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Inconsistent responses in the dichotomous choice contingent valuation with follow-up questions

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ABSTRACT

This essay develops a new method to diagnose inconsistency in dichotomous choice contingent valuation with follow-up questions: in particular, downward bias in the mean WTP. It is shown that the previous methods aimed to explain this inconsistency in responses have ignored statistical inconsistency: *non-perfect correlation* between the initial and follow-up responses and thus have provided wrong predictions to explain respondents' inconsistency pattern. In addition, from an application of our method, it has been proven that one model can not encompass all other possible inconsistency patterns in responses. Test results show that the behavioral inconsistency patterns are different both within and between data sets.

1. Introduction

Over fifteen years have passed since the paradigm-shifting paper "Statistical Efficiency of Double-Bounded Dichotomous Choice Contingent Valuation" by Hanemann, Loomis and Kanninen (1991). During those years, a number of papers have pointed out the merits and demerits of the double-bounded survey format[1]. The arguments favoring the use of the double referendum formats concentrate on its substantial gains in statistical efficiency compared to asking only one question (Hanemann *et al*, 1991). In contrast, others argue that there is often a lack of consistency between the initial and the follow-up responses (Cameron and Quiggin, 1994; Herriges and Shogren, 1996; Alberini, Kanninen, and Carson, 1997; Bateman *et al*. 2001;

[1] Double bounded dichotomous choice formats provide respondents with an immediate follow-up question that either raises or lowers the offered bid depending on the response to the initial bid.

Deshazo, 2002). These researchers have found significant 1) *shifts in the estimates* and 2) *non-perfect correlation* across initial and follow-up willingness-to-pay (WTP) questions.

As for these inconsistency phenomena, each of these researchers has proposed psychological/behavioral model[2]; specifying how subjects react to the sequential elicitation mechanism (yes(nay)-saying bias, strategic motive, cost-expectation, framing effect, anchoring effect and so forth). However, most of them are more concerned with *shift in the estimated mean* but few of these models have paid attention to statistical inconsistency, i.e. *non-perfect correlation* between the first and second responses.

In addition, as their explanations are in controversy, it is contentious to state that one model can encompass all other possible inconsistency patterns. More seriously, even if one can do, sometimes it can provide a misled prediction for inconsistency pattern because in the worst case, it can just provide an average pattern resulted from the gross sum of the several different inconsistency patterns.

In this paper, we propose a general inconsistency-diagnosing method. The key strength of this method is that it can allow for the possibility of less-than-perfect correlation in sequential responses and also easily identify individual inconsistency pattern within 'each bid interval[3]' as well as overall (or average) inconsistency pattern.

Upon examining the above issues, we find that the behavioral explanations for inconsistency patterns with non-perfect correlation are apparently different from those with perfect correlation. This implies that the behavioral model ignoring non-perfect correlation often have provided wrong predictions to explain respondents' inconsistency pattern. Furthermore, we

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[2] Here the psychological/behavioral approaches are an investigation of how individuals adopt the strategies and why to arrive at their stated values.

[3] With our model, we could not identify individual level of inconsistency pattern, however, we can at least identify inconsistency pattern for each bid interval.

find that the inconsistency patterns are varied for different data sets and different bids within data sets. This also implies that we can not provide a simple behavioral model which can explain all other possible inconsistency patterns of the responses between and within data sets. On the other hand, in an attempt to test the results from non-parametric analysis with a conventional parametric approach, we inadvertently find that inconsistency in the iterative responses can seriously reduce the usefulness of the follow-up questions. This issue will be discussed later. We conclude by arguing that the benefits of the dichotomous choice with follow-up question format have been grossly exaggerated.

2. Downward bias in mean WTP and explanations

To begin, we discuss one of anomalies found in dichotomous choice with follow-up questions that a number of previous researchers have continually documented (Carson et al, 1994; Cameron and Quiggin, 1994; McFadden and Leonard, 1995). They have found lower (downward) estimates of mean WTP from follow-up questions than those from the initial question. Cameron and Quggin (1994) explicitly first found that the estimate of the second mean WTP is lower than that of the first mean WTP from the general bivariate probit model.

To analyze this stylized inconsistency pattern (downward mean shifting in the second responses) in the iterative question format, a number of researchers have proposed several explanations. Carson *et al* (1994) and Alberini *et al* (1997) put forward a “government wastage model” and argue that the respondents who initially say ‘yes’ may refuse to pay the increased second amount because they feel that the government would attempt to attain more money than is needed to cover the cost of provision, which will be wasted. In contrast, the respondents who reject the first offered bid may consider the lower second bid a sign of decreased quality of the good provided. The consequence of this explanation is that people are more likely to vote against the second offered bid regardless of whether they accept or reject the first offered bid.

Mitchell and Carson (1989) propose a “strategic behavior model”. They argue that the respondents answer the first question truthfully but answer the second one strategically because they may feel that they are stuck in a bargaining situation when they are asked additional flexible prices. Thus, respondents try to lower the price by rejecting any additional prices. This argument implies the respondents will be more likely to answer “no’ to any follow-up question, regardless of whether their true willingness-to-pays is higher or lower than the follow-up bid.

Finally, Deshazo (2002) proposes a ‘framing effects model’ based on prospect theory aimed at explaining irrational preference reversal between ascending and descending bid sequences within the iterative question format.. He argues that this model predicts a downward bias in WTP in an ascending bid sequence ($b_l \rightarrow b_h$), but not in a descending bid sequence ($b_h \rightarrow b_l$).

Here, we can categorize above three models into two possible cases: *symmetric* or *asymmetric* downward mean shifting. *Symmetric* downward mean shifting implies overall shifting in the second mean WTP regardless of whether the respondents are presented ascending ($b_l \rightarrow b_h$) bids or descending bids ($b_h \rightarrow b_l$). This potential case corresponds to ‘government wastage model’ and ‘strategic behavior model’. On the other hand, as proposed in framing effect model, the downward mean shifting can be *asymmetric*: it occurs with ascending bids but not with descending bids.

We have reviewed various potential explanations for downward bias in mean WTP with iterative question format. The primary drawback with above common behavioral explanations are first, that they do not weigh explicitly the possibility of non-perfect correlation between sequential responses and second, that each model can provide at best the average inconsistency pattern exhibited in a given sample. Thus, in the next chapter, we seek a new method allowing for non-identical stochastic joint distribution, which can test the individual inconsistency pattern within each bid interval

3. New method to diagnose inconsistency in the responses

3.1. Comparison of Probabilities with Perfect Correlation

Prior to the main body, let's define key probabilities (proportions) that will be used for throughout. In a general referendum question format, a respondent is usually requested to answer yes/no from comparison between his underlying WTP and a randomly assigned bid among several bids that the researcher already predetermined. Here we suppose only two different bids (b^l and b^h) are available, corresponding to a lower bid and a higher bid ($b_l < b_h$). Suppose this is a double bounded referendum format. In the initial round of a referendum format questionnaire, the respondents are assigned b^l or b^h randomly and asked to answer 'yes or no'. In the second round, affirmative responses (yes) for the lower bid b^l are immediately followed by a higher bid b^h while negative responses (no) for the higher bid b^h are immediately followed with a lower bid b^l [4]. This stylized format is readily generalized to the standard format and as will be seen, the proposed methods for comparison are directly applicable to the standard symmetric DC with follow-up format.

