# **RESPONSE BIAS IN DOUBLE SCENARIO CVM SURVEY ON ENVIRONMENTAL IMPACTS OF ROAD PROJECTS\***

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# 1. Introduction

Contingent valuation (CV) is among the most used methodology on the valuation of various externalities of road projects such as damage to natural environment, noise pollution, and traffic accidents. It involves asking respondents their willingness to pay (WTP) to maintain or attain a certain level of environmental quality. Close-ended or discrete choice valuation format, endorsed by the National Oceanic and Atmospheric Administration's Blue Ribbon Panel on CV, is commonly used as survey method as it can be easily carried out equating to larger sample size. The answer only involves a choice between 'yes' or 'no' for a certain bid amount C for a certain level of environmental amenity. A variant of this format is the double-bounded discrete choice (DBDC) proposed by Hanemann (1984). This method of doing contingent valuation survey has gained popularity in recent years because of its relative statistical efficiency and ease of implementation.

In the realm of choice modelling, it is being becoming widely acknowledged that the rational man of economics, who is a utility maximizer, is in danger of extinction. Various choice experiments reveal that an individual's choice is not actually governed by standard rational behaviour model as evidenced by the inconsistencies in estimates. Many researches have extensively explored and discuss the complexity of the rationality of an individual's choice (Traversky and Kahnemann, 1974; McFadden, 1998; Ben-Akiva et.al., 1997). This paper presents a framework on the statistical estimation of the inconsistencies of an individual's response 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 alternatives.

# 2. Framework

In this study, the willingness to pay of individual *i* for a double scenario WTP question format is redefined as  $WTP_{ai} = f(\gamma_i, \rho_i, WTP_{ai}, WTP_{bi})$  where  $\gamma$  is a behavioural parameter related to context misconception and  $\rho$  is a parameter explaining correlation between alternative scenarios. Two types of behavioural effect are modelled in this paper, the anchoring (Herridges and Shogren, 1996) and the yea-saying (Blamey, 1999) biases. To deal with the bias that may arise because of the failure to perceive difference in alternative, joint estimation of the two DBDC datasets shall be 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 to account for the correlation of error terms between scenarios valued by the same respondent.

The models are applied to the valuation the impact of Cebu South Coastal Road (CSCR) project located in Cebu City, Philippines on two local cultural heritage sites, Plaza Independencia (PI) and Fort San Pedro (FSP). The CV survey elicited the value that a respondent is willing to pay as additional entrance fee to each of the two sites to preserve and maintain the cultural heritage considering two alternative alignments: (1) elevated highway structure across one site, and (2) sub-surface alignment across one site. The payment vehicles are entrance fee to both of the sites.



Figure 1. Alternative Alignments for Segment 3 of CSCR

<sup>\*</sup> Keywords: CVM, Response Bias, Joint Estimation

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### 3. Empirical Models

In standard discrete choice analysis, the responses should be consistent with the a corresponding indirect utility function that depends on a non-market item to be valued q, and individual's income y, the attributes of the market and the attributes of the individual that shifted his preferences. In principle of random utility maximization, another important component of the indirect utility function is the stochastic variable  $\varepsilon$ . Random utility maximization serves as the linkage of statistical and economic analysis of utility maximization. For instance in a discrete yes/no preference question, by logic of utility maximization, a respondent answers 'yes' if and only if the following identity follows:

$$\Pr\{yes\} = \Pr\{v(q^i, y - \overline{C}, \varepsilon) \ge v(q^o, y, \varepsilon)\}$$
(1)

where  $q^i$  and  $q^o$  are the posterior and initial environmental condition, respectively, and C is the disposable amount to achieve  $q^i$ . The willingness to pay  $\overline{C}$  of individual *i* can be describe by the a vector of socio-economic characteristics  $\beta x$  and the stochastic variable  $\varepsilon_i$  of the respondents which can be denoted as:

$$\overline{\overline{f}}_{i} = \beta x + \varepsilon \tag{2}$$

The DBDC has gained popularity in recent CV studies because of its relative increase in statistical efficiency as compared to single-bounded discrete choice (Hanemann et.al., 1991). This questioning format involves giving a follow-up bid after an initial bid C1, which takes on a higher value, say CU, if the respondent answered 'yes' and a lower value, say CL, if the respondent answered 'no'. It follows that, for any underlying WTP distribution, an equivalent area probabilities  $P_i^{YY}$ ,  $P_i^{YN}$ ,  $P_i^{NN}$ , and  $P_i^{NN}$  can be derived from bounds CL, C1 and CU.

