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Identifying the True Willingness-To-Pay of Bayesian Respondents in a Dichotomous Choice Contingent Valuation Methodology

Jeffrey R. Czajkowski
Department of Economics, Florida International University

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Florida International University

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Abstract:

This paper develops a respondent model of Bayesian updating for a double-bound dichotomous choice (DB-DC) contingent valuation methodology. We demonstrate by way of data simulations that current DB-DC identifications of true willingness-to-pay (WTP) may often fail given this respondent Bayesian updating context. Further simulations demonstrate that a simple extension of current DB-DC identifications derived explicitly from our Bayesian updating behavioral model can correct for much of the WTP bias. Additional results provide some caution to viewing respondents as acting strategically toward the second bid. Finally, an empirical application confirms the simulation outcomes.

JEL Classifications: Q26, Q50, Q51,

Keywords: Bayesian updating, contingent valuation, double-bound dichotomous choice, strategic behavior, true willingness-to-pay

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[†] Ph.D. candidate, Department of Economics, Florida International University, Miami, FL 33199. Email: jczaj001@fiu.edu, Website: www.fiu.edu/~jczaj001. I thank Peter Thompson, Jonathan Hill, Mahadev Bhat, John C. Whitehead, and David Aadland for their comments and suggestions. I am also grateful for helpful comments from numerous conference participants at Camp Resources XIV. Lastly, I want to acknowledge financial support provided by the EPA.

I. Introduction

The implementation by researchers of a double-bound dichotomous choice (DB-DC) contingent valuation methodology (CVM) over a single-bound dichotomous choice (SB-DC) CVM suggests incentive incompatible respondent behavior, which leads to biased (typically downward) willingness-to-pay (WTP) estimates (Carson, et al., 2000). Various specifications exist for researchers to attempt to identify respondent true WTP by accounting for this apparent shift of respondents' latent true WTP between responses to the first and second bid amounts, including models of structural shift (Alberini et al., 1997) and starting-point bias (Herriges and Shogren, 1996). This paper develops a respondent model of Bayesian updating for a DB-DC CVM that is used to demonstrate how existing identifications of unbiased respondent WTP may often fail. However, we also show that a simple extension of the structural shift model, which is derived explicitly from our Bayesian updating behavioral model, can correct for much of the WTP bias.

While CVM respondents have been frequently modeled as Bayesian updaters (Horowitz, 1993; Herriges and Shogren, 1996; McLeod and Bergland, 1999; Whitehead, 2002; Flores and Strong, 2004; and Aadland et al., 2005), updating in a DB-DC CVM is typically restricted to the asking of the second bid amount[2]. If rational respondents are updating due to the second bid amount, we believe it is also reasonable to expect rational respondents to be updating to the first bid amount, and we therefore develop a respondent model of Bayesian updating to allow for this. Consequently, our model of respondent Bayesian updating behavior may be interpreted as an extension of the traditional starting-point bias models where respondents do not update prior to responding to the first bid amount.

[2] Aadland et al. (2005) is an exception to this in the DB-DC case, allowing updating on both the first and second bid amounts.

Using our respondent model of Bayesian updating behavior, we derive structural shift specifications to allow for the identification of respondent true WTP in a DB-DC CVM given updating on the second bid amount only, as well updating on both bid amounts. These specifications are comparable to the traditional structural shift model of Alberini et al., (1997) which only includes a dummy variable for the asking of the second bid amount We show that even if respondent Bayesian updating is restricted only to occur with the asking of the second bid amount, the correct structural shift specification in this context includes an additional term that is a function of the second bid amount. When respondents Bayesian update on both bid amounts, we show that the correct structural shift specification in this context includes additional terms that are functions of the first and second bid amounts, and true WTP from the correctly specified structural shift model is not identifiable.

In order to demonstrate the extent of WTP bias in a respondent Bayesian updating context for the two identifiable structural shift models (the traditional model with only the dummy variable for the asking of the second bid amount, and the model we specify that also includes a term that is a function of the 2^{nd} bid amount), we simulate respondents updating on the second bid amount only, as well updating on both bid amounts. Our simulations show that the traditional structural shift estimation produces biased estimates of the true WTP when researcher and respondent prior beliefs of the true WTP are not congruent, a result that places a heavy emphasis on the precision of the survey pre-test and bid selection. Furthermore, this specification consistently produces biased estimates of the standard deviation of WTP. Conversely, our simulations show that the incorporation of the term that is a function of the 2^{nd} bid amount can correct for much of the WTP bias and standard deviation of WTP bias generated, except at high levels of respondent updating. Moreover, an empirical application of both of the identifiable structural shift models to the *Alaska* Exxon Valdez DB-DC dataset confirms the simulation outcomes, with the key result being that our simple extension of the traditional structural shift model is significantly different from zero.

