WTP distribution; and, lastly, (3) characterization of the response bias with respect to varying degrees of response correlation. Monte-Carlo experiments to test estimation framework are done. The framework was applied to the valuation of cultural heritage preservation efforts in the project Cebu South Coastal Road (CSCR) -Segment 3 in Metro Cebu, Philippines. To avoid on-grade alignment which will have severe impacts to the cultural heritage site, two alternative alignment scenarios, i.e. elevated and subsurface, offering different level of preservation were proposed. Respondents valuation of the non-use cultural heritage value of the site according to the two options necessitating additional funds for preservation are investigated in this paper.

This paper is structured as follows. Section 2 presents some issues associated to DC WTP survey on a multi-scenario context. The estimation framework of response bias in two-scenario WTP is presented in section 3. Section 4 investigates the estimation framework through simulations. The data and data collection techniques is presented in section while analytical results of the case study are presented in Section 5. Conclusions and recommendations are presented Section 6.

2. Modelling Issues in DC WTP in Multi-Scenario Context

Concerns arising from multi-scenario CV survey can be summed up into two items. First is the correlation of responses between scenarios that is possibly caused some the unobserved correlation of the

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alternative goods attributes or the correlation of stochastic elements of the utilities for these goods. Second is the response inconsistencies due to the DBDC questioning format. The following sub-sections discuss the issues concerning these responses inconsistencies.

(1) Correlation of Responses to Different Scenarios

In a common choice-making process, a well-defined choice sets and taste homogeneity is assumed in a well-defined population. However, when presented with choice questions across different alternatives, problems of choice heterogeneity and potential unobservable choice sets are expected[6]. One disadvantage of multi-scenario CV survey is the possible correlation in the stochastic component the utilities between scenarios. The general tendency of a researcher when estimating multi-scenario WTP responses is to treat them singly or individually. This may be sound except when there is strong correlation between responses. When latent WTP functions are correlated across alternatives or when independent and identically distributed (IID) utilities are not valid across scenario, joint estimation of is a way of addressing correlation of responses between alternatives. The only limitation of this model is its computational intensiveness. Where K is the number of scenarios, computation entails a k-dimensional integral of the probability density function for each scenario. Say, in the case of SBDC problem for 3 scenarios A, B, and C, an individual answering no to initial bid $C1_K$ for scenario A and B, and yes to scenario C entails the three dimensional integral below.

$$P(C_{Ai} \leq C1_A, C_{Bi} \leq C1_B, C_{Ci} \leq C1_C) = \int_0^{C_{Ai}} \int_0^{C_{Bi}} \int_{C_{Ci}}^{C_{C\max}} \phi(C_A, C_B, C_C) dc_A dc_B, dc_C \tag{1}$$

Multivariate normal distributions are best for multivariate cases as it allow for covariance structure that offers maximum flexibility for modelling. However, it is very computationally limiting, until recently, evaluation for cases with K>2 impractical. Recent development of various simulation techniques made the evaluation of this integral possible. More so, other techniques such as contingent ranking, contingent choice and mixed contingent voting/and ranking are likewise being employed. Merit of the multivariate Probit models, however, cannot be doubted in terms of explaining correlation. Riddel and Loomis[4] presented a model of joint estimation of multiple CVM scenarios under a DBDC questioning format to deal with the correlation between scenarios on the context of comparatively studying it with seemingly unrelated regression (SURE) model. They presented a closed form model for joint estimation of DBDC WTP with two alternative programs.

(2) Response Biases in Dichotomous Choice with Follow-up

In experimental economics, it is becoming widely acknowledged that the rational man of economics, who is a utility maximizer, is in danger of extinction. Presence of some kind of response effects due to some kind of behavioural tendencies or motivations. This affects the psychometric perception of individuals and influence true WTP. A more complex behaviour can be observed in a multiple scenario context where response bias in one scenario is correlated to the response bias in another scenario. For instance, a respondent s tendency to misstate his true WTP in another scenario may have effect on how he responds in another scenario. More so, in two-scenario context, it may lead to a pattern of response bias characterizing referendum preference between the two. The thinking process is more intricate and is definitely be inappropriately modelled if not considered in a framework allowing for correlation among responses.

In Mc Fadden s framework of individual s choice making behaviour, one of the categorization he discussed is that relating to context misconceptions[7]. Anchoring is a bias that can be included in this type. It belongs to a group of many psychological researches about uncertain quantities[8]. According to these researches, subjects, before stating their own estimate of a quantity contemplate based on a higher or lower uncertain quantity. A robust model of this behaviour explains that subjects start from the anchor and fail to adjust fully to their based beliefs, causing the estimates to be pulled to the anchor. Kahneman and Traversky further state that initial value or starting points often influence bias of the estimates.

