Internal Consistency in Double Bounded Dichotomous Choice Contingent Valuation: Introducing Advanced Disclosure and Explicit Decision Rules in Sequential Learning Designs

Abstract

One of the most commonly observed anomalies in Double Bounded Dichotomous Choice is that of internal inconsistency between the estimated values derived by single bounded and double bounded methods from the same data set. This paper introduces a simple bootstrap method to test the significance of such differences. We add to the idea that the willingness to pay (WTP) differences between Single Bounded Dichotomous Choice (SBDC) and Double Bounded Dichotomous Choice (DBDC) can be attenuated by Sequential Learning following Bateman et al. (2008). To this end, we study the effects in the field of introducing into the DBDC mechanism: i) Advance Disclosure (See Bateman et al. (2004)) and ii) Explicit DBDC Decision Rules as examined in an experimental context by Carson et al. (2009). Results show that introduction of these features into the design of CV surveys significantly reduces variance and anomalies presented in a standard DBDC treatment, thus generating internally consistent and more efficient willingness to pay estimates.

Key words: Contingent valuation; advance disclosure learning; sequential learning, decision rules; single bounded dichotomous choice, double bounded dichotomous choice.

JEL Classification: Q51, C18, D69, C12.
1. Introduction

This paper addresses claims of internal inconsistency in Double Bounded Dichotomous Choice (DBDC) Contingent Valuation datasets. The influential paper by Carson and Groves 2007 claims as a “stylised fact” that “the willingness to pay (WTP) estimates based upon just the first question is higher than the WTP estimate based upon both questions”. The analysis in this paper is based on Monte Carlo Simulation tests for consistency between single bounded and double bounded estimates from the same dataset as explained in Matthews et al., 2009 and used in Bateman et al., 2008. This is a simple but novel test to establish consistency or inconsistency in a DBDC data set in a statistically rigorous manner and is used extensively in what follows.

Our paper is focused on behavioural processes which may attenuate or remove this inconsistency between SB and DB estimates from the same dataset. We build on the earlier paper of Bateman et al., 2008 which demonstrated that in a sequence of valuations, sequential learning effects were effective in attenuating this SB-DB anomaly. This approach was termed Learning Design Contingent Valuation or LDCV in Bateman et al., 2008. In the present paper we extend this idea of sequential learning to examine whether similar attenuation of the SB-DB anomaly may result from Advanced Disclosure Learning where the sequence of goods to be valued and the nature of the Double Referendum are explained to respondents before the valuation task. This idea of Advanced Disclosure Learning was pioneered successfully in a paper on visible choice sets and scope sensitivity by Bateman et al., 2004. We test whether Advanced Disclosure Learning of the sequence and DBDC mechanism can attenuate the SB-DB anomaly. In this paper we also test whether providing explicit Decision Rules for the outcome of the Double Referenda as tested in an economic experiment by Carson et al., 2009 will further attenuate the SB-DB
anomaly in our field CV survey. Furthermore, we introduce an analysis of the impacts of these three features on the variance and distributions of welfare measures.

The rest of the paper is organized as follows. In section 2 the learning design with advance disclosure and explicit decision rules are explained. Section 3 describes the methodology and hypothesis tests followed by a presentation of the results in Section 4. Finally, Section 5 concludes the paper.

2 Learning Design with Advance Disclosure and Explicit Decision Rules CV

The concept of Learning Design Contingent Valuation (LDCV) was originally introduced by Bateman et al., 2008. It consists of presenting repeated valuation tasks to respondents and in doing so, respondents learn the way the Double Bounded Dichotomous Choice (DBDC) mechanism works and gain experience of their underlying WTP. This feature is consistent with the Discovered Preference Hypothesis (DPH) developed by Plott (1996). The DPH states that consistent preferences are built by experience gained through repetition. Bateman et al., 2008 show that initial valuation of unfamiliar goods were not based on well-formed preferences and both choices and decisions under such conditions can result in inconsistent estimates, which may also display high variance. Previous research has showed that repetition allows respondents to acquire experience and consequently reduce or eliminate anomalies as for example the WTA/WTP disparities (Coursey et al., 1987, Shogren et al., 1994, 2001; List and Shogren 1999; Bateman et al., 2008) and preference reversals (Cox and Grether 1996; Braga and Starmer, 2003). Practice and repetition allows learning and experience of the valuation mechanism, generating as a consequence, internally consistent welfare measures.
In contrast to repetition, the concept of *advance disclosure* in CV has been developed by Bateman et al., 2004 for valuing embedded goods. Advance disclosure consists of informing respondents, before they perform the valuation tasks, about the number of goods they are going to value and the sequence in which they will be presented. We add to the idea presented by Bateman et al., 2004, an advanced explanation of the DBDC mechanism respondents would face and the multiple valuation tasks to be undertaken. We study the effect on the values of a single good (Renewable energy sources - RES) against two different baseline alternatives, thermo electricity and hydropower. This is an innovative use of contingent valuation to value a desired outcome against two feasible alternative baselines.