Given the continued use of DB-DC CVMs by researchers and practitioners, as well as the persistent notion that respondents are in fact uncertain about their true WTP (see, e.g., Li and Mattsson, 1995; Ready et al, 1995; Cameron and Englin, 1997; Wang, 1997; Loomis and Ekstrand, 1998; Park, 2003), our results are noteworthy. Indeed, a practical solution is offered that identifies true WTP for uncertain respondents that are rationally acting as Bayesian updaters in a DB-DC CVM (certainly for those suspected of only updating on the second bid amount). The results also advise caution to the perception that respondents are acting strategically toward the asking of the second bid amount (Carson, et al., 2000), or as Aadland et al. (2005) state that, "Once one takes this Bayesian perspective of WTP formation, the recent discussion of the incentive incompatibility of DB-DC formats changes markedly."

This paper is organized as follows: Section II outlines the respondent Bayesian updating model; Section III discusses the identification of true WTP given the Bayesian framework; Section IV provides an overview of the data simulation; Section V presents the results of the estimation; Section VI applies both of the identifiable structural shift models to the *Alaska* DB-DC dataset ; and Section VII provides concluding comments.

II. Respondent Bayesian Updating Model

Each of the *i*th individual DB-DC CVM respondents has WTP_i consisting of two components

$$WTP_i = \theta + \mu_i \qquad [1]$$

where θ is an unknown component that is common to all respondents, and μ_i is a known, idiosyncratic component. A possible interpretation of [1] is that respondent i knows he values the natural resource that is the focus of the CVM by more or less than the average person, by an amount μ_i. In this interpretation, the expectation over all individuals is simply $E(\mu) = 0$. Although respondent i does not know θ, he holds prior beliefs that it is a draw from a normal distribution with mean $\bar{\theta}_i$ and variance ${\sigma_\theta}^2$.

Let b_{i1} and b_{i2} denote the first and second bid amounts offered to respondent i as per the DB-DC CVM standard protocol. Given respondent i's WTP uncertainty, he interprets each of the $j = 1,2$ offered bids as a signal of the true value of θ such that he believes

$$b_{ij} = \left(\theta + \alpha_{ij}\right) + \varepsilon_{ij} \qquad [2]$$

where α_{ij} is a constant known by individual i, and he assumes that $\varepsilon_{ij} \sim N\left(0, {\sigma_{\varepsilon_{ij}}}^2\right)$. That is, he interprets $b_{ij} - \alpha_{ij}$ as independent and unbiased signals of θ.

From [1], respondent i's prior belief of WTP_i is that it is normally distributed with mean $\bar{\theta}_i + \mu_i$ and variance ${\sigma_\theta}^2$. Let WTP_{ij} denote $E(WTP_i)$ after receiving j offered bids. Then, $WTP_{i0} = \bar{\theta}_i + \mu_i$. Using standard Bayesian formulae for normal conjugates[3], i's posterior beliefs of WTP_i after receiving the first bid, b_{i1}, is normal with mean

$$WTP_{i1} = \mu_i + \frac{\bar{\theta}_i \cdot {\sigma_{\varepsilon_{i1}}}^2}{\left({\sigma_\theta}^2 + {\sigma_{\varepsilon_{i1}}}^2\right)} + \frac{\left(b_{i1} - \alpha_{i1}\right) \cdot {\sigma_\theta}^2}{\left({\sigma_\theta}^2 + {\sigma_{\varepsilon_{i1}}}^2\right)} \qquad [3]$$

and variance

[3] While other Bayesian updating representations could ostensibly be used, the normal conjugate importantly allows for tractable results

$$\sigma_{i1}{}^2 = \frac{\sigma_\theta{}^2 \cdot \sigma_{\varepsilon_{i1}}{}^2}{\left(\sigma_\theta{}^2 + \sigma_{\varepsilon_{i1}}{}^2\right)} \qquad [4]$$