In DBDC, along with the complexity of the elicitation process come some inconsistencies in terms of estimates. Inconsistencies in DBDC modelling mainly arise from the questioning pattern and the respondent s psychological circumstances. In this case, anchoring bias can be defined more specifically as the tendency of the respondent to anchor his WTP on the first bid. Various models of anchoring have been done in various studies. Two models have been found investigating anchoring, that of Hanneman[9] and that of Herrige and Shogren[10]. Haneman approached response effects analogous to anchoring in terms of resentment and acquiescence scenario. He respecifies the interval model by adding a background response probability of a respondent saying no in the probability that a respondent answers yes in the second bid. Herriges and Shogren[10], on the other hand, approach anchoring by postulating that the respondent changes his valuation of the item after the first bid, forming some function of his original WTP such that:

$$WTP = (1-\gamma)WTP_{TRUE} + \gamma C1 \tag{2}$$

If C1, is the first bid, WTP_{TRUE} is his true preference, and WTP is the preference after the first bid, Herriges and Shogren[10) claim that some parameter γ that takes on a value from 0 to 1 can be factored to the C1 and WTP_{TRUE}. If γ is 0, there is no anchoring the equation collapses back to the original presumption of equal WTP during the first and second bid.

3. Modelling Framework of Response Bias in Two-Scenario WTP

When an individual is asked about two alternative programs, there may be correlation in the answer of the respondents as the programmes may have inherent correlation the researcher has overlooked or the respondents has some unobserved attribute which causes him to make some strategic behaviour. A respondent, over preference for one alternative, may cause respondent to make strategic behaviour to decrease significantly his WTP for that alternative. If presented a DBDC question, these response bias may be observed in the way how a respondent strategically make decision on his WTP for different scenario by anchoring his/her answer to the first bid. Figure 1 shows conceptual cognitive behaviour when asked a two-scenario DC WTP question.

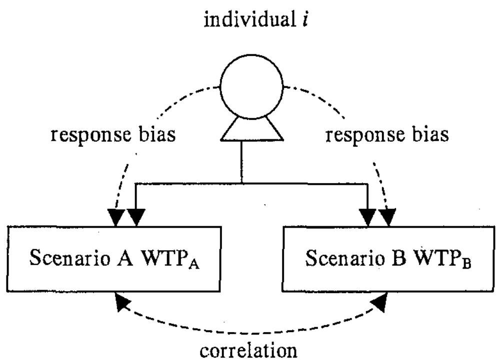


Figure 1. Cognitive choice behaviour in two-scenario WTP question

This study offer a framework for estimation of response bias of an individual when presented with alternatives or scenarios as caused by, first, his failure to put into context the choice question he is facing and, second, his failure to differentiate alternative scenarios is presented. The willingness to pay of individual i for a double scenario WTP question format with alternative A and B is defined to include parameters γ_i and ρ_i where γ_i is a behavioural parameter related to context misconception and ρ_i is the correlation coefficient of the Bi-variate function $\phi\,(WTP_{Ai}, WTP_{Bi}, \rho_i)$. This study proposed a way of relaxing the independence from irrelevant alternative (IIA) assumption by incorporating parameter explaining respondent behavioural tendency and correlation between alternative scenarios in the estimation. The behaviour of the response bias shall be investigated when modelled singly or jointly to take into consideration the anchoring bias. To deal with the bias that may arise because of the failure to perceive differences in alternative, joint estimation of the two DBDC datasets shall be likewise modelled to determine correlation of errors. Since a respondent s preference over the good presented in different scenarios is assumed to be based on a single utility process, the underlying stochastic and behavioural components of WTP answers may be correlated. In this regard, DBDC data of different scenarios simultaneously account for the correlation of error terms between scenarios valued by the same respondent.

