REVIEW:

A study on the use of 'contingent valuation' as a method for economic evaluation of the environment

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Abstract

Contingent valuation (CV) is widely used as a method to evaluate passive values of the natural environment. It is based on economic theories that assume utility maximization, which provides a solid theoretical basis to contingent valuation methods including dichotomous choice valuation questions that are being used more frequently. This paper reviews the economic and statistical theories behind contingent valuation and presents methods of analyzing its response data in R language. Although contingent valuation is subject to some controversy over its methodology, we conclude that its weaknesses may be overcome by incorporating respondents' bound rationality into contingent valuation surveys.

Keywords: Contingent valuation (CV), Dichotomous evaluation, Environment, Environmental economics, Passive (non-use) values

Introduction

Contingent valuation (CV) is a method to evaluate the non-use or passive values of the natural environment by asking what amount respondents are willing to pay to improve the quality of the environment or to prevent it from deteriorating. In a CV survey, respondents are presented with a series of policy scenarios where the quality of the environment improves or deteriorates in response to protective measures or industrial developments. After ensuring the respondents have reached a sufficient understanding of the policy alternatives and their consequences, a CV survey asks the respondents how much they are willing to pay for the improvement of the environmental quality or how much they are willing to accept for the loss of some environmental values. The mean and median of the willingness to pay (willingness to accept) can be estimated by analyzing the CV responses statistically.

Other prominent environmental economic valuation methods include the hedonic approach and the travel cost method. The hedonic approach appraises the economic value of the natural environment with an assumption that the evaluation of the environmental features is reflected in real estate prices. The travel cost method estimates the economic value of a natural attraction such as a national park by considering the travel cost to it as the potential price for the natural attraction.

Both the hedonic approach and the travel cost method are effective where a market exists for goods and is believed to reflect the values of the natural environment. However, it is often the case that no market exists at all to reflect the environmental values. Contingent valuation on the other hand is supposed to reveal the environmental values by inquiring the respondents, and is applicable for the wide range of non-market item appraisals such as conservation of forests and coastal ecosystems, improvement of air quality, and so on.

This paper first reviews the economic and statistical theories of CV and presents methods of analyzing CV response data in R language. Secondly, it studies the criticisms against CV and responses that attempt to answer them. Finally, it shows that an explicit incorporation of bound rationality into utility maximization models may address these problems in CV.

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Methodology

One of the main issues regarding contingent valuation is how we should evaluate the observed responses and estimate a respondent's willingness to pay (WTP). In this section, we will introduce economic utility theories and describe how they arrive at stochastic models that allow us to estimate WTP. We will use the simplest linear logistic model to illustrate the basic logic behind these theories. Finally, we also look at some more complicated WTP distribution models which are widely used in the practice of CV surveys.

Firstly, we formulate the following standard utility function $u(\mathbf{x})$, where $\mathbf{x}$ denotes a vector of goods $x_1, x_2, \ldots, x_n$. A consumer is expected to maximize her utility under a budget constraint $y = \mathbf{px}$ where y denotes her income and $\mathbf{p}$ denotes a vector of prices of the goods $p_1, p_2, \ldots, p_n$. When the utility function satisfies a set of attributes such as quasi-concaveness, this utility maximization problem can be solved. Given a set of prices and income, the quantities of goods can be determined as a result of utility maximization.

Here, an indirect utility function $v(\mathbf{p}, y)$ can be introduced. We reformulate the indirect utility function so that we can take into account the environmental concerns. We assume the prices $\mathbf{p}$ are constant and omit the notation of the indirect utility function. A new form of the indirect utility function is represented as $v(\mathbf{q}, y)$ where q denotes a vector of non-market items to be valued, $q_1, q_2, \ldots, q_m$.

Now let's assume that the government plans to implement a new environmental policy which will change the status of non-market items from $\mathbf{q_0}$ to $\mathbf{q_1}$. We also assume that this change is favorable to all the consumers (e.g. improvement of air quality) but consumers need to bear a part of the cost for the implementation of the policy. A rational consumer will approve the policy only if:

$$v(\mathbf{q_1}, y - c) \geq v(\mathbf{q_0}, y), \tag{1}$$

where c denotes the cost which the consumer must bear for the policy implementation. The maximum amount of the consumer's bearable cost (*willingness to pay,* WTP) is C such that:

$$v(\mathbf{q_1}, y - C) = v(\mathbf{q_0}, y). \tag{2}$$

The utility functions discussed so far are all deterministic. Now we introduce a stochastic component to the indirect utility function $v(\mathbf{q}, y, \epsilon)$ where ϵ denotes a random variable that corresponds to some probability distribution. This type of utility functions is called a *random utility function*.