Inconsistencies in DBDC modelling mainly arise from the failure of respondents to discern choice contexts. Though various studies have proven the reliability of DBDC elicitation format over other elicitation formats such as open-ended or single bounded discrete choice format, biases may still arise due to the questioning pattern and respondent's psychological conditions. One way of checking the consistency of DBDC data is by checking the proportion of the respondents who said 'yes'/'no' to the first and second bid. Assuming the process follows the same stochastic making process, these should be equal except for some sampling variations. The ground is however not always followed by DBDC data. To address this, two methods shall be employed to improve consistency of DBDC estimates: (1) considering response effects by including behavioural parameter to standard models, and (2) joint estimation of between two scenario.

## 3.1. Behavioural Effect Models

The leading research paradigm on behavioural inconsistencies in choice making is that of Tversky and Kahneman tackling cognitive anomalies (i.e. circumstances in which individuals exhibit surprising departures from rationality). Many CV studies tried to model some of these cognitive anomalies in the statistical estimation of discrete choice responses. Among these cognitive anomalies are the anchoring and yea-saying biases.

## Anchoring

Anchoring bias is the tendency of the respondent to anchor his second bid to his first bid. In a resentment scenario, the second bid causes difference in utility, such that  $u_1 > u_2$ . This condition can be modelled directly as a WTP distribution combined with a response effect. For the resentment scenario, one can extend the effect by introducing a background disposition to say 'no' to the second bid. Herriges and Shogren (1996) approach anchoring by postulating that the respondent changes his valuation of the item after the first bid, forming some function of his original WTP. If C1, is the first bid, and C2 is his WTP after the first bid, Herrige and Shogren postulated that some parameter  $\gamma$  that takes on a value from 0-1can be factored to the First bid and mean WTP (See Equation 3). If  $\gamma = 0$ , there is no anchoring the equation collapses back to the original presumption of equal WTP during the first and second bid. Given this, double-bounded response probability formulas take the form of equation 9 assuming normal distribution follows.

# Yea Saying

Yea saying is the propensity of the respondent to answer 'yes' in the WTP bidding process. These biases can be modelled depending on the researchers objective of how to explain this bias. For instance, Blamey (1999) modelled yea saying as multiplier effect of the bids where a yes answer was observed. In this model different parameters for the yea saying in each bid can be derived. (See Equation 5 and 6)

#### Table 2. Response Effects Models

Description	<b>Response Premise</b>		<b>DBDC</b> Probabilities		
Anchoring	$C_2 = (1 - \gamma)C_1 + \gamma C$		$P_i^{YY} = 1 - G_c[(CU - \gamma C1)/(1 - \gamma)]$		
(Herriges and Shogren, 1996)			$P_i^{\text{YN}} = G_c[(CU - \gamma C1)/(1 - \gamma)] - G_c(C1)$		
			$P_i^{NY} = G_c(C1) - G_c[(CL - \gamma C1)/(1 - \gamma)]$		
			$P_i^{NN} = G_c[(CL - \gamma C1)/(1 - \gamma)]$		
		(3)		(4)	
Yea-saying (Blamey et.al., 1999)	$C_{y} = C * e^{\sum_{i} \gamma_{i}^{y} TD_{i}}$ $C_{y} = \ln C + \sum_{i} \gamma_{i}^{y} BID_{i}$		$P_i^{YY} = 1 - G_c \left[ \ln CU - \sum_i \gamma_i^Y BID_i \right]$		
			$P_i^{YN} = G_c \left[ \ln CU - \sum_i \gamma_i^Y BID_i \right] - G_c \left[ \ln C1 - \sum_i \gamma_i^Y BID_i \right]$		
			$P_i^{NY} = G_c \left[ \ln C1 \right] - G_c \left[ \ln CL \right]$		
		(5)	$P_i^{NN} = G_c [\ln CL]$	$( \cap$	
		(5)		(6)	

#### 3.2. Joint Estimation Model

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 unobservable choice sets are expected (Ben-Akiva et.al., 1997). Pooling of data is another method of improving estimates of valuing different scenarios of environmental amenity preservation. In terms of asking the same respondents for WTP for different level of environmental amenity preservation, errors of estimates are likely to be correlated across scenarios. Failing to account for this correlation may lead to erroneous presumption. Riddel (1998) presented a model of joint estimation of multiple CVM scenarios under a double bounded questioning format to deal with the correlation between scenarios. In estimating WTP of individuals in a double-scenario CVM, Equation 2 can be re-specified into the following equation for latent WTP amount as a function of systematic and stochastic components:

$$\overline{C}_{ai} = \beta_a x_{ai} + \varepsilon_{ai}, \quad \overline{C}_{bi} = \beta_b x_{bi} + \varepsilon_{bi}$$
(7)