Finally, a *decision rule* in DBDC refers to the conditions that characterize the provision of the good. In the case of DBDC contingent valuation it refers to the explanation of how the responses to the two referenda influence the decision whether the good will be provided or not and at which cost. Under this context, two key aspects should be explained: i) the percentage of votes required for the referendum to pass and ii) in case the second vote fails, an explanation of whether the good is provided at the first vote price or if it is not provided at all. This is a crucial aspect in valuation studies; by making decision rules clear to respondents, strategic behaviour may be avoided and in consequence $SB_{WTP}$ and $DB_{WTP}$ may be more internally consistent.

In this paper we test the hypotheses that the introduction of the three features mentioned above (repetition, advanced disclosure and explicit decision rules) will attenuate the anomaly presented in DBDC by diminishing the internal inconsistency between single bounded dichotomous choice (SBDC) and DBDC responses, generating internally consistent willingness to pay estimates and variances. In addition, we investigate the effect these features have on the
variances in both SB and DB measures. To this end, we use a split sample approach consisting of three treatments:

- Treatment 1: Control treatment (Control): This treatment replicates the typical CV study where individuals are not told in advance how many goods they will value and how the DBDC elicitation mechanism involves an initial and follow-up vote.

- Treatment 2: Introduction of Advance Disclosure (AD): This treatment uses exactly the same questionnaire used in the Treatment 1 but it includes two additional paragraphs. These paragraphs inform respondents in advance regarding the sequence of goods they are going to value and the number of votes they will face. The objective is to explain the DBDC mechanism. Advanced Disclosure is introduced for the valuation sequence and for the DBDC institution. Details regarding these issues are explained later in this section.

- Treatment 3: Introduction of Advance Disclosure and explicit Decision Rule (AD + DR): In addition to the information introduced in Treatment 2, this treatment presents an explicit explanation regarding the outcome of the two votes and how this relates to provision of the good. The decision rule is introduced immediately after the first valuation question for each good. Decision rules regarding the final vote cannot be introduced before the first valuation question because it would invalidate this response and present a clear incentive for strategic behaviour, allowing respondents to answer “no” to the first referendum and “yes” to the second one in order to secure the provision of the good at a lower cost. In our study it was clearly stated that in the second referendum if a majority of the participants would vote “yes” to the provision of the good, the project would go
through, otherwise the outcome would be the initial status-quo level. It was also clearly stated that the second vote would replace the decision of the first one, and if this second vote does not pass by a majority the good would not be provided at all, and if it passes, the good will be provided at the cost presented in the second vote.

In order to test our hypotheses a tailor-made study was conducted. We designed a questionnaire in which the willingness to pay for renewable energy sources (RES) was elicited. Two valuation tasks were presented sequentially; in both of them the good to be valued was RES, but the baseline or status-quo was changed. For the first valuation the baseline was considered as the construction of large dams in Chilean Patagonia and for the second valuation the baseline was the installation of thermoelectric power plants for future electricity supply in Central Chile. This sequential design presents an innovative contingent valuation feature in terms of valuing consecutively the same good against two alternative baselines, allowing for a better control of the methodological aspects to be studied. Individuals were asked to treat both scenarios independently. The questionnaire was applied in person to households in the two largest cities of Chile (Santiago and Concepcion). Households were chosen from a random selection of streets from all areas of the city following a two stage random sampling procedure, stratified by socio-economic status. Respondents were the persons in charge of paying the electricity bill in the household. The different versions of the questionnaires were distributed randomly across households.

Three questionnaires versions were designed and applied, one for each treatment. Questionnaires were exactly the same except for the wording added to introduce advance disclosure and decision rules. As explained previously, Treatment 2 (Introduction of advance
disclosure) adds to the questionnaire used in Treatment 1 (Control treatment) two kind of advance disclosure:

- Advance Disclosure of the valuation sequence.
- Advance Disclosure of the DBDC institution.