Hanemann and Kanninen (1996) explain the nature of this random component in the indirect utility function:

> "The other key component of the indirect utility function is a stochastic component representing the notion of random utility maximization (RUM). It is the RUM concept which provides the link between a statistical model of observed data and an economic model of utility maximization. In a RUM model it is assumed that, while the individual knows her preferences with certainty and does not consider them stochastic, they contain some components which are unobservable to the econometric investigator and are treated by the investigator as random (Hanemann, 1984b). These unobservables could be characteristics of the individual and/or attributes of the item; they can stand for both variation in preferences among members of a population and measurement error."

If all the elements that determine the utility of a consumer can be observed and the structure of the utility function is known, the consumer's utility will be perfectly predicable. This implies we do not even need bother to inquire consumers for WTP because the WTP can be calculated by an econometric investigator. In reality, however, this is impossible; because we never know all the elements that determine

the utility of a consumer, her behavior will remain unpredictable to some extent. RUM attempts to capture this inherent limitation regarding the prediction of consumer behavior.
With the random component ϵ, the equation (2) becomes:

$$v(\mathbf{q_1}, y - C, \epsilon) = v(\mathbf{q_0}, y, \epsilon). \tag{3}$$

C can be retrieved by solving the equation above. Now we specify an indirect utility function in order for readers to follow the underlying logic more clearly. In the existing literature, the Cox-Box indirect utility function is frequently used (Hanemann and Kanninen, p6):

$$v = \alpha_q + \beta_q[\frac{y^\lambda - 1}{\lambda}] + \epsilon_q, \tag{4}$$

where $q = 0, 1$.
In the special case where $\lambda = 1$, the Cox-Box indirect utility function becomes a linear function:

$$v = \alpha_q + \beta_q y + \epsilon_q. \tag{5}$$

This is the simplest form of indirect utility functions. In this paper, we use this linear function to describe the fundamental logic of RUM-based CV analysis.
By specifying the linear indirect utility function (5) in (3), we obtain:

$$\alpha_1 + \beta_1(y - C) + \epsilon_1 = \alpha_0 + \beta_0 y + \epsilon_0. \tag{6}$$

Therefore,

$$C = \frac{\alpha_1 - \alpha_0}{\beta_1} + \frac{\beta_1 - \beta_0}{\beta_1} y + \frac{\epsilon_1 - \epsilon_0}{\beta_1} \tag{7}$$

McFadden and Leonard (1993) suggest a restricted version of this model with $\beta_1 = \beta_0 \equiv \beta > 0$.
This simplifies the equation above as:

$$C = \frac{\alpha + \eta}{\beta}, \tag{8}$$

where $\alpha \equiv \alpha_1 - \alpha_0$ and $\eta \equiv \epsilon_1 - \epsilon_0$.

In contingent valuation dichotomous choice questions, respondents are asked questions such as "Are you willing to pay A dollars for this project to improve the air quality?" and expected to answer yes or no. A rational respondent should answer yes only if her WTP is larger or equal than the offered amount A. As we saw above, the WTP can be treated as a probable variable because we can never predict a consumer's utility completely. The probability that a respondent answers yes is

$$Pr\{response = "yes"\} = Pr\{C \geq A\}, \tag{9}$$

where C denotes the WTP of the respondent.