At first, we decompose above dichotomous contingent valuation with follow-up format into ascending sequence and descending path.

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[4] Of course, in a symmetric structure of the iterative question format, the negative response for the bid b^l are also followed with a bid that is less than b^l and the affirmative response for the bid b^h are followed with another bid that is higher than b^h. However, we only focus on the intervals $(-\infty \quad b^l)$, $(b^l \quad b^h)$ and $(b^h \quad \infty)$.

Figure 1: Ascending and descending path in iterative question format

As presented in figure 1, within a given bid interval $(b^l\ b^h)$, whether the responses fall in ascending or descending path hinges on the respondents' first assigned bid (b_l or b_h). If the respondent is randomly assigned lower bid, b_l at the initial round, he is determined to follow the ascending path ($b_l \rightarrow b_h$). In contrast, if assigned higher bid, b_h at the initial round, he is determined to follow the descending path ($b_h \rightarrow b_l$). In the ascending path, affirmative answers for bid b^l are divided into yes-yes (YY) and yes-no (YN) path depending on the follow-up responses to the higher bid b^h. Negative answers for bid b^l are classified as no (N) altogether. In the descending sequence, negative answers for bid b^h are divided into no-yes (NY) and no-no (NN) paths depending on the second responses to the lower bid b^l. Positive answers for bid b^h are classified as yes (Y) altogether. Based on these sub-sampling, we can define the probabilities determined by the relative size between respondent's willingness-to-pays and the offered first and second bids (see table 1).

Probabilities	Symbol	Path	Descriptions
$P(WTP_1 > b^h)$	$P(Y)$	Descending	The probability that the first WTP is greater than b^h
$P(WTP_1 > b^l,\ WTP_2 > b^h)$	$P(YY)$	Ascending	The probability that the first WTP is greater than b^l and the second WTP is also greater than b^h
$P(WTP_1 < b^h,\ WTP_2 > b^l)$	$P(NY)$	Descending	The probability that the first WTP is less than b^h but the second WTP is greater than b^l
$P(WTP_1 > b^l,\ WTP_2 < b^h)$	$P(YN)$	Ascending	The probability that the first WTP is greater than b^l but the second WTP is less than b^h
$P(WTP_1 < b^h,\ WTP_2 < b^l)$	$P(NN)$	Descending	The probability that the first WTP is less than b^h and also the second WTP is less than b^l
$P(WTP_1 < b^l)$	$P(N)$	Ascending	The probability that the first WTP is less than b^l

Table 1: Summary of key probabilities in DCCV with follow-up WTP question

First, we compare probabilities between ascending and descending paths when we assume that the initial and the follow-up responses are perfectly correlated ($\rho = 1$). We can depict the probabilities described in table 1 in the quadripartite area in figure 2.

(a) No mean shift (b) Symmetric mean shift (c) Asymmetric mean shift

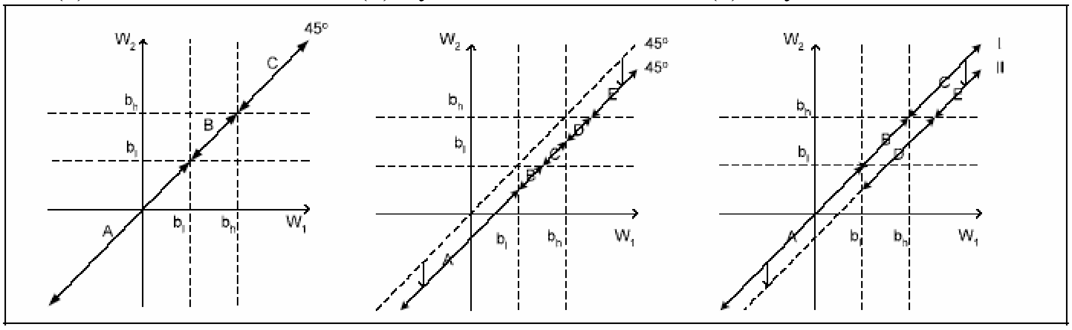

Figure 2: Comparison of probabilities in three different cases when ρ=1

In figure 2, the horizontal axis corresponds to WTP 1 (W_1) and the vertical axis to WTP 2 (W_2). The $45°$ line is a cross-section of a joint distribution of W_1 and W_2 when its correlation coefficient is perfectly one.

3.1.1 No mean shift and perfect correlation

Prior to investigating potential inconsistencies, we will begin with a baseline: *No-mean-shift and perfect correlation* across the initial and the second WTP, which is the main assumption made by Hanemann, Loomis and Kanninen (1991). As shown in figure 2 (a), the probability of a 'yes' to a higher bid (b_h), $P(Y) = P(W_1 > b_h)$, corresponds to sub-line ***C***, and the probability of a 'yes-yes' to ascending bids (b_l, b_h), $P(YY) = P(W_1 > b_l, W_2 > b_h)$ is also sub-line ***C***. $P(Y)$ is collapsed to $P(YY)$ because two lines are identical. Similarly, the probability of a 'yes-no' response to the ascending bid sequence (b_l, b_h), $P(YN) = P(W_1 > b_l, W < b_h)$ corresponds to sub-line ***B***, and the probability of a 'no-yes' response to the descending bid sequence (b_h, b_l), $P(NY) = P(W_1 < b_h, W_2 > b_l)$, also corresponds to sub-line ***B***. Here also $P(YN) = P(NY)$ because two lines are identical. Finally, in the same manner, the probability of a 'no' to the lower bid b_l is equivalent to the probability of a 'no-no' response to the descending bid sequence (b_h, b_l) since both are corresponding to sub-line ***A***, that is, $P(N) = P(NN)$. In sum, in case of no-mean-shift and perfect correlation between two responses in the raw response data, the conditions implicitly assumed by Hanemann *et al*.(1991), we can expect to observe $P(Y) = P(YY)$ in the upper interval, $P(YN) = P(NY)$ in the middle interval and $P(N) = P(NN)$ in the lower interval. This three equality condition provides a baseline because any violation may imply 'mean shift' or 'non-perfect correlation' or a mix of them.