For Advance Disclosure of the valuation sequence we informed respondents of the number of valuations they would face, the order they were going to be presented, the good (RES) and the two baselines alternatives (hydropower and thermoelectric) against which the introduction of RES is valued. Advance disclosure of the sequence was introduced at the beginning of the questionnaire, together with the presentation of the scenario. The exact wording used for this type of advance disclosure is as follows:

“In producing the 15% extra electricity required in Chile we are looking at how much more you would be willing to pay for this renewables alternative over the two other types of energy. In what follows you will be asked how you would vote if a referendum was held to choose between renewable energy and each of the other alternatives in this order: First, renewable energy versus hydropower and second renewable energy versus thermoelectric ”.

Advance Disclosure of the DBDC Institution consisted of informing respondents before presenting the valuation questions, about how many referenda they will vote in and the number of valuation questions they were going to be asked. In our case, we informed respondents in advance that they will vote in two referenda each involving two valuation questions explained as follows:
“Because the exact cost of the projects is not known today, we will ask you to vote on 2 different costs for each project. These costs represent the range into which the actual cost should fall. In what follows, you will vote for or against each alternative. You are asked how you would vote if the good could be provided at one of the two costs. This is followed directly by a second vote on how you would vote if the good could be provided at the second of the two costs.”

For Treatment 3 (Introduction of advanced disclosure and decision rule), we further introduce a phrase explaining the rules for provision of the good. The key element on this aspect is to make clear that the second vote would replace the outcome of the first vote and if this second vote fails then RES will not be provided at all. The explanation of the decision rule was introduced immediately after the response to the first referendum or valuation question for each good; therefore it affects only the second response. The wording used in this treatment was the following:

*Now imagine that the cost to you was $________ (the higher or lower second price) and the outcome of this second vote replaces that of the first vote, so that if a majority vote “Yes” in favour of this proposal the renewable energy projects are developed and if a majority vote “No” the Patagonian dams project will go ahead. We will not ask you to vote again at another cost on this proposal.*

*Would you vote Yes or No?*
3 Econometric Methodology and Hypotheses tests

From the referendum data we estimated logit models for both SB and DB CV responses in order to identify the effect of advance disclosure, decision rules and repetition on the WTP\textsubscript{SB-DB} differences and on the variance of WTP distributions within and across treatments.

In order to test for empirical differences in mean WTP between SB and DB estimates, we use a bootstrap technique (Efron; 1993; Bateman et al., 2008; Matthews et al., 2009). The reason for selection of this method is the non-independence of the values obtained for the two elicitation questions. The responses for the DB depend on the responses given to the first bid in the SB and are given by the same individual, thus generating non-independent responses.\footnote{In calculating the variance of the differences given by \( \text{var}(WTP_i - WTP_j) = \text{var}(WTP_i) + \text{var}(WTP_j) - 2 \cdot \text{cov}(WTP_i - WTP_j) \), the problem arises in that the \( \text{cov}(WTP_i - WTP_j) \) is not zero, and consequently the use of a statistical test for independent samples would provide incorrect results.} Therefore, the covariance between these two values is different to zero and the application of a conventional t-test would be inappropriate.

Five hypotheses on the relationship between the SB and DB data for each good are tested in this paper: i) the effect of advance disclosure on internal consistency; ii) the effect of explicit decision rules on internal consistency; iii) the effect of sequential learning; iv) the hypothesis of equal variances between treatments and v) hypothesis of identical distributions for different treatments. The first three hypotheses are based on the SB-DB differences in mean WTP and relate to our objective of studying the effect of different treatments on internal consistency between SB and DB welfare measures, while the fourth and fifth hypotheses are based on the variances and distributions obtained from the individual bootstraps respectively.
3.1) Hypothesis Test 1: The effect of Advance Disclosure on Internal Consistency.

Our first hypothesis tests whether the introduction of advance disclosure of multiple goods and the description of DBDC mechanism reduces the differences between single and double bounded welfare estimates, generating measures that are internally consistent. Thus, the null hypothesis of no difference between SB-DB mean WTP ($WTP_{SB-DB}$) is:

$$H_0: E[WTP_{SB}] = E[WTP_{DB}], \quad (1)$$

This hypothesis can be rewritten as:

$$WTP_{SB-DB} = E[WTP_{SB}] - E[WTP_{DB}] = 0 \quad (2)$$

We contrast Treatment 1 (Control) and Treatment 2 (Advance Disclosure - AD) to test at the outset the effects of Advanced Disclosure alone on the internal consistency of the SB and DB WTP. The findings of this test indicates whether Advanced Disclosure of the mechanism and the multiple goods to be valued can attenuate the SB-DB difference as previously demonstrated for a sequence of repetitive valuations in Bateman et al., 2008.

