A Cautionary Note on Tests for Incentive Incompatibility and Starting-Poing Bias

David Aadland
Utah State University

Arthur J. Caplan
Utah State University

Follow this and additional works at: https://digitalcommons.usu.edu/eri

Recommended Citation
https://digitalcommons.usu.edu/eri/265
A CAUTIONARY NOTE ON TESTS FOR INCENTIVE INCOMPATIBILITY AND STARTING-POINT BIAS

by

DAVID AADLAND

Department of Economics & Finance
University of Wyoming
P.O. Box 3985
Laramie, WY 82071

and

ARTHUR J. CAPLAN

Department of Economics
Utah State University
3530 Old Main Hill
Logan, UT 84322-3530

July 2003
A CAUTIONARY NOTE ON TESTS FOR INCENTIVE INCOMPATIBILITY AND STARTING-POINT BIAS

David Aadland, Associate Professor
Department of Economics and Finance
University of Wyoming
P.O. Box 3985
Laramie, WY 82071-3985

Arthur J. Caplan, Assistant Professor
Department of Economics
Utah State University
3530 Old Main Hill
Logan, UT 84322-3530

The analyses and views reported in this paper are those of the author(s). They are not necessarily endorsed by the Department of Economics or by Utah State University.

Utah State University is committed to the policy that all persons shall have equal access to its programs and employment without regard to race, color, creed, religion, national origin, sex, age, marital status, disability, public assistance status, veteran status, or sexual orientation.

Information on other titles in this series may be obtained from: Department of Economics, Utah State University, 3530 Old Main Hill, Logan, UT 84322-3530.

Copyright © 2003 by David Aadland and Arthur Caplan. All rights reserved. Readers may make verbatim copies of this document for noncommercial purposes by any means, provided that this copyright notice appears on all such copies.
A CAUTIONARY NOTE ON TESTS FOR INCENTIVE INCOMPATIBILITY AND STARTING-POINT BIAS

David Aadland and Arthur J. Caplan

ABSTRACT

In a recent study by John Whitehead in 2002 ("Incentive Incompatibility and Starting-Point Bias in Iterative Valuation Questions"), he proposes incentive-incompatibility and starting-point-bias tests for iterative willingness-to-pay questions. We show that if restrictions associated with the nature of starting-point bias are not imposed on the estimation, one obtains inconsistent estimates of the structural parameters and may draw inaccurate conclusions regarding the extent of incentive incompatibility and starting-point bias in contingent-valuation survey data.

JEL classifications: Q26, C35

Key words: Incentive incompatibility, starting-point bias, contingent valuation
A CAUTIONARY NOTE ON TESTS FOR INCENTIVE INCOMPATIBILITY AND STARTING-POINT BIAS

1. Introduction

In a recent study, Whitehead (2002) proposes incentive-incompatibility and starting-point-bias tests for iterative dichotomous-choice willingness-to-pay questions. The tests represent a potentially important contribution because they provide a straightforward and relatively simple method to detect and control for two well-documented problems associated with discrete-choice contingent-valuation survey data (Boyle, Bishop, and Welsh, 1985; Herriges and Shogren, 1996; Cameron and Quiggin, 1994; Alberini, Kanninen, and Carson, 1997). In this note, we show that failure to impose certain restrictions implied by the nature of starting-point bias will lead to inconsistent estimates of the structural parameters. Using a Monte Carlo simulation, we find that failure to impose these restrictions leads to a substantial overestimate of starting-point bias and evidence of incentive incompatibility even when none exists in the actual data. Our theoretical arguments are laid out in Section 2 and supported with a simple Monte Carlo experiment in Section 3. Section 4 concludes.

2. Theoretical Model

Consider the valuation of a public good via a double-bounded dichotomous-choice questionnaire. As in Whitehead (2002) and Herriges and Shogren (1996), assume that respondent \( i, i = 1, ..., n \), is given an initial bid \( A_{ii} \) and answers “yes” if her true willingness to pay, \( WTP_{ii} \), is greater than \( A_{ii} \) and answers “no” otherwise. Assume the respondent’s true willingness to pay is generated according to

\[ WTP_{ii} = \max(0, \text{Random}(\theta)) \]

\[ \theta \sim \text{Uniform}(0,1) \]

\[ A_{ii} = \alpha + \beta \theta + \varepsilon \]

\[ \varepsilon \sim \text{Normal}(0, \sigma^2) \]

\[ \alpha, \beta, \sigma \] are parameters.