With (8) in place,

$$Pr\{response = "yes"\} \quad = \quad Pr\{C \geq A\}$$

$$= Pr\{\frac{\alpha+\eta}{\beta} \geq A\}$$
$$= Pr\{\eta \geq -\alpha + \beta A\}. \quad (10)$$

Let G_η denote the cumulative distribution function of η, and g_η be the corresponding density function. By the definition of the cumulative distribution function:

$$Pr\{response = "yes"\} = 1 - G_\eta(-\alpha + \beta A) \quad (11)$$

η is a random variable, which corresponds to some probability distributions. A logistic distribution is frequently assumed for η due to its mathematical simplicity. If η corresponds to a standard logistic distribution:

$$Pr\{response = "yes"\} = 1 - \frac{1}{1+\exp(\alpha - \beta A)}$$
$$= \frac{1}{1+\exp(-\alpha + \beta A)}. \quad (12)$$

Now n CV respondents answer dichotomous choice valuation questions. Let y denote the response "yes" when $y = 1$ and "no" when $y = 0$. If the observed responses for the questions are $y_1, y_2, \ldots, y_n$ for given bids $A_1, A_2, \ldots, A_n$, the likelihood function $L(\alpha, \beta)$ for this observation is:

$$L(\alpha,\beta) = \prod_{i=1}^{n}(\frac{1}{1+\exp -\alpha + \beta A_i})^{y_i}(1 - \frac{1}{1+\exp(-\alpha+\beta A_i)})^{1-y_i} \quad (13)$$

Therefore, the log-likelihood function becomes:

$$\log(L(\alpha,\beta)) = \sum_{i=1}^{n}[y_i \log(\frac{1}{1+\exp(-\alpha+\beta A_i)})$$
$$+(1-y_i)\log(1 - \frac{1}{1+\exp(-\alpha+\beta A_i)})] \quad (14)$$

The best parameters which fit the observation will be estimated by maximizing this log-likelihood function. This is achieved by solving the following equations:

$$\frac{\partial \log(L(\alpha,\beta))}{\partial\alpha} = 0 \quad (15)$$
$$\frac{\partial \log(L(\alpha,\beta))}{\partial\beta} = 0. \quad (16)$$

They yield respectively:

$$\sum_{i=1}^{n}[y_i(1-z_i) - (1-yi)z_i] = 0 \quad (17)$$

$$\sum_{i=1}^{n}(-A_i)[y_i(1-z_i)-(1-yi)z_i] \;=\; 0 \tag{18}$$

where $z_i = 1/(1+\exp(-\alpha+\beta A_i))$.

These equations can be solved with a numeric calculation method such as Newton-Raphson.

The Hessian matrix of the log-likelihood function $\log(L(\alpha, \beta))$ is defined as:

$$H = \begin{pmatrix} \partial^2 \log L/\partial\alpha^2 & \partial^2 \log L/\partial\alpha\partial\beta \\ \partial^2 \log L/\partial\beta\partial\alpha & \partial^2 \log L/\partial\beta^2. \end{pmatrix} \tag{19}$$

The variance-covariance matrix V is obtained from the Hessian matrix:

$$V = (-H)^{-1}. \tag{20}$$

In the variance-covariance matrix V, the (1, 1) element represents the variance of α and the (2, 2) element represents the variance of β. The square roots of the variances represent the standard errors of these parameters. The confidence intervals can be calculated from the standard errors since the maximum likelihood estimated parameters of α and β asymptotically correspond to normal distributions (Hanemann, and Kanninen, p27).

Now that we have retrieved the parameters α and β, we can obtain the probability distribution to which WTP corresponds.

Since η corresponds to a standard logistic distribution, the mean of η, $E(\eta) = 0$. With (8),

$$\begin{aligned} E(C) &= E(\frac{\alpha+\eta}{\beta}) \\ &= \frac{\alpha + E(\eta)}{\beta} \\ &= \frac{\alpha}{\beta} \end{aligned} \tag{21}$$

The mean of WTP, $E(C)$, is α/β under the assumptions that the indirect utility function is expressed in (5) and the random variate η corresponds to a standard logistic distribution.

So far, we have assumed a specific indirect utility function. In the literature, other distributions such as normal, log-normal, log-logistic, and Weibull are also studied as WTP distributions (Hanemann and Kanninen, 1996). In this section, we take an example of a log-logistic model, and then discuss the double bound dichotomous choice question format.