3.1.2 Symmetric downward mean shift in the second WTP and perfect correlation

Adopting the same technique, we now explore a case of a symmetric downward-mean-shift in the second WTP ($\text{Mean}(W_2) < \text{Mean}(W_1)$), (see Alberini *et al* 1997; Carson *et al,* 1994; Hanemann *et al*, 1991; Kanninen, 1995; McFadden and Leonard, 1995; Mitchell and Carson, 1989). This case corresponds to 'government wastage model' or 'strategic behavioral model' presented in chapter 2 where the sequentially offered questions (follow up question format) seem to cause symmetric downward shifting in the second mean WTP. As seen in figure 2 (b), downward mean shifting in the second WTP pushes down the whole distribution vertically. Now, the straight 45 º line is a cross-section of the downward-shifted joint distribution while the dotted line represents that of the original joint distribution. In this case, $P(Y)$ corresponds to sub-line ***D+E*** while $P(YY)$ is sub-line ***E.*** Apparently, $P(Y) > P(YY)$ since $P(Y) \supset P(YY)$. On the other hand, $P(YN)$ is sub-line ***B+C+D*** while $P(NY)$ is sub-line ***C***, thus $P(YN) > P(NY)$ since $P(YN) \supset P(NY)$. Finally, $P(N)$ is sub-line ***A*** while $P(NN)$ is sub-line ***A+B***, thus $P(N) < P(NN)$ since $P(NN) \supset P(N)$. In sum, in the case of symmetric downward mean shift and perfect correlation, we would expect $P(Y) > P(YY)$ in the upper interval, $P(YN) > P(NY)$ in the middle interval and $P(N) < P(NN)$ in the lower interval.

3.1.3. Framing effect hypothesis (asymmetric downward mean shifting) and perfect correlation

Now we utilize our previous technique to mimic 'framing effects' hypothesis introduced by Deshazo (2002). According to his hypothesis, there would be asymmetric downward-mean-shifts in the second WTP: existing with *ascending and sequential path* but not with *descending path* at all. For example, there is mean shifting in YY and YN responses but not in Y, N, NY, NN responses. In figure 2 (c), we draw two 45º lines corresponding to two cross-section of joint distributions: the line (I) for original joint distribution and the line (II) for downward shifted one. Thus, the probabilities of Y, N, NY and NN responses are tracked on the original distribution (I) while the probabilities of YY and YN are tacked on the shifted one (II). $P(Y)$ is sub-line ***C*** along the original line (I) while $P(YY)$ is sub-line ***E*** along the shifted line (II). Clearly, $P(Y) > P(YY)$ since line ***C*** is longer than line ***E*** for a given level of WTPs. Similarly, $P(NY)$ is sub-line ***B*** on the original line (I) while $P(YN)$ is sub-line ***D*** on the shifted line (II). Again $P(YN) > P(NY)$ since line D is longer than line B. Finally, $P(NN)$ is sub-line ***A*** along the original line (I) while $P(N)$ is sub-line ***A*** on the same line (I). Thus, $P(YN) = P(NY)$. In sum, with asymmetric downward mean-shifting with perfect correlation, we would expect, in the upper interval, $P(Y) > P(YY)$, in the middle interval, $P(YN) > P(NY)$ and in the lower interval, $P(YN) = P(NY)$.

3.2. Comparison of Probabilities with Non-Perfect Correlation

To the point, we have investigated the comparisons of probabilities under the assumption of the perfect correlation ($\rho = 1$). Now, we turn our attention to the non-perfect correlation case ($0 < \rho < 1$). Prior to the main body, we need to comprehend a relationship between a correlation coefficient and a shape of a 'cross-section' of a joint distribution. If a correlation coefficient is positive, a cross-section of the joint distribution of W_1 and W_2 is a set of contours skewed to 45° line.

3.2.1 No mean shifts and non-perfect correlation

Upon the knowledge of the shape of cross section of joint distribution with non perfect correlation, we can begin graphical comparisons of $P(Y)$ *vs* $P(YY)$, $P(NY)$ *vs* $P(YN)$ and $P(N)$ *vs* $P(NN)$ when there is no mean shifts and non-perfect correlation.

(a) $P(Y)$ *vs* $P(YY)$ (b) $P(NY)$ *vs* $P(YN)$ (c) $P(NN)$ *vs* $P(N)$

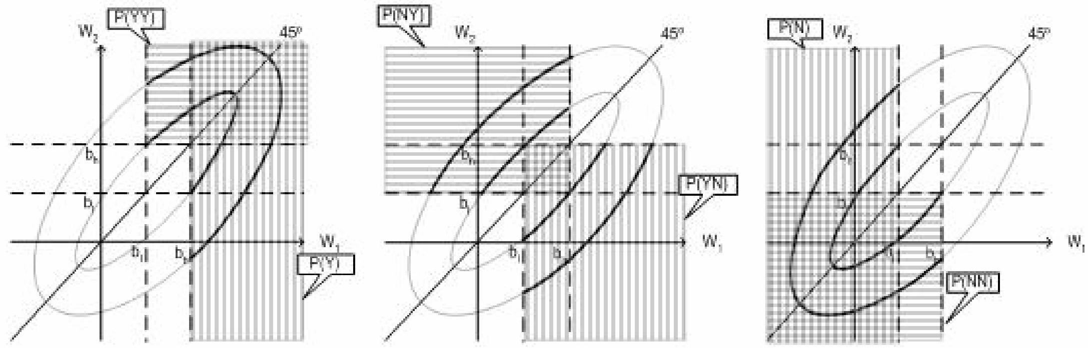

Figure 3: Comparison of the probabilities with no mean shifting when 0< ρ<1

First, we compare $P(Y)$ with $P(YY)$ in figure 3 (a). $P(Y)$ is the vertically shaded area to the right of b_h on the W_1 axis. In contrast, $P(YY)$ is the horizontally shaded area to the right of b_l on the W_1 axis and above b_h on the W_2 axis. We easily note that $P(Y)$ is greater than $P(YY)$ because the latter is truncated at b_l on the W_1 axis. Second, between $P(NY)$ and $P(YN)$ in figure 3 (b), $P(NY)$ is the horizontally shaded area to the left of b_h on the W_1 axis and above b_l on the W_2 axis. $P(YN)$ is the vertically shaded area to the right of b_l on the W_1 axis and below b_h on the W_2 axis. We note that two areas are exactly identical on a pivot of 45º line. Third, we compare $P(N)$ with $P(NN)$ in figure 3 (c). $P(N)$ is the vertically shaded area to the left of b_l on the W_1 axis. $P(NN)$ is the horizontally shaded area to the left b_h on the W_1 axis and below b_l on the W_2 axis. From here, $P(N) > P(NN)$ because the latter is truncated at b_h on the W_1 axis. In sum, the comparing probabilities of no mean shifting and the non-perfect correlation is $P(Y) > P(YY)$ in the upper interval, $P(NY) = P(YN)$ in the middle interval and $P(N) > P(NN)$ in the lower interval.

3.2.2. Symmetric downward mean shifting in the second WTP and non-perfect correlation

Next, we investigate the case of a symmetric downward mean shift in the second WTP is allowed. Of course, we still keep our assumption of $0 < \rho < 1$.

