Preference uncertainty in contingent valuation

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Abstract

In this paper, the results of empirical studies that applied two widely used methods- numerical certainty scale (NCS) and polychotmous choice (PC)- for estimating preference uncertainty adjusted willingness to pay (WTP) in contingent valuation (CV), are summarized. For this review, a number of conclusions are reached. First, there is a lack of consensus about which method is more appropriate for measuring preference uncertainty. Second, although preference uncertainty information has been found useful in detecting the incidence of hypothetical bias in CV studies, a consensus about a standard certainty threshold (or treatment mechanism) at which hypothetical behaviour converges to real behaviour is yet to emerge. Third, insufficient empirical evidence exists about the causal relationship between preference uncertainty scores and the theoretically expected explanatory variables. Finally, the preference uncertainty adjusted PC and NCS models fail to provide a consistent and more efficient welfare estimate compared to the conventional dichotomous choice certainty model.

Key Words: preference uncertainty, contingent valuation, polychotomous choice, numerical certainty scale

1. Introduction

The concept of ‘preference (or respondent) uncertainty’ has gained a significant amount of attention in the stated preference literature over the past fifteen years. Hanemann et al. (1995) first propose a welfare model that incorporates an element of uncertainty about individual preference. Building upon the Hanemann et al. (1995) framework, Li and Mattsson (1995) extended the theory of preference uncertainty to define preference uncertainty as a stochastic error term which arises in a hypothetical valuation scenario as individuals do not know their true values of a good with certainty. Li and Mattsson (1995) argue that ignoring preference uncertainty in stated preference studies may result in measurement bias. Researchers have developed and applied a variety of methods for addressing preference uncertainty in CV studies. A number of empirical studies have used information on preference uncertainty to understand the disparity between hypothetical values and actual economic behaviour (Champ et al., 1997; Ethier et al. 2000; Champ and Bishop, 2001; Poe et al., 2002). In a second phase of preference uncertainty research, attempts have been made to develop calibration techniques to incorporate information about respondent uncertainty into welfare estimates. Empirical evidence indicates that different certainty measurement methods and calibration techniques[1] generate different welfare estimates in terms of value, efficiency of the estimate (related to the notion of standard deviation) and model fit statistics (Shaikh et al. 2007).

[1] In this paper we use the word ‘method’ to denote how preference uncertainty information has been collected from the respondents and use the words ‘calibration technique’ to refer to the way preference uncertainty information has been recoded.

Besides the fact that the effect of preference uncertainty on welfare estimates varies depending upon specific certainty measurement method and calibration technique, the question that currently arises is whether or not these measurement methods and calibration techniques produce consistent results across different studies. More importantly, how useful is it to perform this additional exercise of calibrating respondent uncertainty information? Does this additional information about respondents' levels of confidence help to obtain improved welfare estimates relative to the conventional certainty model? The aim of this paper is to address these emerging issues in the light of two widely used preference uncertainty measurement methods. A number of empirical studies in the CV literature that applied either a numerical certainty scale (NCS) method or a polychotomous choice (PC) method or both methods of measuring preference uncertainty are summarized. The results of these studies are analyzed to address the research questions.

The next section of the paper presents a description of the NCS and PC methods followed by a discussion of different techniques for calibrating uncertain responses. Section Four presents a discussion of the results from preference uncertainty models estimated by Champ and Bishop (2001), Loomis and Ekstrand (1998) and Samneliev et al. (2006). In Section Five, a summary of the validity test results of NCS and PC methods is presented. A summary of the results of preference uncertainty calibrated willingness to pay (WTP) estimates is delivered in Section Six. Section Seven contains discussion and concluding remarks.