Log-logistic Model:

Assume that an environmental policy changes the status of non-market items from $\mathbf{q_0}$ to $\mathbf{q_1}$. Let v_0 and v_1 represent indirect utility states that correspond to $\mathbf{q_0}$ and $\mathbf{q_1}$, respectively. Here we adopt another utility model where v_0 and v_1 are formulated as follows (Hanemann and Kanninen, p10):

$$v_0 \;=\; y+\delta \tag{22}$$

$$v_1 \;=\; y + \delta + \exp(\frac{\alpha + \eta}{\beta}) \tag{23}$$

They yield:

$$Pr\{response = \text{"}yes\text{"}\} = 1 - G_\eta(-\alpha + \beta \log(A)) \tag{24}$$

If η corresponds to a standard logistic distribution, the above formula becomes:

$$Pr\{response = \text{"}yes\text{"}\} = \frac{1}{1 + \exp(-\alpha + \beta \log(A))} \tag{25}$$

This is equivalent to (12) except that it takes the logarithm of A instead of the raw A. This formulation is also frequently used in actual CV surveys due to better data fitting. If $C^*$and C^+denote the median and the mean of WTP respectively (Hanemann and Kanninen, p21):

$$C^* = \exp(\frac{\alpha}{\beta}) \tag{26}$$

$$C^+ = \begin{cases} \exp(\alpha/\beta)\Gamma[1 + (1/\beta)]\Gamma[1 - (1/\beta)] & \text{if } \beta > 1 \\ \infty & \text{if } \beta \le 1 \end{cases} \tag{27}$$

where Γ denotes a gamma function.

A graphical representation of the WTP distribution can be used to represent the mean of WTP. When WTP is non-negative:

$$\tilde{C}^+ = \int_0^{A_{max}} Pr\{\text{"}yes\text{"}\}dA \tag{28}$$

where $\tilde{C}^+$stands for an approximation of the mean of WTP and A_{max} the greatest amount among the bids (Hanemann and Kanninen, p21). This formula allows us to obtain a finite mean of WTP by choosing an upper limit A_{max}.

Double Bound Dichotomous Choice Questions:

The double bound dichotomous choice question format is known as a method to improve the efficiency of parameter estimation by inquiring CV respondents with two-stage questions. For example, in the first question, a respondent is asked “Are you willing to pay 10 dollars for this project?” If the answer is yes, the next question is asked with a higher bid such as “Then are you willing to pay 20 dollars?” Contrarily, if the answer for the first question is no, the next question is asked with a lower bid such as “Then are you willing to pay 5 dollars?” Nowadays, the double bound dichotomous choice question format is widely used in the practice of the CV surveys.

The probabilities of responses for A_1 as a bid in the first question and A_U as a bid in the second question when the answer for the first question is yes, and A_L as a bid in the second question when the answer for the first question is no:

$$Pr\{\text{response} = \text{"yes and yes"}\} \;=\; 1 - G(A_U) \tag{29}$$

$$Pr\{\text{response} = \text{"yes and no"}\} \;=\; G(A_U) - G(A_1) \tag{30}$$

$$Pr\{\text{response} = \text{"no and yes"}\} \;=\; G(A_1) - G(A_L) \tag{31}$$

$$Pr\{\text{response} = \text{"no and no"}\} \;=\; G(A_L) \tag{32}$$

where G is a cumulative distribution function of WTP.

Therefore, the log-likelihood function $\log(L(\alpha, \beta))$ becomes:

$$log(L(\alpha,\beta)) = \sum_{i=1}^{n}[yy_i \log(1 - G(A_U)) + yn_i \log(G(A_U) - G(A_1)) \\ + ny_i \log(G(A_1) - G(A_L)) + nn_i \log(G(A_L))] \tag{33}$$

where $yy_i = 1$ if the response is "yes and yes" and $yy_i = 0$ otherwise. $yn_i, ny_i,$ and nn_i are also defined similarly.

The parameters can be estimated by maximizing the log-likelihood function as we presented in the case of single bound dichotomous questions.

Now let's analyze CV response data. The following programs are written based on an algorithm by Kuriyama (2011). First, we introduce an R language program for a single bound logit model. Then, we extend it to a double bound logit model.