3.2) Hypothesis Test 2: The effect of Explicit Decision Rules on Internal Consistency.

The decision rules hypothesis establishes whether the introduction of additional information on how the final outcome from the two votes are determined would reduces the differences between single and double bounded WTP estimates, thus generating welfare measures that are internally consistent. This effect of introducing explicit decision rules has been

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Note that this hypothesis stands for treatment 2 (AD) and 3 (AD+DR). For the control treatment we expect statistically significant differences between SB-DB welfare measures, confirming the presence of the common anomaly in DBDC contingent valuation (REF).
demonstrated in an economic laboratory experiment by Carson et al., 2009. As in the previous case, the null hypothesis of no differences between SB-DB mean WTP is given by: ³

\[ H_0: E[WTP_{SB}] = E[WTP_{DB}], \]  

(3)

This hypothesis can also be written as:

\[ WTP_{SB-DB} = E[WTP_{SB}] - E[WTP_{DB}] = 0 \]  

(4)

Following the same procedure as in the previous hypothesis we contrast Treatment 2 (Advance Disclosure - AD) with Treatment 3 (Advanced Disclosure and Decision Rules - AD+DR) to test at the outset for the effect of the addition of explicit decision rules on the SB-DB internal consistency.

It is important to note that if Hypothesis 1 passes, the introduction of advance disclosure would be a sufficient condition to generate internal consistency between SB and DB responses. However, if Hypothesis 1 fails but Hypothesis 2 passes, then introduction of decision rules is needed in order to generate internal consistency in DBDC.

### 3.3) Hypothesis Test 3: On the Additional Effect of Sequential Learning.

As demonstrated by Bateman et al., 2008 experience gained through repetition can generate internally consistent estimate for SB-DB values in contingent valuation. This sequential valuation is also included in our design. We expect differences in WTP\(_{SB-DB}\) to diminish and become statistically not significant when respondents face a second valuation. Moreover, we expect this difference to decline further in treatments which combine advance disclosure and

³ Note that this hypothesis stands for treatment 2 (AD) and 3(AD+DR). For the control treatment we expect statistically significant differences between SB-DB welfare measures, confirming the presence of the common anomaly in DBDC contingent valuation.
explicit decision rules with sequential scenarios. In the first case, we examine Sequential Learning in a control treatment, similar to Bateman et al., 2008. In the second case, we examine sequential learning with Advance Disclosure and in the third case Sequential Learning under Advance Disclosure and Decision Rules. In testing for significant differences between SB and DB estimates for the second good valued we are testing whether it requires the addition of Sequential Valuation Learning to Advanced Disclosure to remove the difference. Therefore, the null hypothesis can be expressed in two parts, where \(i=1\) refers to the first valuation scenario, (i.e. RES versus hydropower); and \(i=2\) refers to the second scenario, RES versus fossil fuels and \(k\) corresponds to the treatment considered, with \(k=1\) corresponding to the control Treatment, \(k=2\) corresponding to the AD Treatment and \(k=3\) corresponding to the AD+DR Treatment.

\[
\begin{align*}
  i) \quad & H_0: E[WTP_{1SB}]_{k=1} - E[WTP_{1DB}]_{k=1} \neq 0 & (5) \\
  ii) \quad & H_0: E[WTP_{2SB}]_{k=1} - E[WTP_{2DB}]_{k=1} = 0 & (6) \\
  iii) \quad & H_0: E[WTP_{iSB}]_{k=2} - E[WTP_{iDB}]_{k=2} = 0 \quad i=1,2 & (7) \\
  iv) \quad & H_0: E[WTP_{iSB}]_{k=3} - E[WTP_{iDB}]_{k=3} = 0 \quad i=1,2 & (8)
\end{align*}
\]

If the test in the first treatment passes for the second valuation but not for the first, the finding of Bateman et al., 2008 that LDCV based on repetitive learning or sequential learning is necessary to attenuate SB-DB value difference can be demonstrated.