2. The NCS and PC methods for measuring preference uncertainty

The NCS method and the PC method are two widely used techniques of measuring preference uncertainty in CV studies. Under the NCS method, the standard "Yes/No" dichotomous choice (DC) valuation question is followed up by a numerical certainty scale ranging from 1 to 10 where respondents are asked to indicate the level of certainty about their 'yes/no' voting decision by selecting a certainty score within the scale. Li and Mattson (1995) first constructed a post-decisional confidence rating for assessments of the preservation value of forests in northern Sweden using a follow-up question to a dichotomous-choice (DC) valuation question. Under the PC method, on the other hand, respondents are provided with the opportunity to express their uncertainty by choosing from a set of responses e.g. "Definitely Yes," "Probably Yes," "Maybe Yes," "Maybe No," "Probably No," "Definitely No". Ready et al. (1995) first introduced and applied the PC format and was so able to embed the information on respondent's preference uncertainty directly into the options to the WTP question.

Debate persists about whether the NCS or the PC, provides the better uncertainty measure. Proponents of the NCS method argue that it provides more precise information about the level of certainty as the respondent is able to specify a numerical certainty value in a 1 to 10 or 10% to 100% scale. However, the NCS method is based on two stringent assumptions (Loomis and Ekstrand, 1998). First, it assumes that the respondents are able to assess accurately their own degree of certainty when answering WTP question. Second, it is assumed that all respondents interpret the certainty scale equivalently. Whilst the main argument for measuring preference uncertainty in stated preference studies is that respondents are uncertain about their valuation of the good, the first assumption implies that respondents are certain about their levels of confidence in their voting decision appears to be contradictory. At most, respondents might be expected to indicate a certainty range instead of a point estimate. Furthermore, the second assumption of comparable rating responses across individuals is dubious as it has been observed that respondents show 'scale preference' in which some individuals tend to be low raters or high raters (Roe et al., 1996).

The performance of the PC format has also been debated in the past. Ready et al. (1995) found that the PC questions generate higher rates of "Yes" responses because the respondent can give an affirmative response, without making a strong commitment. Alberini et al. (2003) argued that the PC responses may cause false uncertainty to arise in the stated preference framework simply because the format provides respondents with an inducement to leave unresolved their lack of confidence in answering the valuation question. Samneliev et al. (2006)[2] suggest that the three option PC format may be used as a device to identify the so-called yea-sayers in CV studies. Yea-sayers may tend to select the 'Not Sure' option while in a DC format, yea-saying may generate a greater proportion of yes responses[3]. The authors found 'yes' responses decreased from 38 percent to 32 percent in a split sample DC CV survey when a 'Not Sure' response was made available to respondents.

[2] Note that the work of Samneliev et al (2006) involved an empirical analysis to understand the effect of two different certainty measurement methods (NCS and PC) using split sample treatments. The study reported here is a summary of the empirical preference uncertainty literature and does not include any primary data collection.
[3] The assertion is suggestive not conclusive.

One other pitfall of using the PC format could be denoted as a ‘framing effect’. The meaning of the words that are generally used to elicit respondent uncertainty could be interpreted differently by different respondents (Hanley et al., forthcoming). In particular distinctions between the middle responses are not very straightforward. For example, when a respondent is confronted with the choice between “Probably Yes,” and “Maybe Yes,”, unless the distinction between the terms “Probably” and “May be” are explicitly demonstrated to the respondents, the interpretation of these two responses could be highly subjective and may lead to a potential measurement bias.

3. Treatment for NCS and PC responses

A second issue that surrounds the preference uncertainty debate is how to recode the uncertain responses. The most commonly used technique of incorporating the NCS measure of preference uncertainty is to recode the original ‘Yes/No’ DC responses based on different certainty scale cut-off points. The certainty scale can be applied by calibrating only Yes or only No responses with certainty 8, 9 and/or 10 and treating them as No (or Yes, respectively) or as missing, or calibrating both Yes and No responses. Other widely applied uncertainty calibration techniques are the Asymmetric Uncertainty Model (ASUM) and the Symmetric Uncertainty Model (SUM). In ASUM, the original DC responses are recoded simply by multiplying the Yes(=1)/No(=0) by the certainty score (P)[4]. This specific treatment is known as ‘Asymmetric Uncertainty Model’ because in this method only the ‘Yes’ responses are recoded with a range 1–0.1. In SUM both ‘Yes’ and ‘No’ responses are recoded with their certainty level. A ‘no’ response with