Single Bound Logit Model:

Firstly, we estimate the parameters of a WTP distribution based on the single bound logit model. We assume that the probability that a respondent answers yes for the bid A is formulated as follows:

$$Pr\{response = \text{"}yes\text{"}\} \;=\; 1 - Gc(A) \\ = \frac{1}{1 + \exp(-\alpha + \beta A)}. \tag{34}$$

where G_c denotes a cumulative distribution function of WTP.

$$G_c(A) = \frac{1}{1 + \exp(\alpha - \beta A)} \tag{35}$$

The parameters α and β can be estimated with maximization of the log-likelihood function. Now we analyze the data using samples from Kuriyama (2011). Let's assume that the single bound dichotomous choice questions gave the following responses (the currency unit for bids is Japanese yen):

Bids	Yes	No
500	38	8
1000	31	12
2000	25	15
5000	17	23
10000	17	28
20000	8	36

The parameter estimation is done with the following program code written in the statistical analysis language R.

```
# data setting
rts <- c(500,1000,2000,5000,10000,20000)
ys <- c(38,31,25,17,17,8)
ns <- c(8,12,15,23,28,36)

# program code
max_bid <- max(rts)
ts <- log(rts)
z <- function (a, b, t) 1/(1 + exp(-a + b * t))
ll0 <- function(a, b, t, y, n) y * log(z(a, b, t)) + n * log(1-z(a, b, t))
ll.creator <- function(ts, ys, ns) {function(par) {sum(ll0(par[1], par[2], ts,
ys, ns))}}
ll <- ll.creator(ts, ys, ns)
res = optim(par = c(0,0), fn=ll, control = list(fnscale = -1), hessian = TRUE)
a <- res$par[1]
b <- res$par[2]
var.cov <- -solve(res$hessian)
step <- 100
delta <- max_bid/step
bids <- seq(delta, max_bid, by=delta)
bids <- append(bids, 0.001, after=0)
estimates <-  z(a, b, log(bids))
cs <- (estimates[1:step] + estimates[2:(step+1)]) * delta / 2

# results
mean.of.wtp <- sum(cs)
median.of.wtp <- exp(a / b)
```

The interpretation of the results is as follows:

Variables	Results	Notes
a	6.298638	estimate of $\alpha(\hat{\alpha})$
b	0.76526	estimate of $\beta(\hat{\beta})$
var.cov	$\begin{pmatrix} 0.8856746 & 0.10664933 \\ 0.1066493 & 0.01312902 \end{pmatrix}$	variance-covariance matrix of $\hat{\alpha}$and $\hat{\beta}$
mean.of.wtp	7552.338	estimated mean of WTP
median.of.wtp	3754.523	estimated median of WTP

Double Bound Logit Model:

Similarly using sample data from Kuriyama, let's assume that double bound dichotomous choice questions gave the following responses (the currency unit for bids is Japanese yen):

First Bids	Second Upper	Second Lower	Yes Yes	Yes No	No Yes	Yes Yes
1000	3000	500	18	25	3	23
3000	6000	1000	10	19	13	34
6000	15000	3000	6	14	8	49
15000	40000	6000	2	18	5	49

The parameter estimation is done with the following program code written in the statistical analysis language R.

```
#data setting
rt1s <- c(1000,3000,6000,15000)
rtus <- c(3000,6000,15000,40000)
rtls <- c(500,1000,3000,6000)
yys <- c(18, 10, 6, 2)
yns <- c(25, 19, 14, 18)
nys <- c(3, 13, 8, 5)
nns <- c(23, 34, 49, 49)
# program area
max_bid <- max(max(rt1s), max(rtus), max(rtls))
t1s <- log(rt1s)
tus <- log(rtus)
tls <- log(rtls)
gc <- function(t, a, b) 1/(1 + exp(a - b * t))
pyy <- function(t1, tu, tl, a, b) 1 - gc(tu, a, b)
pyn <- function(t1, tu, tl, a, b) { gc(tu, a, b) - gc(t1, a, b);}
pny <- function(t1, tu, tl, a, b) gc(t1, a, b) - gc(tl, a, b)
pnn <- function(t1, tu, tl, a, b) gc(tl, a, b)
ll0 <- function(a, b, t1, tu, tl, yy, yn, ny, nn)  {
   yy * log(pyy(t1, tu, tl, a, b)) + yn * log(pyn(t1, tu, tl, a, b)) +
   ny * log(pny(t1, tu, tl, a, b)) + nn * log(pnn(t1, tu, tl, a, b)) }
ll.creator <- function(t1s, tus, tls, yys, yns, nys, nns) {
   function(par) { sum(ll0(par[1], par[2], t1s, tus, tls, yys, yns, nys, nns))
}}
ll <- ll.creator(t1s, tus, tls, yys, yns, nys, nns)
res = optim(par = c(5,2), fn=ll, control = list(fnscale = -1), hessian = TRUE)
var.cov <- -solve(res$hessian)
a <- res$par[1]
b <- res$par[2]
step <- 100
delta <- max_bid/step
bids <- seq(delta, max_bid, by=delta)
bids <- append(bids, 0.001, after=0)
estimates <-  1 - gc(log(bids), a, b)
cs <- (estimates[1:step] + estimates[2:(step+1)]) * delta / 2
# results
mean.of.wtp <- sum(cs)
median.of.wtp <- exp(a / b)
```