In estimating WTP of individuals in a double-scenario be specified into the following equation for latent WTP amount as a function of systematic and stochastic components:

$$\bar{C}_{Ai} = \beta_A x_{Ai} + \varepsilon_{Ai} \quad \text{, and} \quad \bar{C}_{Bi} = \beta_{Bi} x_{Bi} + \varepsilon_{Bi}. \tag{3}$$

where a and b are the scenarios A and B under consideration; $\bar{C}_{Ki}$ is the willingness to pay of individual i for scenario $K(K \in A,B)$; $\beta_k x_{ki}$ is the vector of systematic components $\bar{C}_{ki}$; and ε_{ki} is the random error associated with the ith individual and each scenario. In a joint estimation the number of the log-likelihood function takes the form n^K, where n is the number of interval in single scenario estimation and K is the number of scenarios. For SBDC, $n^K = 2^2 = 4$, and for DBDC $n^K = 4^2 = 16$. The four probability components of SBDC include:

$$P_i^{YY} = 1 - \Phi(A_{C1i}) - \Phi(B_{C1i}) + \Psi(A_{C1i}, B_{C1i}, \rho);\ P_i^{YN} = \Phi(B_{C1i}) - \Psi(A_{C1i}, B_{C1i}, \rho);$$
$$P_i^{NY} = \Phi(A_{C1i}) - \Psi(A_{C1i}, B_{C1i}, \rho);\ \text{and}\ P_i^{NN} = \Psi(A_{C1i}, B_{C1i}, \rho). \tag{4}$$

$\Phi(A_{C1i})$ is the normal cdf and $\Psi(A_{C1i}, B_{C1i}, \rho)$ is the Bi-variate normal cdf with correlation ρ as follows:

$$\Psi(A_{C1i}, B_{C1i}) = \int_{-\infty}^{C1_{Ai}} \int_{-\infty}^{C1_{Bi}} \frac{1}{2\pi\ q\sigma_B\sqrt{1-\rho^2}} \exp\left\{\frac{1}{2\rho^2 - 2}\left[(A_{C1i})^2 - 2\rho(A_{C1i})(B_{C1i}) + (B_{C1i})^2\right]\right\} \tag{5}$$

In the same manner, in DBDC, for a respondent saying yes to all the four initial and follow-up questions of the two-scenario DBDC, the probability takes the form:

$$P_i^{YYYY} = P(CU_{Ai} \le \overline{C}_{Ai}, CU_{Bi} \le \overline{C}_{Bi}) = 1 - \Psi(A_{CUi}, B_{CUi}) - \Phi(A_{CUi}) - \Phi(B_{CUi}) \tag{6}$$

In all cases, the latent equations for lognormal distribution are:

$$\begin{aligned} A_{C1i} &= (\ln C1_{Ai} - \beta_i x_i)/\sigma_A, & & B_{C1i} = (\ln C1_{Bi} - \beta_i x_i)/\sigma_B \\ A_{CUi} &= (\ln CU_{Ai} - \beta_i x_i)/\sigma_A, & \text{and}\quad & B_{CUi} = (\ln CU_{Bi} - \beta_i x_i)/\sigma_B \\ A_{CLi} &= (\ln CL_{Ai} - \beta_i x_i)/\sigma_A, & & B_{CLi} = (\ln CL_{Bi} - \beta_i x_i)/\sigma_B \end{aligned} \tag{7}$$

Estimation of incorporating response bias entails redefinition of these latent equations to satisfy behavioural premise as shown in Eq. (2). In this study, only anchoring bias will be investigated. The log-likelihood of the DBDC joint Probit model is written as:

$$\ln L_i = \sum_u \sum_v \sum_w \sum_z \delta_i^{uvwz} \ln P_i^{uvwz} \tag{8}$$

where u, v, w and z take a value of either 1 or 0 for yes or no response, respectively.

One advantage of this estimation technique is being able to determine potential substitution effect of the alternative solutions. In single estimation, estimates leads to a confidence region around the mean that is not influenced by the entire correlation matrix. It is expected that a joint estimation, which extend correlation matrix across the alternative tightens the confidence region. For a lognormal distribution, if the confidence region falls where WTP for scenario A is equal to the WTP for scenario B, we can reject the hypothesis that a respondent is more willing to pay for one alternative than the other. It is therefore less likely that a confidence ellipsoid approximates the 45 degrees line when the correlation structure is good.

4. Model Simulation

In the following analysis, lognormal distribution is used to estimate randomly generated normal and multivariate normal random WTP. This type of distribution limits WTP values into positive values. The parameters of interest in this lognormal distribution $LN(\mu, \sigma^2)$ are the mean ($\mu_{LN} = \exp(\mu + 0.5\sigma^2)$); the median ($\exp(\mu)$); and the variance ($\sigma_{LN}^2 = [\exp(2\mu + \sigma^2]\cdot[\exp(\sigma^2 - 1])$ [11]. Simulations are done to test general characteristics of the joint estimation framework with and without anchoring bias according to degree of correlation. The bidding process was simulated under different levels of correlation. It was assumed that the respondent is faced a multiple-scenario WTP questions by which the two goods has the same level or distribution. The bidding design described in Box 1 in the next chapter was used to simulate the hypothetical WTP question for alternate items with same quality/quantity level. The assumed normal mean and standard deviation are 10 and 3, respectively.