(a) $P(Y)$ *vs* $P(YY)$ (b) $P(NY)$ *vs* $P(YN)$ (c) $P(NN)$ *vs* $P(N)$

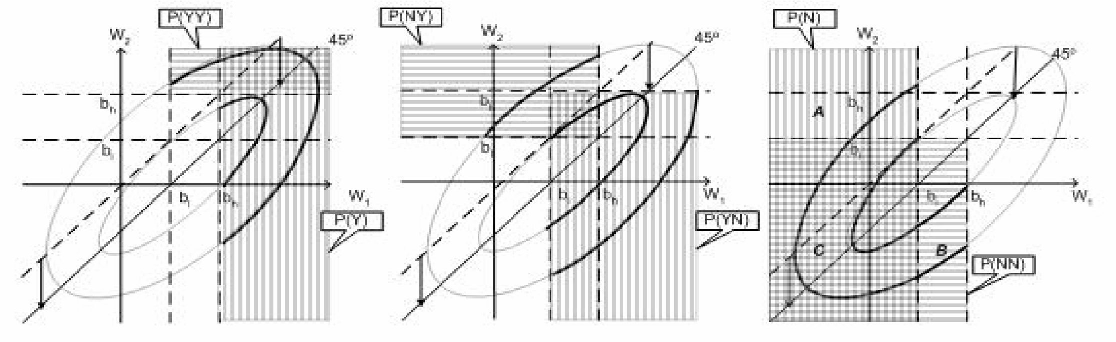

Figure 4: Comparison of probabilities with downward mean shifting when 0< ρ<1

In figure 4, the whole joint distribution moves down vertically. The straight line stands for the shifted 45º line on the shifted distribution while the dotted line is on the original one. First, $P(Y)$ *vs* $P(YY)$ in (a). $P(Y)$ is the vertically shaded area while $P(YY)$ is the horizontally shaded area. Obviously, $P(Y) > P(YY)$ because, here the area of P(Y) becomes bigger but that of P(YY) smaller than previous no-mean shifting case since the whole joint distribution moves down vertically.

Second, $P(NY)$ and $P(YN)$ in (b), $P(NY)$ is the horizontally shaded area while $P(YN)$ is the vertically shaded area. Again, $P(YN) > P(NY)$ still holds because the area of $P(YN)$ becomes bigger but that of $P(NY)$ smaller than previous no-mean shifting case due to the same reason as before.

Third, $P(N)$ and $P(NN)$ in (c), $P(N)$ is the horizontally shaded area (***A+C***) while $P(NN)$ is the vertically shaded area (***A+B***). Unlike to previous two cases, here, we can not easily determine which area is bigger: Area ***A*** can be greater than area ***B*** or vise versa or identical, which relies on severity of mean shift in the second WTP. For example, *moderate* mean shifting in the second WTP still can make $P(N) > P(NN)$. In contrast, *severe* mean shifting in the second WTP can make $P(N) \leq P(NN)$.

In sum, the comparing probabilities of the symmetric mean shifting and the non-perfect correlation is $P(Y) > P(YY)$ in the upper interval, $P(YN) > P(NY)$ in the middle interval and $P(N) >, < \ and\ = P(NN)$ in the lower interval.

3.2.3. Framing effect hypothesis (asymmetric downward-mean shifting) and non-perfect correlation

Finally, we investigate 'framing effects model' in a case of non-perfect correlation between W_1 and W_2. As before, the framing effects model predicts that there be a downward mean shift on the ascending and sequential path but not on the descending path at all. Comparing probabilities are provided in figure 5.

(a) $P(Y)\ vs\ P(YY)$ (b) $P(NY)\ vs\ P(YN)$ (c) $P(NN)\ vs\ P(N)$

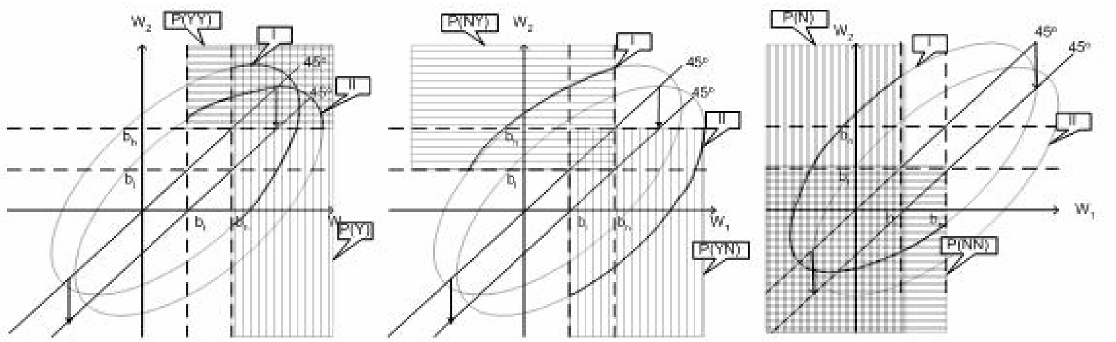

Figure 5: Comparison of probabilities in 'framing effects model' when 0< ρ<1

In figure 5, we draw two joint distributions corresponding to original one (I) and shifted one (II), respectively. The probabilities of the sequential responses within ascending path (YY and YN) follow distribution (II) while the rest of the responses follow distribution (I). In addition, the bold segments on the cross-section of the joint distribution are provided to contrast the comparing probabilities with ease (for example, the longer bold-line, the higher probability).

First, between $P(Y)$ and $P(YY)$ in (a), $P(Y)$, on the descending path is the vertically shaded area along original distribution (I). Conversely, $P(YY)$ in the ascending and sequential path is the horizontally shaded area along the shifted distribution (II). A graphical comparison between the areas of $P(Y)$ and $P(YY)$ shows that $P(Y) > P(YY)$ always holds because the area of $P(YY)$ is truncated at b_l on the W_1 axis and shrunk due to its distribution moves down vertically.

Second, between $P(NY)$ and $P(YN)$ in (b), $P(NY)$, on the descending path is the horizontally shaded area on the original distribution (I). $P(YN)$, on the ascending and sequential path is the vertically shaded area on the shifted distribution (II). A comparison between these two probabilities shows that the area of $P(YN)$ encompass lager portion than that of $P(NY)$ because $P(YN)$ becomes larger since its distribution (II) is shifted down vertically, thus $P(YN) > P(NY)$ holds.

Finally, between $P(NN)$ and $P(N)$ in (c), $P(NN)$, on the descending path is the horizontally shaded area along the original distribution (I). $P(N) = P(WTP_1 < b_l)$, in the ascending sequence but non sequential response is the vertically shaded area along the original distribution (I).

(a) $\rho = 1$

	No mean shift			Symmetric downward mean shifting			Asymmetric downward mean shifting (Framing effect)		
Interval	Ascend		Descend	Ascend		Descend	Ascend		Descend
Up	$P(YY)$	=	$P(Y)$	$P(YY)$	<	$P(Y)$	$P(YY)$	<	$P(Y)$
Mid	$P(YN)$	=	$P(NY)$	$P(YN)$	>	$P(NY)$	$P(YN)$	>	$P(NY)$
Low	$P(N)$	=	$P(NN)$	$P(N)$	<	$P(NN)$	$P(N)$	=	$P(NN)$

(b) $0 < \rho < 1$

	No mean shift			Symmetric downward mean shifting						Asymmetric downward mean shifting (Framing effect)		
				Moderate			Severe					
Interval	Ascend		Descend	Ascend		Descend	Ascend		Descend	Ascend		Descend
Up	$P(YY)$	<	$P(Y)$	$P(YY)$	<	$P(Y)$	$P(YY)$	<	$P(Y)$	$P(YY)$	<	$P(Y)$
Mid	$P(YN)$	=	$P(NY)$	$P(YN)$	>	$P(NY)$	$P(YN)$	>	$P(NY)$	$P(YN)$	>	$P(NY)$
Low	$P(N)$	>	$P(NN)$	$P(N)$	>	$P(NN)$	$P(N)$	$\leq$	$P(NN)$	$P(N)$	>	$P(NN)$