The interpretation of the results is as follows:

Variables	Results	Notes
a	6.686459	estimate of $\alpha(\hat{\alpha})$
b	0.9090847	estimate of $\beta(\hat{\beta})$
var.cov	$\begin{pmatrix} 0.35530243 & 0.043215536 \\ 0.04321554 & 0.005455678 \end{pmatrix}$	variance-covariance matrix of $\hat{\alpha}$and $\hat{\beta}$
mean.of.wtp	5753.115	estimated mean of WTP
median.of.wtp	1564.24	estimated median of WTP

The estimate of the variance-covariance matrix is slightly different from that of Kuriyama (2011). It is conjectured that the balance stems from the difference of optimization algorithms used in Microsoft Excel and R language.

Discussion

The Exxon Valdez oil spill in 1989 was the first case in which contingent valuation was used to assess damages in a lawsuit. While this case brought CV into global prominence, the spreading use of CV also led to a great number of criticisms. In response to these criticisms, the National Oceanic and Atmospheric Administration (NOAA) of the United States in 1993 convened an advisory panel consisting of renowned economists including Novel Award winners Kenneth Arrow and Robert Solow. The goal of the panel was to discuss whether CV is reliable enough to estimate the passive-use values of the environment and if so, to recommend desirable survey designs to survey planners.

The report of the NOAA panel (Arrow et al. 1993) identified the following biases in CV:

- Willingness to accept is typically much larger than willingness to pay. That is, respondents may ask for a much larger compensation for deterioration of an environmental feature than what they are willing to pay for the same level of improvement.
- Respondents may not be as rational as the models postulate. Typically, respondents in a CV survey are presented with a hypothetical policy scenario which is likely to improve the values of the environment but they might not fully understand what they are asked, and even if they do, they might not answer seriously because the survey scenarios are not real and not binding.
- Self-reported willingness tends to be overstated compared with "actual" willingness to pay. A respondent who claims to pay a certain amount for an environmental improvement usually does not pay as much when an actual opportunity of contribution is given.
- Embedding effect; WTP does not necessarily increase as the quantity of goodness grows. For example, the average amounts of WTP to prevent 2,000, 20,000 and 200,000 wild birds from dying may be almost the same.
- A CV survey asks respondents about only one problem, while many problems may exist in reality. The estimate of WTP can be overstated if respondents take only the asked problem into account, but not all the potential problems.

- CV respondent may fail to seriously consider their budget constraints. They may fail to take into account the fact that they must abandon some private consumption in order to pay for environmental protection measures.
- It is difficult to determine the relevant population from which respondents are sampled. While an environmental issue may affect people in an extensive area, those who are less affected by the specific issue should be under-sampled.
- "Warm Glow" effects; what respondents express in CV surveys may only reflect their goodwill to worthy causes. Their motivations may be similar to those who pledge charitable donations.