[4]If Pay=1, then Prob(Yes)=1*P; if Pay=0, then Prob(Yes)=0.

perfect certainty takes on the usual value of 0, while a ‘yes’ with perfect certainty equals 1. A ‘yes’ response with a follow-up certainty response of 60% is coded 0.6. In contrast, for a ‘no’ response with a follow-up certainty response of 60% is coded 1−0.6=0.4.

The treatment of the PC responses is even more subjective and ad-hoc than the NCS process. As the information gathered through the PC format about a respondent’s level of confidence is purely qualitative in nature, the interpretation and therefore, the treatment of different PC responses may vary widely across different people. In a three option PC format (Yes, No, Not Sure/Undecided), a common approach has been to treat the ‘Not Sure/Undecided’ responses as either ‘No’ or ‘missing’ (Vossler et al., 2003). In a multiple choice PC format, recoding can be applied in a variety of combinations, e.g. calibrating all ‘Yes’ responses (‘Definitely Yes’, ‘Probably Yes’, ’Maybe Yes’) as 1 and the rest as 0, or calibrating only ‘Definitely Yes’ responses as 1 and the rest as 0 or calibrating only ‘Definitely Yes’ and ‘Definitely No’ responses as 1 and 0 and to treat the rest as missing.

4. Preference uncertainty and economic theory

In this section the results of econometric models estimated to establish a causal relationship between the levels of preference uncertainty and one or a group of theoretically and intuitively expected independent variables are discussed. Although no explicit theoretical model to explain variations in preference uncertainty has been developed as yet, there is a general agreement about some hypotheses that has emerged after Loomis and Ekstrand (1998) estimated their econometric model. The variables are more ‘intuitive’ than ‘theoretical’. Hypotheses about the causes of respondents being uncertain about their true values for a good include a lack of knowledge about the good to be valued, insufficient interest, inability to make a quick decision, the presence of substitute and complement goods, the survey instrument and the respondents’ lack of understanding about the contingency in question (Shaikh et al., 2007). To date, only three studies that the authors are aware of have estimated a preference uncertainty model by regressing the self reported numerical preference uncertainty scores against intuitively expected explanatory variables. We are unaware of any study that has attempted to explain the variations in PC responses. Loomis and Ekstrand (1998) estimated an ordinary least square (OLS) regression model on pooled (both Yes and No responses) data. Champ and Bishop (2001) estimated an ordered probit regression model whereas Samneliev et al. (2006) estimated two logistic regression[5] models separately for Yes and No responses.

Loomis and Ekstrand (1998) find a quadratic relationship between self reported preference uncertainty and bid levels. This implies that, ceteris paribus, at extremely low and high bids respondents are more certain of their responses and less certain at the intermediate bid levels. Loomis and Ekstrand (1998), furthermore, find significant positive relationship between preference uncertainty scores and respondent’s prior knowledge about the particular endangered species and a respondent visiting the area proposed for protection in the survey. Although, the two independent variables are likely to be highly correlated, the findings have intuitive implications. This indicates that the

[5] If certainty score equals to 10 for a Yes (No) response then dependent variable take the value 1, otherwise takes zero.

respondent's level of certainty is positively related to their prior knowledge about the goods to be valued and that a respondent visiting the place that is included in the survey question enhances the confidence level about her voting decision.

However, the studies by Champ and Bishop (2001) and Samneliev et al. (2006) fail to provide similar empirical evidence. Instead they indicate that self reported preference uncertainty scores reflect respondents' attitudes towards the hypothetical market (a form of protest response). Champ and Bishop (2001) find respondents, who liked the idea of a wind-generated electricity program and agreed that the program is worth the extra cost, expressed higher certainty levels. Likewise, Samneliev et al. (2006) find respondents who in principle objected to imposing user fees on private access to public lands were more certain in rejecting the bid levels.