---

1 The authors acknowledge support from the National Science Foundation grant #0108159.

2 For simplicity, we only consider the double-bounded dichotomous-choice model. Extending the model to allow for multiple dichotomous-choice questions is a straightforward exercise.
where $X_i$ is a vector of explanatory variables observable to the researcher, $\beta$ is a vector of coefficients, and $\epsilon_i$ is an unobservable i.i.d. normally distributed error term. If the respondent answers "yes" to the initial willingness-to-pay question, then a follow-up bid $A_{2i} > A_{1i}$ is given, otherwise $A_{2i} < A_{1i}$. The respondent's answer to this follow-up question is determined by the WTP function

$$WTP_{2i} = (1 - \gamma)WTP_{1i} + \gamma A_{1i} + \delta.$$  

WTP$_{2i}$ is therefore a weighted average of the true willingness to pay and the opening bid plus a "shift" parameter, $\delta$. Starting-point bias (i.e., "anchoring" to the initial bid) exists if $0 < \gamma < 1$ and does not exist if $\gamma = 0$. Likewise, incentive incompatibility exists (does not exist) if $\delta < 0$, $(\delta = 0)$.

Whitehead (2002) then proposes an empirical test for starting-point bias and incentive incompatibility by creating a pseudo-panel dataset and estimating the parameters using a random-effects probit model. According to (1) and (2), the probability that the $i^{th}$ respondent answers "yes" to the $j^{th}$ question, $j = 1,2$, is

$$\text{Prob}(WTP_{ji} > A_{ji}) = \Phi((\beta'X_i + \beta_\gamma A_{1i}D_j + \beta_\delta D_j - A_{ji} + \lambda_{ji}) / \sigma),$$  

where $\Phi$ represents the standard normal cumulative density function, $\sigma$ represents a constant error variance, $D_2 = 1$, $D_1 = 0$, and $\lambda_{ji} = (1 - \beta_\gamma)A_{ji}D_j$. Other than specifying logarithmic willingness to pay, there are two crucial differences between (3) and Whitehead's equation (10)—both of which are associated with restrictions related to the nature of the starting-point bias. First, Whitehead omits the $\lambda_{ji}$ term altogether, which leads to inconsistent estimates of the

---

3Without loss of generality, we assume that $A_{2i} = 2A_{1i}$ when the initial willingness-to-pay question is answered "yes" and $A_{2i} = 0.5A_{1i}$ when answered "no."
parameters (Greene 2003, page 679). Second, it must be recognized—based on equation (2)—that
the parameters in (3) are interrelated according to

\[ \beta_y = \gamma(1-\gamma) \]  
\[ \beta_\delta = (\beta_y \delta)/\gamma \]  
\[ \beta_A = \beta_Y/\gamma. \]  

Failure to impose these restrictions leads to inefficient (and if \( \lambda_{ji} \) is omitted, inconsistent)
estimates of the structural parameters.\(^4\) We now turn to a Monte Carlo experiment, which serves
to support our theoretical arguments.

3. Monte Carlo Experiment

Begin by assuming that respondent \( i \)'s true willingness to pay is given by

\[ \text{WTP}_{1i} = 5 + 10X_i + \varepsilon_i, \]  

\[ \text{(5)} \]

where \( \{X_i\} \) are fixed draws from a uniform distribution on the \((0,1)\) interval and \( \{\varepsilon_i\} \) are drawn
at random from a standard normal distribution. The willingness-to-pay value used for the second
valuation question is given by (2).

For this experiment, we assume that there is no incentive incompatibility (\( \delta = 0 \)) and a
moderate amount of starting-point bias (\( \gamma = 0.25 \)). Based on (2) and (5), we then create 500
artificial data sets (\( n = 1000 \) each) by drawing 500 independent sequences of \( \{\varepsilon_i\} \). The opening
bids, \( A_{1i} \), are drawn with equal probability from the set \( \{4,5,...,16\} \). This range is
approximately two standard deviations above and below the expected willingness-to-pay value

\[^4\text{An alternative interpretation of the differences between (3) and Whitehead's equation (10) is that the}
model with starting-point bias suffers from within-group heteroscedasticity. To see this, substitute (4a) – (4c) into
(3), which gives \( \text{Prob}(\text{WTP}_{1i} > A_{1i}) = \Phi((\beta'X_i - A_{1i})/\sigma) \) and \( \text{Prob}(\text{WTP}_{2i} > A_{2i}) = \Phi(((1 - \gamma)\beta'X_i + \gamma A_{1i} + \delta - \gamma A_{2i})/\sigma^*) \), where \( \sigma^* = (1-\gamma)\sigma \). It is especially important to account for this within-group heteroscedasticity when
estimating binary-choice models, because unlike standard regression models, it leads to inconsistent estimates of the
structural parameters (Greene 2003, page 679). \]
of 10. The subsequent bids, A_{2i}, are set equal to 0.5A_{1i} if WTP_{1i} < A_{1i} and 2A_{1i} otherwise. As in Whitehead (2002), we create pseudo-panel data with a dependent variable equal to one if WTP_{ji} > A_{ji} for j = 1,2 and zero otherwise. The parameters in (3) are estimated using a random-effects probit model with the correlation parameter (\rho) for the within-group error terms set equal to one.\footnote{The “within-group error terms” to which we refer are \( \varepsilon_i \) and \((1 - \gamma)\varepsilon_i\), the latter being implicit in (2).} This restriction on \rho is consistent with the theory presented above and Whitehead (2002), where the only fundamental error term is the group-specific one (\( \varepsilon_i \)).