To test Hypotheses 1 and 2 and 3, a non-parametric bootstrap technique (Efron and Tibshirani, 1993; Matthews et al 2009) is used to obtain the distribution of differences \(WTP_{SB-DB}\), hence computing the standard error of differences \(se(WTP_{SB-DB})\) controlling for the sampling design where values are obtained for mean \(WTP\) from the same sample of respondents. This
method was originally outlined in Bateman et al., 2008 and Matthews et al., 2009 and involves repeated sampling with replacement from the original sample of households (the primary sampling unit) thus implicitly taking into account the covariance between these samples. This technique also controls for non-independence of values from several models using the same sample of households and allows for non-normal distributions which are common in non-market valuations. If $WTP_{SB-DB}$ is the estimate of difference in WTP, then for a single bootstrap sample, $b$, drawn with replacements, the estimate from the $b^{th}$ sample is $WTP_{SB-DB} (b)$. The estimated standard error of $WTP_{SB-DB}$ using $b$ bootstrap samples each of size $n$, is equal to the original sample size, is then given by:

$$se(WTP_{SB-DB}) = \sqrt{\frac{\sum [WTP_{SB-DB} (b) - WTP_{SB-DB}]^2}{(b-1)}}$$

An empirical distribution of differences $WTP_{iSB-DB}$ is created using 10,000 replications of $E[WTP_{iSB}] - E[WTP_{iDB}]$. We use the percentile method to calculate confidence intervals and analyze the differences in the mean WTP. An empirical confidence interval at the 5% significance level is composed by removing 2.5% of the probability from each tail of the $WTP_{iSB-DB}$ distribution. The results of the confidence intervals and the respective $WTP_{iSB-DB}$ differences are determined by inspecting the empirical distributions of differences. The null hypothesis is rejected if the 95% confidence interval for $WTP_{iSB-DB}$ is composed of strictly positive or strictly negative values, meaning that the difference between mean SB-DB estimates ($WTP_{SB-DB}$) is strictly positive or strictly negative. The null hypothesis is accepted if $WTP_{SB-DB}$ is composed of both negative and positive values and can be shown to contain a value of zero difference.
3.4) Hypothesis Test 4: Effect of Advance Disclosure and Decision Rules on Variance.

Introduction of Advance Disclosure and Decision Rules may have an effect on both the mean and variance of SB and DB estimated welfare measures separately. This hypothesis would establish whether the introduction of these features would produce more accurate and efficient welfare estimates defined as a reduction in the variance as we move from the uninformed first valuation control treatment to the advanced disclosure and decision rules treatments. We focus on this hypothesis about the variance, as follows:\(^4\):

\[
H_0: \quad \text{Var}_{\text{SB}(\text{Control})} - \text{Var}_{\text{SB}(\text{AD})} > 0 \\
H_0: \quad \text{Var}_{\text{SB}(\text{Control})} - \text{Var}_{\text{SB}(\text{AD} + \text{DR})} > 0 \\
H_0: \quad \text{Var}_{\text{SB}(\text{AD})} - \text{Var}_{\text{SB}(\text{AD} + \text{DR})} > 0
\]

3.5) Hypothesis Test 5: identical distributions for SB-DB WTP.

In addition to the study of the effect of Advance Disclosure and Explicit Decision Rules on the differences in SB and DB means, we are interested in investigating to what extent these introductions influence the overall distribution of estimated WTP from the SB and DB cases. For this purpose, we illustrate the statistical distributions of the SB and DB estimates and compare their convergence.

\(^4\) Hypothesis written for single bounded (SB) but also applied between double bounded (DB) estimates.
4 Results

In total 1093 responses were collected, but due to item non-response and protest, 1003 responses were available for analysis. The survey was conducted as personal interviews in the metropolitan areas of Santiago and Concepcion, the two largest cities in Chile. The respondents were those responsible for paying the electricity bill for the household.

Our first and second hypotheses tests whether the introduction of Advance Disclosure (AD) and Explicit Decision Rules (DR) has any impact in reducing the anomalies associated with DBDC Contingent Valuation in terms of diminishing the differences between SBDC and DBDC estimates of WTP. To this end, we first estimated logit models for single and double bounded responses for a baseline treatment for the advance disclosure treatment and for the AD + DR treatment. In order to focus our study on the impact of these two features on the calculated welfare measures, we include the bid vector as the single explanatory variable. Models are presented in Table 1. As expected, the parameter estimates on the bids are negative and significant in all cases and are of similar magnitude. Using the estimated parameters we calculate the WTP for RES over hydropower (first valuation) and over thermoelectric (second valuation) for each treatment. Results are summarized in Table 2. WTP is reported in Chilean Pesos\(^5\) and standard errors were calculated using the Delta Method. We used the software NLogit for estimations. We also report in Table 2 the differences in absolute terms between the SB and DB (\(\text{WTP}_{\text{DIFF}}\)) with confidence intervals calculated using the bootstrap procedure in order to account for the dependent nature of the data. These results are produced for the treatments which are the subject of the hypothesis tests specified in section 3.1 to 3.5.