Given that the respondent is updating on both bid amounts under the reasonable assumption that they interpret both bids as being independent, when receiving the second bid, b_{i2}, [3] and [4] become *i*'s prior beliefs such that the posterior beliefs after hearing b_{i2} are also normal with mean

$$WTP_{i2} = \mu_i + \frac{\left(WTP_{i1} - \mu_i\right) \cdot \sigma_{\varepsilon_{i2}}{}^2}{\left(\sigma_{i1}{}^2 + \sigma_{\varepsilon_{i2}}{}^2\right)} + \frac{\left(b_{i2} - \alpha_{i2}\right) \cdot \sigma_{i1}{}^2}{\left(\sigma_{i1}{}^2 + \sigma_{\varepsilon_{i2}}{}^2\right)} \qquad [5]$$

and variance

$$\sigma_{i2}{}^2 = \frac{\sigma_{i1}{}^2 \cdot \sigma_{\varepsilon_{i2}}{}^2}{\left(\sigma_{i1}{}^2 + \sigma_{\varepsilon_{i2}}{}^2\right)} \qquad [6]$$

Substituting for $\left(WTP_{i1} - \mu_i\right)$ and $\sigma_{i1}{}^2$ in [5] and [6] from [3] and [4], [5] and [6] can be rewritten such that

$$WTP_{i2} = \mu_i + \frac{\left(b_{i2} - \alpha_{i2}\right)\left(\sigma_\theta{}^2 \cdot \sigma_{\varepsilon_{i1}}{}^2\right)}{\sigma_\theta{}^2\left(\sigma_{\varepsilon_{i1}}{}^2 + \sigma_{\varepsilon_{i2}}{}^2\right) + \left(\sigma_{\varepsilon_{i2}}{}^2\right)\left(\sigma_{\varepsilon_{i1}}{}^2\right)} + \frac{\left(\sigma_{\varepsilon_{i2}}{}^2\right)\left[\left(b_{i1} - \alpha_{i1}\right)\left(\sigma_\theta{}^2\right) + \left(\bar{\theta}_i\right)\left(\sigma_{\varepsilon_{i1}}{}^2\right)\right]}{\sigma_\theta{}^2\left(\sigma_{\varepsilon_{i1}}{}^2 + \sigma_{\varepsilon_{i2}}{}^2\right) + \left(\sigma_{\varepsilon_{i2}}{}^2\right)\left(\sigma_{\varepsilon_{i1}}{}^2\right)} \qquad [7]$$

and

$$\sigma_{i2}{}^2 = \frac{\sigma_\theta{}^2 \cdot \sigma_{\varepsilon_{i1}}{}^2 \cdot \sigma_{\varepsilon_{i2}}{}^2}{\sigma_\theta{}^2\left(\sigma_{\varepsilon_{i1}}{}^2 + \sigma_{\varepsilon_{i2}}{}^2\right) + \left(\sigma_{\varepsilon_{i2}}{}^2\right)\left(\sigma_{\varepsilon_{i1}}{}^2\right)} \qquad [8]$$

Using $WTP_{i0} = \bar{\theta}_i + \mu_i$, [3] and [7] can be simplified further to

$$WTP_{i1} = WTP_{i0} + \frac{\left(b_{i1} - \alpha_{i1} - \bar{\theta}_i\right) \cdot \sigma_\theta{}^2}{\left(\sigma_\theta{}^2 + \sigma_{\varepsilon_{i1}}{}^2\right)} \qquad [9]$$

and

$$WTP_{i2} = WTP_{i0} + \frac{\left(b_{i2} - \alpha_{i2} - \overline{\theta}_i\right)\left(\sigma_\theta^{\ 2}\right)\left(\sigma_{\varepsilon_{i1}}^{\ 2}\right) + \left(b_{i1} - \alpha_{i1} - \overline{\theta}_i\right)\left(\sigma_\theta^{\ 2}\right)\left(\sigma_{\varepsilon_{i2}}^{\ 2}\right)}{\sigma_\theta^{\ 2}\left(\sigma_{\varepsilon_{i1}}^{\ 2} + \sigma_{\varepsilon_{i2}}^{\ 2}\right) + \left(\sigma_{\varepsilon_{i2}}^{\ 2}\right)\left(\sigma_{\varepsilon_{i1}}^{\ 2}\right)} \qquad [10]$$

III. Identification of True WTP

In conducting a CVM, the goal of the researcher is to obtain the respondent's prior beliefs of WTP, WTP_{i0}. For example, as Herriges and Shogren (1996, pg. 117) note, "... it is the household's prior held beliefs that the policymaker should be interested in, not the posterior WTP estimates that are artificially influenced by an optimal bid design." Therefore, we consider the ability to identify a respondent's true WTP, WTP_{i0}, from our Bayesian updating framework for the three different possible respondent signaling perspectives of our model: 1) neither bid provides a signal; 2) only the 2nd bid provides a signal; or 3) both bids provide a signal.