To address these issues, the NOAA panel recommended the following items be taken into account in the CV survey design:

- Avoid open-ended questions because they are sensitive to a scenario's trivial details and lead to respondents' strategic behavior. Use of dichotomous questions is suggested since they are less likely to be subject to those biases.
- CV survey results should be interpreted conservatively since responses tend to be overstated. Dichotomous questions are better in this regard because they usually give more conservative results than open-ended questions.
- An appropriate sample type and size should be chosen for a CV survey. Non-responses must be minimized.
- Face-to-face interviews are preferable for eliciting reliable responses.
- Pretests are important since they help detect biases before the main surveys are implemented and lead to an improvement of the survey reliability.
- A willingness to pay (WTP) format should be used instead of the willing to accept (WTA) because WTP is the conservative choice.
- Adequate information must be provided to and understood by respondents about the environmental program scenarios presented in surveys.
- Respondents must be reminded of alternatives. They should be informed that they are able to choose a substitutive market and non-market items under budget constraints.
- A "no-answer" option should be explicitly allowed on the top of the "yes" and "no" options on dichotomous valuation questions.
- The survey should ask why a respondent answers yes or no.
- In the final report, WTP summaries should be presented by respondents' attributes such as income, prior knowledge of the site, and attitudes toward the environment.

The NOAA panel concluded that CV surveys were reliable enough provided that the surveys followed the panel's guideline as closely as possible (Arrow et al, p44).

> "The Panel concludes that under those conditions (and others specified above), CV studies convey useful information. We think it is fair to describe such information as reliable by the standards that seem to be implicit in similar contexts, like market analysis for new and innovative products and the assessment of other damages normally allowed in court proceedings. As in all such cases, the more closely the guidelines are followed, the more reliable the result will be. It is not necessary, however, that every single injunction be completely obeyed; inferences accepted in other contexts are not perfect either."

However, the CV antagonists severely criticized the NOAA panel report. Among the most notable was Diamond and Hausman (1994). They insisted that contingent valuation was deeply flawed and concluded that "contingent valuation surveys do not measure the preferences they attempt to measure" (Diamond and Hausman, p46). According to them, the fundamental problems of CV relate to the political decision making process on environmental issues (Diamond and Hausman, p58):

> "We concluded that such (contingent valuation) welfare analysis would not be a guide to good policy. Our conclusion is often challenged by the common Washington fallacy that even if stated willingness-to-pay is inaccurate, it should be used because no alternative estimate exists for public policy purposes. Put more crudely, one hears the argument that 'some number is better than no number'."

While some of Diamond arguments are convincing, one cannot dismiss the fact that only contingent valuation can offer concrete evaluation on the passive use values of the natural environment. Our conclusion is that a gradual progress on environmental economic valuation may be satisfactory and we can expect that someday we will have better measures for environmental evaluation.

Conclusion

So far we have looked at economic and statistical theories behind contingent valuation as well as criticisms and responses. While, at least to date, CV is the only comprehensive method that can produce concrete estimates on the welfare of environmental programs, some of the antagonists' criticisms are also worth considering. The most potentially damaging defect of contingent valuation would be its assumption of perfect rationality. In the majority of literature, CV theories postulate that respondents have perfect knowledge on the questions asked and respond in a completely rational way.

Naturally, this is not the case in reality. Oliver Frör (2008) insists that CV survey planners need to incorporate respondents' bounded rationality into their survey designs. According to Frör, bounded rationality is defined as follows:

> "Bounded rationality assumes that decision makers in the real world have to cope with a number of constraints like limited information availability (limited time to acquire information) and limited computational capacities and capabilities which makes it necessary for them to employ heuristics, simplified decision rules often based on past experience, to achieve satisfactory albeit not optimal outcomes."

After reviewing some empirical studies of cognitive psychology on contingent valuation, Frör concluded that the concept of bounded rationality was helpful in understanding how respondents in a CV interview would process the information. Bounded rationality is based on the assumption that individuals face some limitations in making decisions under real world circumstances because there are various information constraints and limits to their computational capacities and etc. Therefore the respondents to CV interviews may find themselves in a situation that requires them to economize on the scarce cognitive resources they have access to so that they can make a decision and respond to the CV questions. In doing so, they may use various low-effort strategies based on heuristic cues, etc.

Therefore, it can be expected that CV respondents take into account not only their utility functions but also the scarcity of their cognitive resources when making decisions. If we can successfully incorporate this economy of cognitive resources explicitly into quantitative models in utility maximization, we may be able to elicit more reliable responses from CV respondents. The authors strongly believe that further studies will be required in this direction for a sound development of contingent valuation theories.

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