Table 3 below shows the result of the estimation. Results show that joint generally present more significant model than that of single estimation. Bar is placed over the simulated data parameter estimates. The point estimates, indicated by the μ_{Ai} and μ_{Bi}, are, however, closer to true value when estimated in single estimation. On the other hand, it results shows that in term of standard deviations σ_{Ai} and σ_{Bi}, joint estimations offer better estimates. These suggest tighter and more accurate confidence interval around mean in the joint rather than the single estimation. The significance of the $\widetilde{\rho}$ increases as the level of correlation increases.

Table 3. Simulation results, n=1000, $\mu_A = \mu_B$ =2.26, $\sigma_A = \sigma_B$ =0.29

	ρ (true)=0.2				ρ (true)=0.5				ρ (true)=0.7			
	Single		Joint		Single		Joint		Single		Joint	
Scenario A												
$\tilde{\mu}_A$	2.26	(139.8)	2.32	(164.5)	2.24	(148.0)	2.29	(168.2)	2.25	(146.3)	2.30	(174.0)
$\tilde{\sigma}_A$	0.36	(34.6)	0.28	(27.2)	0.35	(35.3)	0.29	(27.5)	0.35	(36.7)	0.28	(25.4)
Scenario B												
$\tilde{\mu}_B$	2.27	(152.8)	2.31	(174.6)	2.23	(142.4)	2.29	(169.4)	2.25	(142.9)	2.30	(176.6)
$\tilde{\sigma}_B$	0.33	(33.8)	0.27	(26.8)	0.35	(35.3)	0.27	(27.8)	0.35	(37.4)	0.27	(27.3)
$\tilde{\rho}$			0.25	(4.0)			0.43	(6.9)			0.65	(14.7)
Log-likelihood												
Scenario A	-729				-738				-728			
Scenario B	-692				-730				-725			
Joint			-992				-1009				-962	

Table 4 presents a simulation same as above but with a simulated anchoring effect (γ_{ANC}) of 0.9 in the normal WTP distribution (Eq.2) along assumed correlation effect. The results shows the same tendency mean estimates to be closer to true value in single and standard deviation true value to be closer in joint estimation. However, it is noteworthy that anchoring bias, even at high level of 0.90, appears to be insignificant in single estimation. Moreover, negative estimates of the anchoring are derived in some results of single estimation. This indicates the weakness of single estimation in estimating anchoring bias particularly when there is correlation between the items.

Table 4. Simulation results with anchoring, n=1000, $\mu_A = \mu_B$ =2.26, $\sigma_A = \sigma_B$ =0.29

	ρ (true)=0.2				ρ (true)=0.5				ρ (true)=0.7			
	Single		Joint		Single		Joint		Single		Joint	
Scenario A												
$\tilde{\mu}_A$	2.24	(136.5)	2.31	(135.6)	2.26	(145.3)	2.33	(130.7)	2.25	(144.6)	2.32	(146.3)
$\tilde{\sigma}_A$	0.34	(26.4)	0.29	(22.5)	0.33	(24.8)	0.29	(22.6)	0.33	(26.4)	0.27	(21.9)
$\tilde{\gamma}_A$	0.06	(1.7)	0.16	(3.9)	-0.02	-(0.6)	0.12	(3.1)	-0.05	(1.3)	0.05	(1.3)
Scenario B												
$\tilde{\mu}_B$	2.26	(146.2)	2.33	(116.8)	2.25	(147.1)	2.33	(116.1)	2.24	(150.1)	2.33	(129.3)
$\tilde{\sigma}_B$	0.32	(23.6)	0.30	(21.5)	0.34	(24.4)	0.33	(21.2)	0.32	(24.3)	0.28	(21.7)
$\tilde{\gamma}_B$	-0.02	-(0.5)	0.12	(2.9)	0.01	(0.4)	0.22	(5.4)	-0.05	(1.3)	0.13	(3.9)
$\tilde{\rho}$			0.19	(2.9)			0.42	(7.2)			0.62	(13.8)
Log-likelihood												
Scenario A	-667.1				-682				-704			
Scenario B	-667.8				-710				-717			
Joint			-946.5				-962				-915	

Based on the simulations above, merit of the joint estimation in terms of tighter confidence interval around mean and its ability to predict anchoring bias cannot be doubted. In all cases, though single estimation provides closer point estimates, joint estimation outweigh this by providing better models which are more reliable when applied in general data.