Table 2: Summary of comparison of probabilities in terms of ascending and descending sequence

3.2.4. Implication

Table 2 summarizes all above comparisons of probabilities between $\rho = 1$ and $0<\rho<1$. Of particular interests, first, we compare the symmetric downward mean shifting cases between $\rho = 1$ and $0 < \rho < 1$. Here, only *the probabilities in the low intervals*, that is $P(N)$ *vs* $P(NN)$, will be compared because the relative sizes of other probabilities in upper and middle interval are same for both cases. When $\rho = 1$, the symmetric downward mean shifting in the second mean WTP makes $P(N) < P(NN)$. In contrast, when $0 < \rho < 1$, it makes the relative size between $P(N)$ and $P(NN)$ ambiguous (>, < or =), in fact, relying on severity of mean shifting (moderate or severe). Clearly, this statement would disagree with previous studies (Mitchell and Carson (1989), Carson *et al* (1994) , Alberini *et al* (1997)) because they argue that a behavioral inconsistency pattern such as "government wastage hypothesis" or "strategic behavior", always makes the respondents provide excessive 'no' responses for follow-up responses (here, no-no response) more than would be expected in incentive free response (here, no). As a result, these predictions make $P(N) < P(NN)$. However, our analysis shows that their arguments are unsuitable to non perfect correlation: all relative sizes are possible (>, < or =) in downward mean shifting case.

Second, we investigate asymmetric downward mean shifting case (framing effect model). Again only *the probabilities in the low interval* ($P(N)$ *vs* $P(NN)$) will be compared due to the same reason as before. Deshazo (2002) argues that 'framing effects model' can always predict $P(N) = P(NN)$ because the respondents who say 'no' to the initial bid are free of framing effect regardless of lying in ascending or descending sequences. Conversely, our graphical analysis shows that his 'framing effects model' prediction is not applicable with non perfect correlation ($0 < \rho < 1$) because the probability of 'no' becomes larger than that of 'no/no'

($P(N) > P(NN)$) under the shadow of non-perfect correlation. Continued with this argument, if we observe $P(YY) < P(Y)$, $P(YN) > P(NY)$ and $P(N) = P(NN)$ with $0 < \rho < 1$ in the raw data, then right prediction on this inconsistency pattern should be 'severe downward mean shifting' instead of 'framing effect model' (see Deshazo (2005)).

Third, assume that we observe $P(YY) < P(Y)$, $P(YN) > P(NY)$ and $P(N) > P(NN)$ with the possibility of $0 < \rho < 1$ in the raw data, then the possible behavioral explanation is binary: 'moderate downward-mean-shifting' or 'framing effects'. Theoretically, the only difference between two explanations is a behavioral assumption of whether the mean shifting in the second WTP is "symmetric" or "asymmetric".

4. Data analysis

In this section, we provide five data sets to illustrate the previous discussion. The first example[5] is a data set from a CV survey employing face-face interviews to ask respondents for a public program preventing saline flooding in Norfolk Broad, a major freshwater wetland area of National Park located in East Anglian region of the United Kingdom (1995). We use only the sub-sample which contains the second follow-up bid because the original large data contains a third follow-up bid. The second example is a data from the CV survey conducted in California to estimate people's WTP to avoid certain shortages of water supply level with certain frequencies. We recover the full data from the percentage of each response and total responses both of which are available in Kanninen and Khawja (1995). The third example is data from the CV survey conducted in 1992 to measure the loss of passive use benefits caused by the 1989 Exxon Valdez

[5] The data is taken from the paper "Efficiency gains afforded by improved bid design versus follow-up valuation questions in discrete choice CV studies" by Riccardo Scarpa and Ian Bateman.

oil spill in Prince William Sound available in Carson *et al* (1992). The fourth example is data from the CV survey conducted by the Australian Resource Assessment Commission in 1990 as part of a benefit-cost analysis effort to evaluate options for the use of resource of Kakadu Conservation Zone available in Carson *et al* (1994). Only the sub-sample that administrated a moderate environmental impact scenario ("minor impact") is used. The fifth example is a data set from the CV surveys conducted by Ministry of agricultural forestry and fisheries of Japan to measure the amenity effects of "Water Environment Improvement Project" in 1998 (Terawaki (2003)) which was intended to conserve or recover the functions of agricultural water supply facilities, such as dam, reservoir and cannel, to provide waterside spaces for recreation while maintaining ecosystem. We use only one sub-sample among 24 districts to illustrate. Table 3 is a summary of the response distributions of the five data sets.

Norfolk Broad CV Study (N=1735)

First bid (Second bid)	Total	Y	N	YY	YN	NY	NN
1(0.5,2)	217	216	1	193	23	0	1
5(2.5,10)	226	221	5	177	44	2	3
10(5,20)	222	212	10	141	71	4	6
20(10,40)	227	203	24	100	103	16	8
50(25,100)	214	144	70	60	84	43	27
100(50,200)	214	121	93	41	80	54	39
200(100,400)	208	84	124	19	65	65	59
500(250,1000)	207	40	167	3	37	55	112

California water CV study (N=3647)

First bid (Second bid)	Total	Y	N	YY	YN	NY	NN
5(2.5, 10)	1057	656	401	328	328	219	182
10(5, 15)	1021	510	511	255	255	292	219
15(10, 20)	803	329	474	110	219	255	219
20(15,30)	766	219	547	73	146	219	328

Alaska CV study (N=1043)

First bid (Second bid)	Total	Y	N	YY	YN	NY	NN
10(5,30)	264	179	85	118	61	7	78
30(10,60)	267	138	129	69	69	31	98
60(30,120)	255	129	126	54	75	25	101
120(60,250)	257	88	169	35	53	30	139

Kakadu CV study (N=1013)							
First bid (Second bid)	Total	Y	N	YY	YN	NY	NN
5(20,2)	253	167	86	150	17	7	79
20(50,5)	252	156	96	136	20	11	85
50(100,20)	255	145	108	124	23	15	93
100(250,50)	253	136	117	105	31	17	100
Japan CV study (N=234)							
First bid (Second bid)	Total	Y	N	YY	YN	NY	NN
5(2.5,10)	38	33	5	21	12	5	0
10(5,30)	46	41	5	25	16	5	0
30(10,50)	38	22	16	18	4	11	5
50(30,100)	38	19	19	4	15	16	3
100(50,300)	22	12	10	5	7	6	4
300(100,500)	29	4	25	0	4	13	12
500(300,1000)	23	5	18	2	3	6	12

Table 3: Summary of Distribution of CV response

Based on the summary of the responses in table 3, we can calculate the underlying probabilities for comparisons. For example, at the bid interval (5, 10) in Norfolk Broad CV study of table 3, the calculations of comparing probabilities along ascending and descending path are provided in table 4:

Symbols	Path	Probabilities	Calculations
$P(YY)$	Ascending	$P(WTP_1 > 5, WTP_2 > 10)$	$\frac{\text{'yes/yes' response for bid 5}}{\text{total response for bid 5}} = \frac{117}{226} = 0.52$
$P(Y)$	Descending	$P(WTP_1 > 10)$	$\frac{\text{'yes' response for bid 10}}{\text{total response for bid 10}} = \frac{212}{222} = 0.95$
$P(YN)$	Ascending	$P(WTP_1 > 5, WTP_2 < 10)$	$\frac{\text{'yes/no' response for bid 5}}{\text{total response for bid 5}} = \frac{44}{226} = 0.19$
$P(NY)$	Descending	$P(WTP_1 < 10, WTP_2 > 5)$	$\frac{\text{'no/yes' response for bid 10}}{\text{total response for bid 10}} = \frac{4}{222} = 0.02$
$P(N)$	Ascending	$P(WTP_1 < 5)$	$\frac{\text{'no' response for bid 5}}{\text{total response for bid 5}} = \frac{5}{226} = 0.02$
$P(NN)$	Descending	$P(WTP_1 < 10, WTP_2 < 5)$	$\frac{\text{'no/no' response for bid 10}}{\text{total response for bid 10}} = \frac{6}{226} = 0.03$

Table 4: Example of calculation of comparing probabilities

Adopting this calculation technique, we can provide all probabilities for comparisons and pair-wise Z-statistics for each data set in Table 5.

Norfolk Broad

First bid (Second bid)	P(YY)	P(Y)	Z-statistic	P(YN)	P(NY)	Z-statistic	P(N)	P(NN)	Z-statistic
(5 10)	0.52	0.95	5.57	0.19	0.02	6.34	0.02	0.03	0.33
(10 20)	0.63	0.89	6.77	0.32	0.07	7.01	0.04	0.04	0.53
(50 100)	0.28	0.57	5.95	0.39	0.25	3.20	0.32	0.18	3.56
(100 200)	0.19	0.40	4.88	0.37	0.31	1.37	0.43	0.28	3.36

California

First bid (Second bid)	P(YY)	P(Y)	Z-statistic	P(YN)	P(NY)	Z-statistic	P(N)	P(NN)	Z-statistic
(5 10)	0.31	0.50	8.94	0.31	0.29	1.2	0.38	0.21	8.36
(10 15)	0.25	0.41	7.26	0.25	0.32	3.18	0.50	0.27	10.26
(15 20)	0.14	0.29	7.32	0.27	0.29	0.58	0.59	0.43	6.50

Kakadu

First bid (Second bid)	P(YY)	P(Y)	Z-statistic	P(YN)	P(NY)	Z-statistic	P(N)	P(NN)	Z-statistic
(5,20)	0.59	0.62	0.60	0.06	0.04	1.16	0.34	0.34	0.06
(20 50)	0.54	0.58	0.87	0.07	0.06	0.74	0.38	0.36	0.38
(50 100)	0.49	0.53	1.10	0.09	0.07	1.09	0.42	0.40	0.69

Alaska

First bid (Second bid)	P(YY)	P(Y)	Z-statistic	P(YN)	P(NY)	Z-statistic	P(N)	P(NN)	Z-statistic
(10 30)	0.45	0.52	1.51	0.23	0.12	3.57	0.33	0.37	0.96
(30 60)	0.26	0.51	6.00	0.26	0.10	4.88	0.46	0.4	1.38
(60 120)	0.21	0.34	3.34	0.29	0.12	5.05	0.5	0.54	0.91

Japan

First bid (Second bid)	P(YY)	P(Y)	Z-statistic	P(YN)	P(NY)	Z-statistic	P(N)	P(NN)	Z-statistic
(5 10)	0.32	0.89	6.44	0.55	0.11	4.72	0.13	0	2.37
(10 30)	0.09	0.58	5.38	0.80	0.37	4.41	0.11	0.053	0.95
(30 50)	0.32	0.50	1.64	0.26	0.42	1.45	0.42	0.079	3.70
(50 100)	0.11	0.57	3.83	0.39	0.29	0.84	0.50	0.14	3.15
(100 300)	0.10	0.14	0.46	0.47	0.72	1.76	0.43	0.11	2.57
(300 500)	0	0.22	2.47	0.14	0.65	4.24	0.83	0.13	6.83

Table 5: Comparing probabilities and Z-statistics for all data sets[6]

[6] Z-statistics is employed to test whether the observed difference in probabilities is statistically significant. If the Z-statistics are greater than 1.96, the two comparing statistics are statistically different with 95% confidence.

2.4.1. Non-parametric comparison of probabilities with data

Now, we apply our nonparametric comparison model to the five different real data sets. Table 6 provides relative size of comparing probabilities and possible explanations for each bid interval in five data sets for ρ=1 and 0<ρ<1, respectively. Except for a few bid cases (*No match cases*)[7], we can provide plausible explanations on inconsistency patterns based on table 2. Interestingly, we can provide apparently different explanations for the same bid interval depending on whether our expectation is either ρ=1 or 0<ρ<1. For example, as for bid intervals (5, 10) and (10, 20) in Norfolk Broad data, a behavioral model that claims ρ=1 across sequential responses would expect that the downward mean shifting in these intervals would be asymmetric (*framing effect*) whereas our behavioral model that allows for the possibility of non perfect correlation (0<ρ<1) would expect that it is symmetric and strong (*government wastage or strategic motive*). Implications behind these two different explanations are quite different; the framing effect model expects that there would be a downward bias in ascending sequence but not in descending sequence. In contrast, our behavioral model expects that there would be overall downward biases both in ascending and in descending sequences.

In fact, based on non-parametric result in table 6, one may conclude that the framing effect model can be the most suitable expectation for overall inconsistency pattern found in five different data sets. In contrast, according to our behavioral model with non-perfect correlation, we can claim that there is no single pattern of inconsistency which can dominate all other data sets or across bids within a data set. In the Norfolk data, there would be a strong-downward-mean shift for lower bids ((5,10) and (10,20)) and moderate-downward-mean shift or framing effect for mid bids (50, 100) and no mean shifting for higher bids (100, 200). Conversely, in the

[7] These no match cases can be a upward-mean shifting in the second WTP or negative correlation between the first and second WTP ($\rho < 0$)

Alaska data, there would be overall a strong-downward-mean shift in the second WTP for both mid and upper intervals. Therefore, from these two data sets, we may anticipate that the responses in Alaska data would be more severely downward shifted than Norfolk data.

On the other hand, in California data, no-mean-shift in responses would be a possible expectation. Meanwhile, Kakadu data also shows no-mean-shift in responses. The only difference is that, as shown in table 6, the sequential responses in California data set would be less correlated while those in Kakadu data set would be almost perfectly correlated. Thus interpretations on no-mean shifting between two data sets should be divergent: the sequential responses from Kakadu data come from almost identical distributions while those from California data would have identical means inadvertently. The Japan data set shows irregular pattern in responses; a moderate-downward-mean shift or framing effect for the bid (5, 10), a strong-downward-mean shift for the bid (10, 30), no-mean-shift for the bid (50, 100) and no match for some bids. These anomalies might be caused by an unrestricted correlation departed from our expected domain of correlation coefficient ($0 \le \rho \le 1$).