where a and b are the scenarios under consideration,  $\overline{C}_k$  is the willingness to pay of individual *i*,  $\beta_k x_{ki}$  is the vector of systematic components  $\overline{C}_k$  of and  $\varepsilon_{ki}$  is the random error associated with the *i*th individual and each alternative. If these equations are to be estimated jointly, the DBDC number of interval for the potential bid amounts C1, CU and CL. Thus, in a two scenario DBDC question format the probability that an individual will respond yes to the to all four questions (i.e. 'yes'-'yes' to scenario a and 'yes'-'yes' to the scenario b) is given by:

$$P_i^{YYYY} = P(CU_{ai} \le \overline{C}_{ai}, CU_{bi} \le \overline{C}_{bi}) = 1 - F(CU_{ai}, CU_{bi})$$

$$\tag{8}$$

where the bi-variate normal c.d.f. is denoted by:

$$F(CU_{ai}, CU_{bi}) = \int_{-\infty}^{CU_{ai}} \int_{-\infty}^{CU_{ai}} \frac{1}{2\pi\sigma_a \sigma_b \sqrt{1-\rho^2}} \exp\left\{\frac{1}{2\rho^2 - 2} \left[\left(\frac{C_{ia} - \mu_a}{\sigma_a}\right)^2 - 2\rho\left(\frac{C_{ia} - \mu_a}{\sigma_a}\right)\left(\frac{C_{ib} - \mu_b}{\sigma_b}\right) + \left(\frac{C_{ib} - \mu_b}{\sigma_b}\right)^2\right]\right\}$$
(9)

The log-likelihood of this model can be written as:

$$\ln L_i = \sum_m \sum_n \sum_p \sum_q \delta_i^{mnpq} \ln P_i^{mnpq}$$
(10)

where *m*, *n*, *p* and *q* take a value of either 1 or 0 for 'yes' or 'no' response, respectively.

#### 4. Results

Using probit specifications, the results show that compared to the estimates of the standard basic DBDC model, internalising response effects, i.e. anchoring and yea saying, improve the fit of models for all scenarios and payment vehicles. Table 3 presents the result of the estimation for one payment vehicle (i.e. FSP additional entrance fee). The significance of the parameters explaining the response effects however varies according to the scenario and payment vehicle used. For instance, the valuation of the sub-surface scenario shows more significant tendency to anchor bids than for the elevated alignment. In terms of yea saying, on the other hand, it appears that a respondent has greater tendency to say 'yes' the lower the bids are as can be seen from the sub-surface scenario WTP yea saying behaviour parameter estimates.

Results also showed that incorporating RP data and other explanatory variables provide a more robust model. It is also clear that there is correlation between the underlying choice making context between scenario a and b as can be seen in Figure 2. Thus, including correlation parameter tightens the model fit.

Variable Definition	<b>Elevated Scenario</b>			Sub-surface Scenario					
	Normal	Anchoring	Yea- Saying	Normal	Anchoring	Yea- Saying			
μ	1.73691 (28.33290)	1.73857 (26.48560)	1.62739 (22.97066)	2.08965 (29.07550)	2.25311 (12.71500)	2.26276 (24.07220)			
$\delta_{\gamma}$	1.02146 (16.78410)	1.05878 (8.30133) 0.04008	1.15186 (14.3403)	1.13566 (17.95980)	1.55208 (5.63160) 0.30462	1.33212 (14.47270)			
$\gamma_{1}^{Y}$ (Bid 1)		(0.33324)	11.21860		(2.26571)	1.31827			
$\gamma_1^Y$ (Bid 2)			(0.00000) 10.10090 (0.00000)			(1.58622) 4.93814 (0.00226)			
$\gamma_3^Y$ (Bid 3)			9.91267 (0.00000)			8.43265 (0.00000)			
Summary Statistics:									
N	344	344	344	344	344	344			
$\ell(0)$	-496.82	-496.82	-496.82	-618.31	-618.31	-618.31			
$\ell(\hat{B})$	-421.07	-421.01	-377.08	-458.17	-455.05	-414.099			
$-2(\ell(0)-\ell(\hat{B}))$	151.51	151.62	239.48	320.28	326.52	408.42			
$\rho^2$	0.15248	0.15259	0.24101	0.25900	0.26404	0.33027			

Table 3. WTP Estimates for Scenario A and B



Figure 2 WTP PDF of Scenario A and B

## 5. Conclusion

The study shows that including behavioural effects parameters  $\gamma$  to model DBDC response bias like anchoring or yea saying, and the joint estimation of double scenario DBDC data marginally improve the fit of estimates. In the case of the double scenario CV data used in this study, a possible underestimation of the impact value would have been done if the behavioural effects were not considered. Since the significance of the behavioural effects 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. More so, it is recommended that behavioural effects 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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