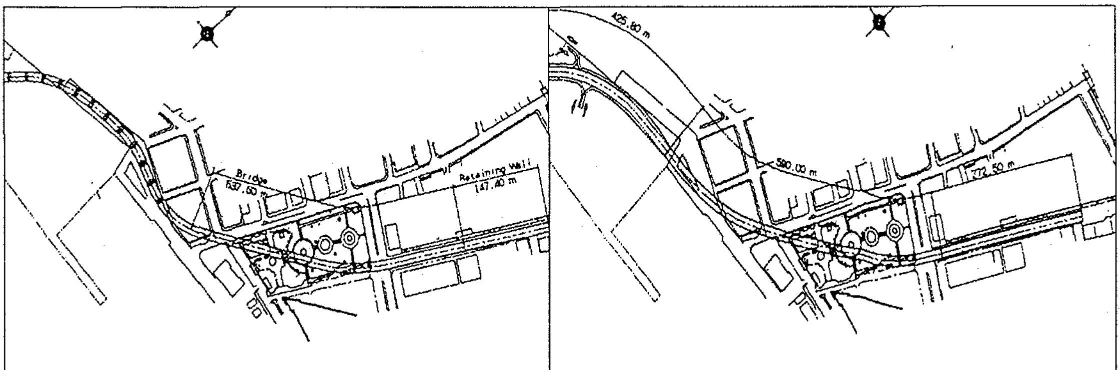
5. Data and Data Collection

(1) Study Area

The single and joint estimation framework of the DBDC WTP and response bias models are applied to the data on the valuation of an environmental impact of a road project considering different alignment scenarios of the Cebu South Coastal Road (CSCR) project in Cebu City. CSCR is an Official Development Assistance project under Japan Bank for International Cooperation s Overseas Economic Cooperation Fund (Loan Agreement No. PH-P158). The loan, which was approved in 1995, amounted to 18,391 million yen

(153.3 million USD) and consists of three segments, namely, (1) Talisay section (2) Causeway section, and (3) Viaduct cum Subway section. Segment 3 is further classified into: (3A) Viaduct section, (3B-1) Approach Section, and (3B-2) Sub-surface (Tunnel) section. At present, the construction of the first and second sections is almost finished. However, additional funding is still needed to pursue and finish the third segment which adopted a sub-surface alignment construction under a local cultural heritage site.

Prior to the actual sub-surface design, the sub-surface component, particularly segment 3B-2, has three alternative alignments, namely: (A) Widening of M.J. Cuenco Avenue along Plaza Independencia site; (B) Elevated highway structure across the Plaza Independencia; and (C) Sub-surface alignment across the Plaza Independencia. The study refers back to these alternatives to determine what value should be associated to cultural heritage preservation effort so as to rationalize additional fund requirement.



Scenario A Elevated highway structure across the Plaza Independencia

Scenario B Subway/ sub-surface alignment across the Plaza Independencia

Figure 2. Alternative Alignments for Segment 3 of Cebu South Costal Road

(2) CV Question and bid design

The hypothetical scenario for the willingness-to pay question was presented as follows. This type of questioning format are deemed to elicit both use and non-use value.

> The Cebu South Coastal road is a proposed major road connecting Talisay and Cebu City. The most feasible alignment of the northernmost portion of the road, however, would directly pass through Plaza Independencia. There are three alternative options on how to go about the project. The following table describes the alternative and its consequences.

ALTERNATIVES	CONSEQUENCE/S
BASE SCENARIO Putting the road on-grade claiming a portion of the Plaza Independencia.	▪ splitting of Plaza Independencia
SCENARIO A -ELEVATED Putting up an elevated road which will run over Plaza Independencia and block the view of Fort Santiago from the plaza.	▪ physical obstruction in Plaza Independencia; ▪ visual obstruction of Fort San Pedro; and ▪ 36% higher than cost of alternative A
SCENARIO B -SUBSURFACE Putting up the road on a subway and not changing the existing condition after the project is done.	▪ high construction and maintenance cost; ▪ 49% higher than cost of alternative A; and ▪ 18% higher than cost of alternative B

The preferred alternative was not elicited. The respondents were asked how much they were willing to pay in a DBDC question format for both alternative A and B to maintain and preserve amenity of the cultural heritage sites. The payment vehicles used were: (1) additional entrance fee to Fort San Pedro, (2) entrance fee to Plaza Independencia, and (3) toll fee. In this paper, only the results for the estimation for additional Fort San Pedro Entrance fee is presented. To remove starting point bias, random drawing of initial and second bids were done. Face to face elicitation method was used for to implement the questionnaires. The WTP elicitation statements and bidding design are shown in the following.