Neither Bid Provides A Signal

If respondent *i* believes that neither of the j = 1,2 offered bids contains a signal, then $\sigma_{\varepsilon_{ij}}^{\ 2} \to \infty$. If this is the case, then from [9] and [10], $WTP_{i2} = WTP_{i1} = WTP_{i0}$. Therefore, true WTP can be identified from the responses to both questions by DB-DC estimation with associated efficiency gains over estimation using only responses to the first bid amount (Hanemann et al., 1991).

2nd Bid Only Provides A Signal

If it is the case that respondent *i* believes that information concerning θ is contained in the second bid only, then $\sigma_{\varepsilon_{i1}}^{\ 2} \to \infty$ and $\sigma_{\varepsilon_{i2}}^{\ 2} < \infty$. From [9] we see that $WTP_{i1} = WTP_{i0}$. However, in this case WTP_{i2} does not follow from [10], as [3] and [4] no longer represent respondent *i*'s prior beliefs when they receive b_{i2}. Instead, respondent i has prior beliefs with mean $\overline{\theta}_i$ and variance σ_θ^2 when they receive b_{i2}. Thus, again using standard Bayesian formulae for normal conjugates, i's posterior beliefs of WTP_i after receiving b_{i2} is normal with mean

$$WTP_{i2} = \mu_i + \frac{\overline{\theta}_i \cdot \sigma_{\varepsilon_{i2}}^2}{\left(\sigma_\theta^2 + \sigma_{\varepsilon_{i2}}^2\right)} + \frac{\left(b_{i2} - \alpha_{i2}\right) \cdot \sigma_\theta^2}{\left(\sigma_\theta^2 + \sigma_{\varepsilon_{i2}}^2\right)} \qquad [11]$$

which, again using $WTP_{i0} = \overline{\theta}_i + \mu_i$, can be simplified further to

$$WTP_{i2} = WTP_{i0} + \frac{\left(b_{i2} - \alpha_{i2} - \overline{\theta}_i\right) \cdot \sigma_\theta^2}{\left(\sigma_\theta^2 + \sigma_{\varepsilon_{i2}}^2\right)} \qquad [12]$$

In this case, it therefore follows from [9] and [12] that $WTP_{i2} \neq WTP_{i1} = WTP_{i0}$. Consequently, WTP estimates derived from the responses to the first bid are able to provide a consistent estimation of true WTP, but estimates derived from responses to both bids will be inconsistent unless an adequate control for the second response is introduced.

Alberini et al.'s (1997) structural shift dummy variable, adapted to our notation, is specified as

$$\begin{aligned} WTP_{i1} &= WTP_{i0} + \eta_i \\ WTP_{i2} &= WTP_{i0} + \delta_i + \eta_i \end{aligned} \qquad [13]$$

where δ_i is the coefficient on a structural shift dummy variable that takes on the value one for responses to the second question. However, it is clear from [12] that the correct specification in a Bayesian updating context should also include an interaction term between δ_i and the magnitude of b_{i2} [4], that is

$$\begin{aligned} WTP_{i1} &= WTP_{i0} + \eta_i \\ WTP_{i2} &= WTP_{i0} - \left(\alpha_{i2} + \overline{\theta}_i\right)\delta_i' + \delta_i'\left(b_{i2}\right) + \eta_i \end{aligned} \qquad [14]$$

[4] Alberini et al. (1997, pg. 319) note that "δ could also be a function of additional explanatory variables including the cost amount or the change in cost amounts."

where $\delta_i' = \sigma_\theta^{\ 2} / \left(\sigma_\theta^{\ 2} + \sigma_{\varepsilon_{i2}}^{\ \ 2}\right)$. Because α_{i2}, $\overline{\theta}_i$, $\sigma_\theta^{\ 2}$ and $\sigma_{\varepsilon_{i2}}^{\ \ 2}$ are not observable, $-\left(\alpha_{i2} + \overline{\theta}_i\right)\delta_i'$ and δ_i' are two individual-specific parameters. Assuming they are common to all individuals (Alberini et al., 1997) such that $\delta_i' = \delta$, yields the system

$$\begin{aligned} WTP_{i1} &= WTP_{i0} + \eta_i \\ WTP_{i2} &= WTP_{i0} + \delta^0 I_2 + \delta^1 I_2\left(b_{i2}\right) + \eta_i \end{aligned} \qquad [15]$$

where I_2 is a dummy variable indicating the asking of the second bid amount. From [15] we see that in a respondent Bayesian updating context, the correct structural shift specification is dependent upon the size of the second bid amount. Therefore, true WTP is able to be identified from the responses to both questions with the appropriate dummy variable specification by stacking the data and estimating a conventional single-bound model (SB-DC) that has two observations for each respondent.