In the third column of Table 1, we report the average parameter estimates across the 500 simulations excluding \( \lambda_{ji} \) and without having imposed the parameter restrictions (4a)–(4c). The estimates in the fourth column are based on (3) with the parameter restrictions imposed. The values in brackets are the cutoff values for the 90-percent confidence intervals across the 500 simulations. Asterisks indicate that the parameter estimates are statistically different than their corresponding true parameter values.

[Insert Table 1]

Begin by focusing on the third column of Table 1. For four of the model’s five parameters, we reject the null hypothesis that the estimates are equal to their true values at the 90\% level. This supports the theoretical argument that the estimated parameters without imposing the appropriate restrictions are biased and inconsistent. It is interesting to note that although the true model is designed to be incentive compatible, the maximum likelihood estimates indicate substantial incentive incompatibility—the shift effect is roughly 30\% of the average willingness to pay. In addition, the average estimate of starting-point bias is

\footnote{The log likelihood function for this problem is \( \sum_{i=1}^{n} \sum_{s=1}^{4} y_{is} \log(p_{is}) \) where \( s \) indexes the four regions associated with respondents’ answers to the bids \( A_{1i} \) and \( A_{2i} \), \( y_{is} \) is a indicator variable equal to one if the \( i \)th respondent places herself in the \( s \)th region, and \( p_{is} \) is the probability (given by the bivariate cumulative normal distribution with \( \rho=1 \)) that the \( i \)th respondent is in the \( s \)th region.}
approximately one and a half times its actual value. These biases are the direct result of having
excluded the term $\lambda_{ji}$ and not having imposed the appropriate restrictions (4a)–(4c). \textsuperscript{7}
Interestingly, the biases associated with the parameter estimates do not appear to bias the overall
mean WTP estimate.

The last column of Table 1 reports the estimates including $\lambda_{ji}$ and with parameter
restrictions (4a)–(4c) imposed. As expected, we fail to reject the null hypotheses that each
parameter estimate is equal to its associated true value. This supports our theoretical argument
that a modified version of Whitehead's model, one that appropriately incorporates restrictions
associated with the nature of starting-point bias, provides a consistent method to test and control
for starting-point bias and incentive incompatibility. Indeed, failure to impose these restrictions
results in biased and inconsistent parameter estimates.

4. Conclusion

The model proposed by Whitehead (2002) provides a convenient and straightforward
method to control for incentive compatibility and starting-point bias in a dichotomous-choice
iterative WTP question format. However, if the restrictions implied by the structural model are
not specifically imposed on the empirical model, inconsistent estimates are obtained for each of
the structural parameters. We demonstrate this result with a simple Monte Carlo experiment.
We find that the degree of starting-point bias is overstated and that incentive incompatibility
arises even when none exists in the actual data. To obtain consistent estimates of incentive
compatibility and starting-point bias, it is therefore necessary for researchers to impose the
restrictions implied by Whitehead's theoretical model directly in the estimation procedure.

\textsuperscript{7}We also performed Monte Carlo experiments with $n = 10,000$. The results are very similar to those
reported in Table 1, albeit with smaller confidence intervals, and are available from the authors by request.
References


<table>
<thead>
<tr>
<th>Parameters</th>
<th>True Values</th>
<th>Without Parameter Restrictions and $\lambda$</th>
<th>With Parameter Restrictions and $\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$ (Intercept)</td>
<td>5</td>
<td>5.374* [5.139, 5.627]</td>
<td>4.990 [4.743, 5.253]</td>
</tr>
<tr>
<td>$\gamma$ (Starting-Point Bias)</td>
<td>0.25</td>
<td>0.358* [0.316, 0.401]</td>
<td>0.251 [0.223, 0.274]</td>
</tr>
<tr>
<td>$\delta$ (Incentive Incompatibility)</td>
<td>0</td>
<td>-3.175* [-3.547, -2.812]</td>
<td>0.008 [-0.184, 0.180]</td>
</tr>
<tr>
<td>$\sigma$ (Error Standard Deviation)</td>
<td>1</td>
<td>0.926 [0.825, 1.019]</td>
<td>0.990 [0.878, 1.094]</td>
</tr>
</tbody>
</table>

Notes: The values in the last two columns are the ensemble averages across 500 independent simulations. The values in brackets are the lower and upper bounds for a 90% confidence interval. A single asterisk denotes a value that is statistically different than the true value at the 90% confidence level.