Box 1. WTP Elicitation Design

Payment cards: 3 [5 7 10 15] 25

(Draw one card from [•])
Initial: If the elevated alignment should be implemented for CSCR, are you willing to pay (fill in with the amount drawn) as a (fill in specific payment vehicle) to preserve and maintain the amenity of these cultural heritage sites?

(If the respondent answers yes, ask him to draw again from higher value cards. If the respondent answers no, ask him to draw again from lower value cards. If the respondent draws 5 and answers no , offer 3 directly. In the same manner, if the respondent draws 15 and answer yes , offer 25 directly.)
Follow-up: How about (fill in with the 2nd amount drawn)?

(3) Survey Data

The survey was conducted within Cebu City from June 28 to July 1, 2001. Prior to that, a small-sample pre-test survey was carried out to test questionnaire clarity and determine an initial distribution of WTP using open-ended elicitation format. Out of the total 348 completed questionnaires, 344 samples were used for analysis. Table 2 shows the characteristics of sample. To capture a sample that is representative of the income distribution of the study area, surveyors were assigned in public places where a more random mix of income level could be derived. There are 199 (57%) male and 149 (43%) female respondents. Majority of the respondents belongs to the age group 20-29 (43%), and are married (55%). About 143 (4%) of the respondents have bachelor s degree while 68 (20%) took vocational or technical courses. Most of the respondents are private employees (36%). Majority (92%) of the respondents belong to income bracket 10,000-14,999 and below. Only 13 respondents are tourists, two of which are foreigners.

Table 2. Sample Characteristics

VARIABLE	Obs.	(%)	VARIABLE	Obs.	(%)
SEX			**OCCUPATION**		
Male	199	57.2	Civil Service	23	6.6
Female	149	42.8	Private Emp.	126	36.2
AGE			Self Emp.	88	25.3
15-19	23	6.6	Labourer	20	5.8
20-24	75	21.6	Unemployed	44	12.6
25-29	74	21.3	Student	47	13.5
30-34	66	19.0	**INCOME**		
35-39	44	12.6	0	93	26.7
40-44	28	8.1	>3000	1	0.3
45-49	17	4.9	3000-5999	70	20.1
50-54	11	3.2	6000-9999	73	21.0
55-59	8	2.3	10000-14999	85	24.4
60-64	2	0.6	15000-19999	16	4.6
CAR OWNERSHIP			20000-29999	4	1.2
0	199	57.2	30000-39999	0	0.0
1	137	39.4	40000-59999	1	0.3
2+	12	3.5	60000 =<	5	1.4
EDUCATION			**MARITAL STATUS**		
None	1	0.3	Single	155	44.5
Primary	3	0.9	Married	191	54.9
Secondary	74	21.3	Others	2	0.6
Technical	68	19.5	**TOURIST**		
Bachelor	143	41.1	Tourist	13	3.7
Masteral	10	2.9	Not tourist	335	96.3
Doctoral	3	0.9			
Student	46	13.2			

Majority of the respondents find Plaza Independencia (76%) and Fort San Pedro (89%) culturally significant. Moreover, there is a clear indication that the cultural heritage values attached to the two sites are present as indicated by majority of the respondents finding the complex visually appealing (78%) and must be passed on to the next generation (89%). Other values identified in the open-ended inquiry are its historic, recreational and tourism values.

6. Model Estimation and Results

This section presents estimation of the two-scenario WTP survey using empirical data from the CSCR cultural heritage preservation valuation survey. Joint and single estimates of lognormal Probit model in with and without anchoring bias are presented.
Estimation of SBDC and DBDC under joint and single estimations was done as shown in Table 5. In this table, parameter estimates of the log-normal distribution μ_K and σ_K were shown as well as the normalized mean, median and variance. The correlation parameter ρ of the joint estimation are likewise shown. Estimation results show that SDDC appears to be more statistically efficient than DBDC. Moreover, estimates from joint resulted to better fit than from single estimation. All of the joint estimation models resulted to significant value of correlation coefficient ρ. Tighter confidence intervals as indicated by the reduction in variance are found in most of the results of joint estimation.