5. Preference uncertainty and hypothetical bias

It has been claimed that the calibration of preference uncertainty information in hypothetical CV responses can eliminate hypothetical bias (Champ and Bishop, 2001). Table 1 presents a summary of certainty calibration cut-off points in the NCS method and the treatment of uncertain responses using a PC method at which different empirical studies found hypothetical behaviour converging to actual behaviour. Champ et al. (1997) first compared certainty calibrated hypothetical DC responses for donating a specific amount for road removal on the north rim of the Grand Canyon with actual donations. The authors found that recoding a 'yes' response with a certainty level of 10 provides results that are similar to actual behaviour. In a follow-up study Champ and Bishop

(2001) report that a certainty cut-off point of ‘8 or higher’ provides the best approximation of actual donations for a wind power program. Ethier et al. (2000) found a certainty cut-off point of seven in both hypothetical mail and telephone survey showing similar participation pattern in an actual survey of sign-up program for green electricity whereas Poe et al. (2002) show that the hypothetical responses at certainty levels greater than or equal to six are not significantly different from the actual sign-up rate.

Few empirical studies have been conducted to date to address hypothetical bias in CV studies using the PC method. Johannesson et al. (1998), in an experimental study, divided hypothetical ‘yes’ responses to buy a box of chocolates into ‘fairly sure’ and ‘absolutely sure’ ‘yes’ responses. They found that the percentage of ‘absolutely sure yes’ responses was lower than the proportion of real ‘yes’ responses. Blumenschein et al. (1998) divided hypothetical ‘yes’ responses into ‘probably sure’ and ‘definitely sure’ responses and treated only ‘definitely sure yes’ responses as ‘yes’. This approach has been found effective in removing hypothetical bias in both laboratory and field experiments (Blumenschein et al., 1998, 2001). Vossler et al. (2003), on the other hand, used an ‘undecided’ response category in a hypothetical CV study and compared the results with actual voting behaviour. The authors found that hypothetical annual mean WTP estimates are not statistically different from actual mean WTP when ‘undecided’ responses are coded as ‘no’.

INSERT TABLE 1 HERE

It therefore appears that there is substantial empirical evidence to support the claim that the preference uncertainty information obtained through the NCS method provide a safeguard against hypothetical bias in CV. For example, respondents demonstrating a certainty score equal to or below five on a one to 10 point scale essentially indicates that, in an actual situation, they would not be willing to pay. However, the empirical evidence is not strong enough to validate the assertion that the certainty calibration techniques are able to completely remove hypothetical bias. The summary of results presented in Table 1 suggests that the range of certainty cut-off points within which hypothetical behaviour has been found similar to actual behaviour is large (between six and 10). Unless a consensus emerges among researchers through more empirical research to the narrow range of certainty threshold levels, the results of hypothetical CV studies need to be considered with due difference to the potential for hypothetical bias. Furthermore, evidence in favour of the PC method being effective in reducing hypothetical bias in CV studies is weak. The convergence of hypothetical PC responses to actual responses is conditional upon the choice of words (absolutely or definitely) and treatment methods (definitely sure=yes or undecided=no). Furthermore, too few empirical studies have been conducted to date to understand the potential of this method in this regard.

6. NCS and PC adjusted WTP estimates

After surveying the preference uncertainty literature, seven empirical studies were identified in which the authors estimated preference uncertainty adjusted WTP and compared the result with a conventional DC CV WTP estimate. Here the effects of accounting for preference uncertainty on estimated WTP in these studies in terms of the value of the welfare estimate, efficiency of the estimate (measured in terms of 95% confidence interval of WTP over mean WTP) and model fit statistics. Table 2 presents a brief description of the contexts of the studies. Although they are diverse in terms of sample size, survey mode and country of origin, the studies are similar in terms of the valuation context. They all attempt to estimate values associated with the provision of an environmental public good[6].