\(^5\) 1 USD = 470 Chilean Pesos (CLP) at the time of the survey.
Table 1. SB and DB logit model estimates of WTP for RES over Hydropower and over Thermoelectric baselines. t-values presented in brackets.

<table>
<thead>
<tr>
<th>HYDROPOWER BASELINE (1\textsuperscript{st} Valuation)</th>
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<th></th>
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<th></th>
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</thead>
<tbody>
<tr>
<td>CONTROL</td>
<td>SB</td>
<td>DB</td>
<td>SB</td>
<td>DB</td>
<td>SB</td>
<td>DB</td>
</tr>
<tr>
<td>Constant</td>
<td>2.37</td>
<td>2.35</td>
<td>2.52</td>
<td>2.36</td>
<td>2.47</td>
<td>2.34</td>
</tr>
<tr>
<td></td>
<td>(7.39)</td>
<td>(11.94)</td>
<td>(8.00)</td>
<td>(11.15)</td>
<td>(8.30)</td>
<td>(11.54)</td>
</tr>
<tr>
<td>Bid</td>
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<td>-0.67</td>
<td>-0.71</td>
<td>-0.72</td>
<td>-0.70</td>
</tr>
<tr>
<td></td>
<td>(-3.33)</td>
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<td>(-4.49)</td>
<td>(-12.44)</td>
<td>(-5.16)</td>
<td>(-13.08)</td>
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<tr>
<td>LL-function</td>
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<td>-151.52</td>
<td>-369.34</td>
<td>-167.63</td>
<td>-375.68</td>
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<td>340</td>
<td>323</td>
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<table>
<thead>
<tr>
<th>THERMOELECTRIC BASELINE (2\textsuperscript{nd} Valuation)</th>
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</thead>
<tbody>
<tr>
<td>CONTROL</td>
<td>SB</td>
<td>DB</td>
<td>SB</td>
<td>DB</td>
<td>SB</td>
<td>DB</td>
</tr>
<tr>
<td>Constant</td>
<td>2.16</td>
<td>2.31</td>
<td>1.92</td>
<td>1.79</td>
<td>1.88</td>
<td>1.96</td>
</tr>
<tr>
<td></td>
<td>(8.48)</td>
<td>(14.00)</td>
<td>(7.69)</td>
<td>(11.61)</td>
<td>(7.71)</td>
<td>(12.88)</td>
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<td>Bid</td>
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<td>-0.45</td>
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<td>LL-function</td>
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<td>-200.68</td>
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</table>
Table 2: WTP and Differences in SB-DB WTP within sample (Standard errors in brackets).

<table>
<thead>
<tr>
<th>TREATMENT</th>
<th>Hydropower Baseline (1st Valuation)</th>
<th>Thermoelectric Baseline (2nd Valuation)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WTP&lt;sub&gt;SB&lt;/sub&gt;</td>
<td>WTP&lt;sub&gt;DB&lt;/sub&gt;</td>
</tr>
<tr>
<td>Control</td>
<td>4776.54 (901.99)</td>
<td>3878.09 (191.04)</td>
</tr>
<tr>
<td>AD</td>
<td>3787.32 (474.09)</td>
<td>3343.65 (161.44)</td>
</tr>
<tr>
<td>AD+DR</td>
<td>3425.03 (350.79)</td>
<td>3349.73 (160.77)</td>
</tr>
</tbody>
</table>

Results in Table 2 support the known fact that DB estimates are more efficient welfare measures, as observed by the significantly lower standard error presented by the WTP<sub>DB</sub> in all the cases (Standard Errors are given in parenthesis in Table 2). This supports the findings of Alberini, 1995 and Haneman et al., 1991 about the efficiency improvements of DBDC. We can observe that absolute differences (WPT<sub>DIF</sub>) between the WTP<sub>SB</sub> and WTP<sub>DB</sub> decreases as we move from the control treatment to the treatments including advance disclosure and explicit decision rules.