Table 5. SBDC and DBDC by single and joint estimation, n=344

	Single		Joint	
	Single bound	Double bound	Single bound	Double bound
Scenario A				
μ_A	1.56 (23.4)	1.74 (28.3)	1.56 (23.3)	1.92 (28.8)
σ_A	0.91 (7.9)	1.02 (16.8)	0.91 (8.7)	0.96 (13.0)
Mean WTP	7.16	9.57	7.16	7.88
Median WTP	4.75	5.68	4.76	10.79
Variance	42.90	95.64	42.84	106.86
Scenario B				
μ_B	1.83 (17.0)	2.09 (29.1)	1.76 (20.4)	2.02 (32.1)
σ_B	1.40 (5.7)	1.14 (18.0)	1.16 (8.3)	0.86 (14.8)
Mean WTP	16.54	15.4	11.41	10.96
Median WTP	6.21	8.08	5.81	7.55
Variance	714.21	316.95	184.72	93.25
ρ			0.85 (31.2)	0.92 (57.5)
Log Likelihood				
Scenario A	-204.14	-421.07		
Scenario B	-219.93	-458.17		
Joint			-361.70	-434.92

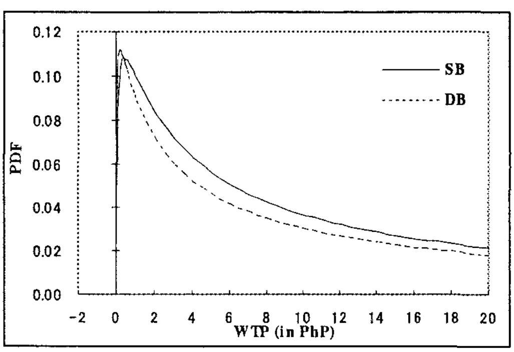


Figure 3. WTP PDF of SB and DB

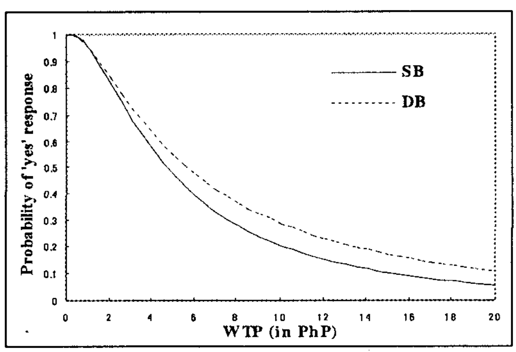


Figure 4. Probability of Yes in WTP bids

Results of single estimation for one payment vehicle and scenario using SBDC and DBDC are illustrated in the following figures. It is apparent from the figures that probabilities of yes reply for higher values are higher for the DBDC than SBDC. Figure 3 and Figure 4 below shows the PDF and the probability of a yes response for the different WTP values. The figure shows that DBDC predicts WTP more accurately as indicated by the tighter variances in Figure 3, and being able to capture yes responses at high bids.

Figure 5 below shows the probability contours of the joint density function. The marginal tendency of a log E[WTP] for Scenario B being greater than for Scenario A as the innermost probability density contour shifted a little to the top of the 45 degree line towards the Y-axis.

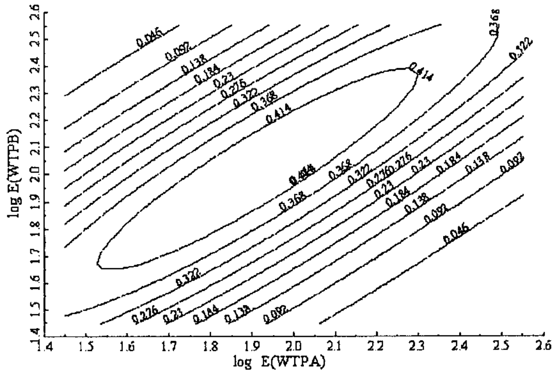


Figure 5. Density Contours of the Joint Probability Distribution

Table 6 shows the estimates of the anchoring parameter γ_K in single and joint estimation as well as the parameter estimates of the log-normal distribution μ_K, σ_K, and ρ. Like the simulation results, the parameters of anchoring are more significant in the joint than in the single estimation. One interesting note, on the other hand, observed from the data is that joint estimates of the anchoring model resulted to a negative and a positive parameter estimate. A potential explanation of this data specific tendency is that when asked in a two-scenario DBDC question format, the respondents probably initially form an uncertain estimate in mind for the two scenarios and form it as anchor in the stating his/her estimates. Negative anchor is observed in the not preferred, and positive anchor is observed in the preferred alternative. Estimate of the bipolar anchors can only be observed in joint estimation as single estimation shows the not preferred scenario having an insignificant anchoring bias.