INSERT TABLE 2 HERE

Tables 3 and 4 present summary results from the empirical studies in terms of the value of preference uncertainty adjusted WTP relative to a standard DC model. It is expected that the preference uncertainty adjusted WTP estimate should be lower than the conventional DC certainty WTP. The logic behind such expectation stems from the hypothetical bias anticipated in CV studies and the ability of preference uncertainty measure to remove the bias. The empirical evidence, however, does not substantiate this expectation consistently across all preference uncertainty measurement methods and calibration techniques.

When preference uncertainty is measured using the NCS method almost all studies find that ASUM and YES8 and YES10 calibration techniques produce lower welfare measure except for Chang et al. (2007) who find ASUM producing a 31 per cent higher mean WTP relative to the standard certainty model. Conversely, SUM was found to produce 27 per cent to 197 per cent higher WTP value compared to the standard DC model. The PC method produces widely different results across empirical studies. Vossler et al. (2003) and Chang et al. (2007) find that the PC calibration techniques produced a lower WTP

[6] Given the diverse nature of the goods, it could be expected that the respondents' level of familiarity with the goods may vary across different studies.

estimate compared to the standard DC model while Whitehead et al. (1998) and Samnaliev et al. (2006) find the opposite result.

INSERT TABLE 3 HERE

INSERT TABLE 4 HERE

Tables 5 and 6 present a summary of the welfare estimate under NCS and PC measure of preference uncertainty in terms of efficiency gain across different certainty calibration techniques. The efficiency of the WTP estimate for each method is measured using the following formula: $EFWTP=(CI_U–CI_L)/$ mean WTP, where CI_U and CI_L are upper and lower bounds of 95 percent confidence interval, respectively (Loomis and Ekstrand, 1998). Preference uncertainty adjusted models are theoretically expected to generate a more efficient welfare estimate relative to the standard certainty model by removing the noise caused by the presence of the stochastic error term (Li and Mattson, 1995). Contrary to this, the empirical evidence presented in Tables 5 and 6 indicate that the preference uncertainty adjusted welfare estimate is less efficient than the welfare estimate obtained through the conventional DC model, irrespective of the measurement method and the calibration technique used. Exceptions are observed in YES10 by Champ et al. (2007) and in SUM by Shaikh et al. (2007). When preference uncertainty is measured using the NCS method, the efficiency loss in the welfare estimate across all studies and different calibration techniques ranges from 6 per cent to 150 per cent. Using the PC uncertainty measurement method, result in efficiency losses ranging from 16 to over 200 per cent.

INSERT TABLE 5 HERE

INSERT TABLE 6 HERE

Tables 7 and 8 compare the effect of preference uncertainty on model fit statistics in the estimated logistic regression models[7] relative to standard certainty model. Using the NCS preference uncertainty measurement method, only Loomis and Ekstrand (1998) and Shaikh et al. (2007) report an improvement in model fit by 10 and 17 per cent respectively when ASUM was used to calibrate the certainty scores. Other calibration techniques under NCS measurement method result in a three to 40 per cent deterioration in model fit. The effect of uncertainty calibration on welfare estimates in terms of model fit statistics is more mixed when preference uncertainty is measured using the PC method. Chang et al. (2007) report a 27 to 37 per cent improvement in model fit when only 'Definitely Yes' and 'Probably Yes' responses are recoded as 'Yes' responses. Whitehead et al. (1998) and Vossler et al. (2003) find model fit deteriorates by more than 50 per cent and 30 percent respectively in the preference uncertainty adjusted models compared to standard DC models.