In order to study if the actual differences in mean WTP<sub>DIF</sub> are statistically significant, we analysed the results using the bootstrap procedure. Employing the percentile method we construct a 95% confidence interval. Table 3 and Figure 1 report the results.
Table 3. Tests of pair wise differences in WTP for SB and DB

<table>
<thead>
<tr>
<th>Hypothesis Test Ho</th>
<th>Mean Value</th>
<th>95% Confidence Interval</th>
<th>Test Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTPSB1 - WTPDB1 = 0</td>
<td>1445.47</td>
<td>-35.95 - 3885.92</td>
<td>Accept</td>
</tr>
<tr>
<td>WTPSB2 - WTPDB2 = 0</td>
<td>513.91</td>
<td>27.99 - 1149.12</td>
<td>Reject</td>
</tr>
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</table>

Treatment 2: AD

<table>
<thead>
<tr>
<th>Hypothesis Test Ho</th>
<th>Mean Value</th>
<th>95% Confidence Interval</th>
<th>Test Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTPSB1 - WTPDB1 = 0</td>
<td>500.11</td>
<td>-92.01 - 1417.45</td>
<td>Accept</td>
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<tr>
<td>WTPSB2 - WTPDB2 = 0</td>
<td>233.94</td>
<td>-18.64 - 498.78</td>
<td>Accept</td>
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</table>

Treatment 3: AD + DR

<table>
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<tr>
<th>Hypothesis Test Ho</th>
<th>Mean Value</th>
<th>95% Confidence Interval</th>
<th>Test Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTPSB1 - WTPDB1 = 0</td>
<td>147.50</td>
<td>-320.98 - 782.64</td>
<td>Accept</td>
</tr>
<tr>
<td>WTPSB2 - WTPDB2 = 0</td>
<td>42.13</td>
<td>-258.18 - 377.32</td>
<td>Accept</td>
</tr>
</tbody>
</table>

We can observe that under the control treatment there is evidence of internal inconsistency between SB and DB WTP given that the null hypothesis of no differences between SB-DB is rejected for the second valuation at 5% level. The failure to reject this hypothesis for the first good at the 5% level is a consequence of the relatively high standard error in the first valuation of the first good (901.99 – see Table 2).\(^6\)

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\(^6\) The null hypothesis of no differences is also rejected for the first good valued at 10% confidence level.
Figure 1. Distribution of differences between SB-DB treatments.
4.1 Results of the Hypothesis Test on Advanced Disclosure.

The inclusion of advanced disclosure both of the valuation sequence and the DBDC institution reduces the $\text{WTP}_{\text{dif}}$ by half from the control treatment for both the first and second good valued (See Table 2).

The results for Treatment 2 (introduction of advance disclosure) in Table 3 shows that at a 5% confidence level the null hypothesis of no differences between SB and DB is accepted for both valuations. Therefore, the introduction of advance disclosure is shown to reduce the internal inconsistency between SB-DB estimates.

4.2 Results of the Hypothesis Test on Explicit Decision Rules.

The introduction of explicit decision rules added to the Advance Disclosures produces a considerable further reduction in the SB-DB difference evidencing the importance of this feature in the reduction of the SB-DB anomaly in CV.

In Table 3, the analysis on the introduction of explicit decision rules is shown to have a highly significant effect in further reducing the internal inconsistency between SB and DB. The null hypothesis is accepted at 5% confidence level, showing the strong effect that decision rules combined with advance disclosure have on further reducing the anomaly of the differences between SB-DB estimates.

4.3 Results of the Hypothesis Test of the Additional Effect of Sequential Learning.

The differences in $\text{WTP}_{\text{SD-DB}}$ show a further decline when we move from the first to the second valuation evidencing the presence of sequential learning, as presented in Hypothesis 3.
The SB-DB differences in the second valuation are generally approximately half those in the first valuation in the Control and AD Treatments. On the other hand, the $\text{WTP}_{\text{DIF}}$ and standard errors diminish substantially in the second valuation for all treatments. This issue is in line with the uncommented findings on variance in Bateman et al. 2008. In consequence, there seems to be further evidence of sequential learning effects, supporting the Discovered Preference Hypothesis found in Bateman et al., 2008. However, in a control treatment the sequential valuation although reducing considerable the actual difference between SB-DB WTP estimates, it is not enough to overcome the internal inconsistency. Therefore, the presence of advance disclosure and explicit decision rules are necessary.