The conclusion drawn from this non-parametric approach is that a simple model can not encompass all possible inconsistency patterns in sequential responses if we allow non-perfect correlation: the behavioral inconsistency patterns are different both within and between data sets. Furthermore, each individual level of psychological inconsistency pattern, not observable even in our non-parametric approach, might be extremely diverse. For example, it is possible to say that each individual may respond to the iterative question survey with his/her own various motive.

Bid Interval	Relative size of comparing probabilities			Possible Explanations $\rho=1$	Possible Explanations $0<\rho<1$
Norfolk Broad					
(5 10)	P(YY)<P(Y)	P(YN)>P(NY)	P(N)=P(NN)	Framing effect	Strong downward mean shift
(10 20)	P(YY)<P(Y)	P(YN)>P(NY)	P(N)=P(NN)	Framing effect	Strong downward mean shift
(50 100)	P(YY)<P(Y)	P(YN)>P(NY)	P(N)>P(NN)	-	Moderate downward mean shift or Framing effect
(100 200)	P(YY)<P(Y)	P(YN)=P(NY)	P(N)>P(NN)	-	No mean shift
Alaska					
Bid Interval	**Relative size of comparing probabilities**			**$\rho=1$**	**$0<\rho<1$**
(10 30)	P(YY)=P(Y)	P(YN)>P(NY)	P(N)=P(NN)	*No match*	
(30 60)	P(YY)<P(Y)	P(YN)>P(NY)	P(N)=P(NN)	Framing effect	Strong downward mean shift
(60 120)	P(YY)<P(Y)	P(YN)>P(NY)	P(N)=P(NN)	Framing effect	Strong downward mean shift
California					
Bid Interval	**Relative size of comparing probabilities**			**$\rho=1$**	**$0<\rho<1$**
(5 10)	P(YY)<P(Y)	P(YN)=P(NY)	P(N)>P(NN)	-	No mean shift
(10 15)	P(YY)<P(Y)	P(YN)<P(NY)	P(N)>P(NN)	*No match*	
(15 20)	P(YY)<P(Y)	P(YN)=P(NY)	P(N)>P(NN)	-	No mean shift
Kakadu					
Bid Interval	**Relative size of comparing probabilities**			**$\rho=1$**	**$0<\rho<1$**
(5,20)	P(YY)=P(Y)	P(YN)=P(NY)	P(N)=P(NN)	No mean shift	-
(20 50)	P(YY)=P(Y)	P(YN)=P(NY)	P(N)=P(NN)	No mean shift	-
(50 100)	P(YY)=P(Y)	P(YN)=P(NY)	P(N)=P(NN)	No mean shift	-
Japan					
Bid Interval	**Relative size of comparing probabilities**			**$\rho=1$**	**$0<\rho<1$**
(5 10)	P(YY)<P(Y)	P(YN)>P(NY)	P(N)>P(NN)	-	Moderate downward mean shift or Framing effect
(10 30)	P(YY)<P(Y)	P(YN)>P(NY)	P(N)=P(NN)	Framing effect	Strong downward mean shift
(30 50)	P(YY)=P(Y)	P(YN)=P(NY)	P(N)>P(NN)	*No match*	
(50 100)	P(YY)<P(Y)	P(YN)=P(NY)	P(N)>P(NN)	-	No mean shift
(100 300)	P(YY)=P(Y)	P(YN)=P(NY)	P(N)>P(NN)	*No match*	

Table 6: Comparison of probabilities for each bid interval and possible explanations.

4.2. Parametric analysis

It is also interesting to explore a conventional parametric approach to test whether it is consistent with our previous non-parametric expectations. The underlying estimation technique is a bivariate probit model which allows non-identical means and non-perfect correlation. Table 7 provides the estimated results from bivariate probit model: the first and the second mean WTP and correlation coefficient.

Estimates	Norfolk Broad	California	Alaska[8]	Kakadu	Japan
$\hat{\mu}_1$	236.19	10.34	58.72	128.77	161.10
(st_d)	(9.37)	(0.38)	(5.82)	(27.61)	(23.82)
$\hat{\mu}_2$	144.20	10.30	-22.95	146.06	244.24
(st_d)	(9.77)	(0.75)	(18.56)	(24.95)	(84.93)
$\hat{\rho}$	0.14	0.04	0.68	0.95	-0.17
(st_d)	(0.05)	(0.03)	(0.04)	(0.01)	(0.12)
Log- Likelihood (full model)	-1852.39	-4900.18	-1299.72	-1080.86	-287.62
Log- Likelihood (same mean restriction)	-1871.58	-4900.18	-1326.28	-1081.09	-288.02
LR test	38.38*[9]	0	53.12*	0.46	0.8

Table 7: Bivariate probit models and statistical tests of five sample data

One important result is that the estimated correlation coefficients from all data are far from perfect except those from Kakadu data (0.95), which means that in most of data sets, the first responses as well as the second responses are derived from related but different distributions. Of particular interest, the estimated correlation coefficient from Japan data set is negative, which is in agreement with our previous hypothesis that the domain of correlation might depart from (0,1). Intuitively, the respondents in Japan data facing sequential questions may have tendency to

[8] The original estimation of this Alaska data is conducted with log linear model of WTP because a normal distribution fits poorly this survey data. However, with different purpose of analysis, I estimate this data set with linear model of WTP (see R.T. Carson et al (1992))
[9] * indicates that the hypothesis of identical means is rejected with 95% confidence level.

reverse their initial responses systematically when offered with follow-up bid, or possibly have a peculiar preference of defending the follow-up questions by intent.

Once again, in accordance with nonparametric comparison in table 2.6, the estimate results from the Norfolk Broad data (236.19 for 1st WTP *vs* 144.20 for 2nd WTP) and the Alaska data (58.72 for 1st WTP *vs* -22.95 for 2nd WTP) show a severe-downward-mean shift in the second WTP. Furthermore, as predicted, the size of the downward mean shifting in the estimated second mean WTP from Alaska data is greater than that from Norfolk data set (99.14% more). Also, as predicted, the estimate results from the California data (10.34 for 1st WTP *vs* 10.30 for 2nd WTP) and the Kakadu data (128.77 for 1st WTP *vs* 146.06 for 2nd WTP) show no-mean-shift according to likelihood ratio test (LRT) presented in the last row in table 7. However, as we expected in the nonparametric method, the estimated correlation coefficient of California data is close to zero (0.04) whereas that of Kakadu is close to one (0.95). Interestingly, the estimated results from the Japan data set also show no mean shifting according to LR test although the downward-mean-shift for some lower bids was found in non-parametric model. Most likely, the negative correlation between the first and the second responses causes these anomalies.

To conclude, we test how inconsistency in responses can affect the statistical efficiency with follow-up question. Hanemann et al (1991) and most subsequent studies have argued that the double-bounded model and its many variations provide efficiency gains beyond the simple single-bound referendum. Here we show that this is not necessarily the case.