INSERT TABLE 7 HERE

INSERT TABLE 8 HERE

7. Discussion and conclusion

The aim of the paper was to address emerging issues in the CV literature in relation to accounting for preference uncertainty. Summarizing the results from empirical studies that have applied the NCS and/or the PC measure of preference uncertainty, the

[7] Model fit statistics for Champ et al. (1997) and Samneliev et al. (2006) were not available in the published papers.

consistency of treatment impacts has been investigated. In terms of the percentage difference between the preference uncertainty adjusted welfare estimates and the model fit statistics, we find that the results are somewhat mixed. Under the PC method of certainty measurement, some empirical studies find preference uncertainty adjusted welfare estimate is lower than the standard certainty estimate. At the same time, an improvement in the model fit is achieved. Other empirical studies show that the incorporation of preference uncertainty information produces higher welfare estimate and causes a weaker model fit. The empirical results are consistent across different studies as well as different measures and calibration techniques when comparing the efficiency gain (or loss) of the preference uncertainty adjusted WTP relative to the standard certainty model. Preference uncertainty adjusted WTP estimates are less efficient than the conventional certainty models regardless of the measurement methods (NCS or PC) and the calibration techniques used to incorporate the uncertainty information.

The second aim addressed in this paper is to assess the usefulness of collecting and calibrating preference uncertainty information in stated preference studies. The empirical stated preference literature provides strong evidence in favour of the widespread claim that calibration of preference uncertainty information obtained through the application of the NCS method helps to detect the extent of hypothetical bias in CV studies. However, an analysis of the empirical results shows that the NCS and PC preference uncertainty adjusted models fail to generate a more efficient welfare estimate compared to the conventional certainty model. The usefulness of incorporating preference uncertainty information in CV studies, hence, largely depends on the benefit that could be achieved from the removal of hypothetical bias relative to the cost of the efficiency loss in the welfare estimator. Therefore, although the NOAA Blue Ribbon Panel on CV advocates implementing response formats that allow for expressions of uncertainty (NOAA, 1993), the preference uncertainty adjusted welfare estimates should be assessed cautiously before use in crucial policy formulation processes.

The theoretical expectation behind the introduction of preference uncertainty into stated preference studies was to estimate more consistent and efficient welfare estimates compared to the conventional DC model by removing the measurement error. However, the empirical evidence drawn from application of two of the most widely used preference uncertainty measures suggest that incorporation of uncertainty information results in largely inconsistent and less efficient welfare estimates. Furthermore, very little empirical evidence is available to show that self reported preference uncertainty scores obtained through NCS method are constructed with economic theory. Given the considerable amount of disagreement among the economists regarding the appropriate approach to measuring preference uncertainty, the failure to obtain a useful estimator that incorporates uncertainty information and the insufficient amount of empirical support for theoretically expected explanations of variation in levels of preference uncertainty, the fundamental issue that needs to be addressed at this point in the development of preference uncertainty research is whether or not respondent uncertainty can be measured accurately.

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Table 1 Treatment of uncertain responses in NCS and PC method to match actual behaviour.

NCS Method				
	Champ et al. (1997)	**Champ and Bishop (2001)**	**Ethier et al. (2000)**	**Poe et al. (2002)**
Certainty cut-off point	Yes=10	Yes=8 or higher	Yes=7 or higher	Yes=6 or higher

PC Method				
	Johannesson et al. (1998)	**Blumenschein et al. (1998)**	**Blumenschein et al. (2001)**	**Vossler et al. (2003)**
Treatment of uncertain responses	Absolutely Sure (=Yes) < Actual Yes	Definitely Sure Yes=Yes	Definitely Sure Yes=Yes	Undecided= No

Table 2 Summary of the studies.

Study	Survey Mode	Sample Size	Country	Good	Method
Champ et al. (1997)	Mail survey	1200 (approximately)	USA	Road removal on the North Rim of the Grand Canyon	YES10[d]
Loomis and Ekstrand (1998)	Mail survey	1600	USA	Preserving the Mexican Spotted Owl	ASUM[a], SUM[b], YES8[c], YES10[d]
Whitehead et al. (1998)	Telephone interview	600	USA	Quality improvements in the lagoon water	PRYES[h]
Vossler et al. (2003)	Telephone interview	500	USA	Acquiring open space	NSN[f]
Samneliev et al. (2006)	Mail survey	1600	USA	User fees for private access in public lands	YES8[c], YES10[d], NSY[e], NSN[f]
Shaikh et al. (2007)	Mail survey	344	Sweden	Preserving the forest in Northern Sweden.	ASUM[a], SUM[b]
Chang et al. (2007)	Face to face survey	810	Korea	Conservation of a lagoon	ASUM[a], SUM[b], DEFYES[g], PRYES[h], MBYES[i]