4.4 Results of the Hypothesis Test of the effect of Advance Disclosure and Decision Rules on Variances

Results in Table 2 show a significant reduction in variance when advance disclosure and decision rules are introduced in the valuation questionnaire. Results from Treatments 2 and 3 present lower variances for all estimates (SB and DB in both valuations) than the control Treatment. Results from the Levene test show that all these differences in variance are statistically significant. The same effect is found when comparing Treatment 2 with Treatment 3, except for the second valuation where the additional introduction of decision rules show a slight increase in variances. However, the application of the Levene test shows that for this last case the difference in variance is not statistically significant. This indicates that the sequential learning produces no further effect on variances when the decision rules are added to the advance disclosure in a DBDC contingent valuation.
4.5 Results of the Hypothesis Test of Identical Distributions for SB-DB WTP

In order to illustrate the differences in distributions between SB and DB WTP, we plot the kernel distributions of each welfare measures in the different treatments. Results are shown in Figure 2 with a clear convergence of SB and DB WTP distributions in the valuation of the second good. Moreover, this convergence is accentuated when we move from the control treatment to the following treatments including advance disclosure and explicit decision rules. It is noticeable that a high divergence is shown by SB and DB WTP distributions derived from a typical CV survey, where no advance disclosure and decision rules are introduced. This divergence is due to the high variance of the SB WTP estimates. This difference is slightly attenuated in the second valuation, demonstrating a learning effect. Individuals learn how the DBDC mechanism works and produce more consistent WTP responses. On the other hand, the introduction of advance disclosure in treatment 2 produces a similar effect to that of sequential learning in the control treatment. The fact that individuals are told in advance how the DBDC mechanism works produces responses more internally consistent and to some extent equivalent to what they would learn in a sequential valuation task. As expected, in the second treatment, the divergence between the both measures decreases in the second valuation. Finally, the inclusion of decision rules is shown to produce a close convergence, generating very similar welfare distributions between SB and DB, especially in the second valuation where distributions are shown to be almost equal.
Figure 2: SB and DB WTP Distributions.

**TREATMENT 1: CONTROL TREATMENT**

<table>
<thead>
<tr>
<th>Hydro</th>
<th>Thermo</th>
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<tbody>
<tr>
<td>SB and DB</td>
<td>SB and DB</td>
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</table>

**TREATMENT 2: ADVANCE DISCLOSURE**

<table>
<thead>
<tr>
<th>Hydro</th>
<th>Thermo</th>
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</thead>
<tbody>
<tr>
<td>SB and DB</td>
<td>SB and DB</td>
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</table>

**TREATMENT 3: ADVANCE DISCLOSURE + DECISION RULES**

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<th>Thermo</th>
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<tbody>
<tr>
<td>SB and DB</td>
<td>SB and DB</td>
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5 Conclusions

This paper has studied the effect of the introduction of advance disclosure learning, explicit decision rules and sequential learning on the reduction of anomalies between single and double bounded welfare estimates in a DBDC contingent valuation study. We show that the inclusion of these features significantly reduces this anomaly producing internally consistent welfare measures. Furthermore, the resulting estimates also present significantly lower variances.

Opposed to the classical believe that contingent valuation studies must ask one shot single bounded questions we find that initial valuations suffer from both large variances and widely different values between the single bounded and the double bounded follow up valuations. As a consequence, although we found a large difference between SB and DB estimates in the first valuation, we cannot reject at the 5% significance level the hypothesis that these differences are not statistically significant. This is because of the abnormally large variance on the initial SB valuation. This fact supports the previous finding of Bateman et al., 2008.

We show evidence in our control treatment that application of typical CV valuations characterized by one good and a one-off DB valuation produces results that suffer from internal inconsistency and high variances. Introduction of sequential valuation shows to significantly reduce the large variance. However, in a two valuation sequence of a typical CV, it is not enough to produce internal consistency between SB-DB estimates. We find that the introduction of the concept of advance disclosure learning reduces both the internal inconsistency and the large variance, but the strongest effect is found by adding the additional decision rules as defined by Carson et al., 2009 where WTP_{SB-DB} differences almost disappear.

This paper show the relevance of providing in advance to respondents clear and complete information regarding the goods to be valued, the order in which they are presented, the way the
DBDC mechanism works and the decision rule regarding the provision of the good in order to produce well formed internal consistent responses. These are features of importance to be considered in CV designs for double bounded dichotomous choice contingent valuation studies as it overcomes a major objection to the validity of this preferred CVM format.

6 References