Table 6. Estimates with anchoring parameters by single and joint estimation

	Single	Joint
Scenario A		
μ_A	1.74 (26.49)	1.91(27.72)
σ_A	1.06 (8.30)	0.90 (8.62)
γ_A	0.04 (0.33)	-0.14 (1.46)
Mean WTP	9.96	10.12
Median WTP	5.69	6.78
Variance	112.07	83.98
Scenario B		
μ_B	2.26 (12.65)	2.07 (23.74)
σ_B	1.56 (5.61)	1.02 (10.22)
γ_B	0.31 (2.30)	0.23(2.80)
Mean WTP	32.23	13.37
Median WTP	9.57	7.91
Variance	4337.61	187.55
ρ		0.93(61.02)
Log-likelihood		
Scenario A	-421.01	
Scenario B	-455.05	
Joint		-428.13

To observe the behaviour of the point estimates as the degree of correlation changes, ρ was set as a constant in the estimation is set at different levels. Results shows that when anchoring parameter are plugged into the equation, values shifted down fcr the not preferred scenario and shifted up for the preferred scenario. The general tendency of the difference between the WTP estimates per scenario is to decrease as correlation increases. Since ρ is quite high for this application, it can be deduced that the respondents had trouble in distinguishing between alternatives.

In summary, results based on application show that moving from SBDC to DBDC and single to joint estimation improve soundness of model. Results also show better description of the anchoring bias in the joint than in single estimation. When characterised parallel with correlation, bias of each scenario tend to pull estimates from converging. Clearly, in this application, it is clear that correlation of responses suggest indifference between scenarios which is possibly caused by respondent anchoring to bid cues to distinguish between choices.

7. Conclusion

Analysing response data from a two-scenario CV survey, some of the findings are summarised below.

• Results from DBDC models are observed to be more statistically significant than SBDC. Higher point estimates can be derived from DB than SB as DC can still capture affirmative responses in higher WTP bid ranges.

• There are efficiency gains in terms of significance of parameter estimate and goodness of fit by shifting from single to joint estimation particularly when the correlation coefficient is high. However, if only mean point estimates are given weight, single estimation yield acceptable results.

• Easier convergence and a tighter confidence region can be achieved though joint estimation of the models. This may be due to the correlation of the stochastic components between scenarios. More so, the reduction in the difference of the WTP between scenarios may be due to two possible factors: first, the computation of the coefficient covariance matrix in a joint estimation, and, second, the failure of respondents to more concretely distinguished between quality level than quantity level.

• In the empirical application, joint estimation of models with anchoring bias resulted to positive and negative anchors formed by respondents. Without considering anchoring, estimates of two-scenario interval model tend to converge as correlation increases. Putting anchoring bias parameter to interval model address this by pulling the estimates apart for better distinction of the alternative values.

In view of these observations, some of the recommendations in the conduct of CV survey and data analysis are summarised below.

• Since significance of the response bias parameters actually depends upon the soundness of the instruments used and clarity of the CV question, it is pertinent that this be given consideration in CV questionnaire preparation.

• It is recommended that response bias and joint estimation be considered in the statistical analysis of double scenario CV data to account for any associated inconsistencies produced in the course of the survey due to erratic human nature.

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Assessing Double-Scenario CV Responses in Valuing Environmental Impact of Road Projects*

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When a respondent is faced with a two-scenario willingness-to-pay question, inconsistencies in answer are deemed to happen because of failure to discriminate between scenarios and elicitation format. This study investigates response biases by single and joint estimation of scenarios to account for correlation between responses. The models are applied to the valuation of the environmental impact of a road project with two alternative alignments on a cultural heritage site. Results show that if not addressed properly, these biases can cause misestimating contingent values.

複数の道路整備代替案に対するＣＶＭ手法を用いた歴史遺産へのインパクト評価*

ミッシェル・パルモグ**，溝上章志***，柿本竜治****

フィリピンのセブ南海岸道路プロジェクトでは，歴史的遺産がある地域を保全することの経済的価値を計測するために，複数の道路整備代替案に対してＣＶＭ調査を行った．本研究では，1)実施された複数代替案に対するダブルバウンドの二項選択方式の調査データには，同一回答者による回答に起因する相関と下方修正バイアスが含まれており，2)これらを明示的に支払い意志額モデルに導入すること，3)支払い意志額を代替案ごとに個別に推定するのでなく，同時推定することによって，支払い意志額の推定値の統計的信頼性を向上させた．