Note:
[a]ASUM is the asymmetric uncertainty model.
[b]SUM is the symmetric uncertainty model.
[c]YES8 is where only yes responses recoded to 1 with certainty levels of 8,9 or 10. All other responses are coded zero.
[d]YES10 is defined similarly as YES8, except using only 10 certainty levels as yes responses.
[e]NSY is where 'Yes and Not Sure' responses are recoded as 1 and rest zero.
[f]NSN is where only 'Yes' responses are recoded as 1 and rest as zero.
[g]DEFYES is only 'definitely yes' responses are recoded to 1 and rest recoded to zero.
[h]PRYES is 'definitely yes and probably yes' responses are recoded to 1 and rest recoded to zero.
[i]MBYES is 'definitely yes, probably yes and may be yes' responses are recoded to 1 and rest recoded to zero.

Table 3 Percentage change in the preference uncertainty adjusted WTP estimates relative to standard DC model: NCS method.

DC models	Champ et al. (1997)	**Loomis and Ekstrand (1998)**	**Samneliev et al. (2006)**	**Shaikh et al. (2007)**	**Chang et al. (2007)**
ASUM		29% ↓	-	80% ↓	31% ↑
SUM		27% ↑	-	197% ↑	84% ↑
YES8		54% ↓	39% ↓	-	-
YES10	77%↓	86% ↓	61% ↓	-	-

Table 4 Percentage change in the preference uncertainty adjusted WTP estimates relative to standard DC model: PC method.

PC Models	**Whitehead et al. (1998)**	**Vossler et al. (2003)**	**Samneliev et al. (2006)**	**Chang et al. (2007)**
DFYES	-		-	75% ↓
PRYES	25% ↑		-	34% ↓
MBYES	-		-	6% ↓
NSY	-		67% ↑	-
NSN	-	32%↓	11% ↑	-

Table 5 Percentage change in the efficiency of the welfare estimates compared to standard DC model: NCS method.

DC Models	Champ et al. (1997)	**Loomis and Ekstrand (1998)**	**Shaikh et al. (2007)**	**Chang et al. (2007)**	**Samneliev et al. (2006)**
ASUM		16% ↓	137 % ↓	9% ↓	-
SUM		23% ↓	60% ↑	2% ↓	-
YES8		22% ↓	-	-	49% ↓
YES10	50%↑	149% ↓	-	-	129% ↓

Table 6 Percentage change in the efficiency of the welfare estimates compared to standard DC model: PC method.

PC Models	**Whitehead et al. (1998)**	**Vossler et al. (2003)**	**Samneliev et al. (2006)**	**Chang et al. (2007)**
DFYES	-		-	119% ↓
PRYES	49% ↓		-	20% ↓
MBYES	-		-	16% ↓
NSY	-		61 % ↓	-
NSN	-	26%↓	231 % ↓	-

Table 7 Percentage changes in the model fit relative to standard/conventional DC model: NCS method.

DC Models	**Loomis and Ekstrand (1998)**	**Chang et al. (2007)**	**Shaikh et al. (2007)**
ASUM	10% ↑	19% ↓	17% ↑
SUM	21% ↓	3% ↓	40% ↓
YES8	10% ↓	-	-
YES10	28% ↓	-	-

Table 8 Percentage changes in the model fit relative to standard/conventional DC model: PC method.

PC Models	**Whitehead et al. (1998)**	**Vossler et al. (2003)**	**Chang et al. (2007)**
DFYES	-		37% ↑
PRYES	56% ↓		27% ↑
MBYES	-		27% ↓
NSN		33%↓	