The procedure is as follows: we compare the standard deviations of the mean WTPs between single bounded model and a restricted bivariate probit model. Here, we provide estimate results from single bounded model as a baseline because it is known that it is free of inconsistency problem. As for the restricted bivariate probit model, although statistically wrong for some data, we force the mean and variances of WTP to be identical across the first and the second WTP while the correlation coefficients are allowed to be freely estimated. Table 2.8 shows the summary of the estimate results from single bounded model and the restricted bivariate probit model.

	Norfolk Broad		California		Alaska		Kakadu		Japan	
	SB*	RBP*	SB	RBP	SB	RBP	SB	RBP	SB	RBP
μ	236.64 (9.4)**	191.5 (6.98)	10.34 (0.38)	10.43 (0.36)	58.7 (5.71)	28.38 (7.30)	123.16 (30.1)	150.22 (23.54)	160.85 (24.13)	181.50 (25.07)
σ	201.11 (9.85)	237.6 (10.43)	17.63 (1.21)	22.29 (1.5)	144.1 (19.97)	188.89 (21.18)	317.14 (110.3)	472.43 (83.53)	250.74 (39.00)	371.82 (56.08)
ρ	-	0.09 (0.05)	-	0.13 (0.03)	-	0.7 (0.04)	-	0.95 (0.01)	-	-0.07 (0.11)

* SB: single bounded model and RBP: restricted bivariate probit model
** Standard deviation reported in parenthesis

Table 8: The comparison of efficiency from single bounded model and restricted bivariate probit model

As highlighted in Table 8, the apparent statistical efficiency gains using the follow-up question can be found in estimated mean WTP from restricted bivariate probit model of 'Norfolk Broad' data and 'Kakadu' data (see the standard deviations of mean WTP). However, we should carefully note that statistical efficiency gain from restricted bivariate probit model of Norfolk Broad data comes at the cost of biasedness in mean WTP because in that data, there is great difference in the estimated mean WTPs from single bounded model and that from the restricted bivariate probit model (236 for SB and 191.5 for RBP), indicating that estimated mean WTP from the restricted bivariate probit model might be seriously biased[10]. Conversely, we can not find any apparent efficiency gain from the follow-up question in the rest of the data sets. In particular, the most interesting findings in the above estimation results are that possibly, we can lose statistical efficiency by adding the follow-up question. As can be seen in the estimate results

[10] . The likelihood ratio test for the hypothesis that the first mean WTP is identical to the second mean WTP is rejected with 95% confidence level (38.38 >5.99) (see Table 8), and thus the estimated mean WTP from restricted bivariate probit model assuming identical mean and identical variance would be also downward biased.

from ‘Alaska’ data and ‘Japan’ data, the standard deviation of the mean WTP from the restricted bivariate probit model is greater than that from the single bounded model (in Alaska data set, 5.71 for SB vs 7.30 for RBP; in Japan data set, 24.13 for SB vs 25.07 for RBP). Overall conclusion driven from these analyses is that the only possible case to earn more efficiency gain with follow-up question is when there is almost perfect consistency between the first and the second responses (the almost perfect correlation and no mean shifting).

5. Conclusions

This paper has explored the consequence of the DCCV with follow-up question format. The conclusion drawn from this paper is two-folded. First, the graphical comparisons of probabilities between the initial and follow-up responses shows that ignoring non-perfect correlation can provide wrong predictions for analyzing behavioral inconsistency pattern usually found in iterative question formats. Second, the non-parametric application of our inconsistency-diagnosing method to five real data sets suggests that efforts to provide a general mechanism on individual inconsistency pattern in responses are futile. We demonstrate that a general inconsistency pattern can not be anticipated with a single behavioral explanation; we find that inconsistency patterns are different both within and between data sets. As a result, from the individual perspective, we may fail to predict how each person reacts to the initial and follow-up question in general. In parametric comparisons, we confirm that the estimate results are in accordance with non-parametric expectation; except for one data set (Kakadu data), there is the potential for less-than-perfect correlation and uncontrollable mean-shifting (moderate or strong downward mean shifting). In addition, this paper also verified that the efforts to increase efficiency in estimation by simply adding the follow-up question is only supported when there is apparent consistency between the first and the second responses. Otherwise, we find that the estimated parameters are either seriously biased or less (equally) efficient than that from the single question format. We therefore have serious reservations about the continued use of the dichotomous-choice with follow-up format. At best it is biased and at worst, less efficient than a simple single dichotomous choice question.

References

[1] A. Alberini, B. Kanninen and R.T. Carson, Modeling response incentive effects in Dichotomous choice Contingent Valuation Data, *Land Economics*, 73(3) 309-24 (1997).

[2] I.J. Bateman, I.H. Langford, Andrew P. Jones and Geoffrey N. Kerr, Bound and Path effects in double and triple bounded dichotomous choice contingent valuation, *Resource and Energy economics*, 23, 191-213 (2001)

[3] T. Cameron and J. Quiggin, Estimating using contingent valuation data from a 'dichotomous choice with follow-up' questionnaire, *Journal of environmental economics and management* 24, 218-234 (1994)

[4] R. T. Carson, R. C. Mitchell, W. M. Hanemann, R. J. Kopp, S. Presser, and P. A. Ruud, "A contingent valuation study of Lost Passive Use Values Resulting from the Exxon Valdez Oil Spill" Report to the General Attorney of the State of Alaska," (Nov. 1992)

[5] R.T. Carson, L. Wilks, and D. Imber, Valuing the preservation of Australia's Kakadu Conservation Zone, Oxford Economic Paper. 46, 727-749 (1994)

[6] J.R. Deshazo, Designing Transactions without Framing effects in iterative Question formats, *Journal of Environmental Economics and Management*, 43, 360-385 (2002)

[7] W.M. Hanemann, J. B. Loomis, and B. Kanninen, Statistical efficiency of double-bounded dichotomous choice contingent valuation, *American Journal of Agricultural Economics*, 73, 1255-1263 (1991)

[8] J.A. Herriges and J. F. Shogren, Starting Point Bias in dichotomous Choice Valuation with Follow-up Questioning, *Journal of Environmental Economics and Management,* 30 (1), 112-131 (1996)

[9] B. Kanninen, Bias in discrete response contingent valuation, *Journal of Environmental Economics and Management*, 28, 114-125 (1995)

[10] D. McFadden and G. Leonard, Issues in the contingent valuation of environmental goods: Methodologies for data collection and analysis, *Contingent Valuation: A Critical Assessment*, North-Holland, Amsterdam (1995)

[11] R. Mitchell and R. Carson, Using Surveys to Value Public Goods: The Contingent Valuation Method, *Resources for the Future*, Washington, DC (1989)

[12] R. Scarpa and I. Bateman, Efficiency Gains Afforded by Improved Bid Design versus Follow-up Valuation Questions in Discrete-Choice CV Studies, *Land Economics*, May, 76(2), 299-311 (2000)

[13] T. Terawaki, Second Nonparametric Approach for Double-Bound Dichotomous Choice Contingent Valuation, Discussion paper No. 02005, College of Economics, Ritsumeikan University, Version Nov 30 (2003)