Both Bids Provide A Signal

Finally, if it is the case that respondent *i* believes that information concerning θ is contained in both bid amounts, then $\sigma_{\varepsilon_{i1}}^{\ \ 2} < \infty$ and $\sigma_{\varepsilon_{i2}}^{\ \ 2} < \infty$. If this is the case, from [9] and [10] we have $WTP_{i2} \neq WTP_{i1} \neq WTP_{i0}$. Consequently, unbiased estimates of WTP will only be able to be derived if an adequate control for both responses is implemented in the estimation.

Again, adapting Alberini et al.'s (1997) structural shift dummy variable to our notation with respondent updating on both bid amounts we have that

$$\begin{aligned} WTP_{i1} &= WTP_{i0} + \delta_{i1} + \eta_i \\ WTP_{i2} &= WTP_{i0} + \delta_{i2} + \eta_i \end{aligned} \qquad [16]$$

where δ_{i1} is a coefficient on a structural shift dummy variable that takes on the value one for responses to the first question, and δ_{i2} is a coefficient on a structural shift dummy variable that takes on the value one for responses to the second question. Allowing the δ_i's to be functions of the bid amounts (which naturally follows from our respondent Bayesian updating context as per the second term on the right-hand side of both [9] and [10]) [16] can now be specified as

$$\begin{aligned} WTP_{i1} &= WTP_{i0} - \left(\alpha_{i1} + \bar{\theta}_i\right)\delta'_{i1} + \delta'_{i1}\left(b_{i1}\right) + \eta_i \\ WTP_{i2} &= WTP_{i0} - \left(\alpha_{i2} + \bar{\theta}_i\right)\delta'_{i2} + \delta'_{i2}\left(b_{i2}\right) - \left(\alpha_{i1} + \bar{\theta}_i\right)\delta''_{i2} + \delta''_{i2}\left(b_{i1}\right) + \eta_i \end{aligned} \quad [17]$$

where $\delta'_{i1} = \sigma_\theta{}^2 / \left(\sigma_\theta{}^2 + \sigma_{\varepsilon_{i1}}{}^2\right)$, $\delta'_{i2} = \left(\sigma_\theta{}^2\right)\left(\sigma_{\varepsilon_{i1}}{}^2\right) / \sigma_\theta{}^2\left(\sigma_{\varepsilon_{i1}}{}^2 + \sigma_{\varepsilon_{i2}}{}^2\right) + \left(\sigma_{\varepsilon_{i2}}{}^2\right)\left(\sigma_{\varepsilon_{i1}}{}^2\right)$, and $\delta''_{i2} = \left(\sigma_\theta{}^2\right)\left(\sigma_{\varepsilon_{i2}}{}^2\right) / \sigma_\theta{}^2\left(\sigma_{\varepsilon_{i1}}{}^2 + \sigma_{\varepsilon_{i2}}{}^2\right) + \left(\sigma_{\varepsilon_{i2}}{}^2\right)\left(\sigma_{\varepsilon_{i1}}{}^2\right)$. Assuming the individual-specific parameters are common to all individuals, the following system is specified

$$\begin{aligned} WTP_{i1} &= WTP_{i0} + \delta^0 I_1 + \delta^1 I_1\left(b_{i1}\right)\eta_i \\ WTP_{i2} &= WTP_{i0} + \delta^2 I_2 + \delta^3 I_2\left(b_{i2}\right) + \delta^4 I_2 + \delta^5 I_2\left(b_{i1}\right) + \eta_i \end{aligned} \quad [18]$$

There are restrictions on these parameters, for example, if $\alpha_{i1} = \alpha_{i2}$, then $\delta^2 / \delta^3 = \delta^4 / \delta^5$. But despite these potential restrictions, it is clear that WTP_{i0} cannot be identified.

For the three different possible respondent signaling perspectives of our Bayesian updating model, we have shown that the identification of true WTP is only possible for two of them given that the appropriate WTP estimation model has been specified. Since in conducting a CVM it is the goal of the researcher to obtain the respondent's true WTP, it is essential to understand the extent of bias (and if possible to correct for it) inherent in the estimated WTP if it is the case that respondents are updating on both bids and the researcher cannot specify the correct WTP estimation model, or where respondents are only updating on the second bid but the researcher has specified a WTP estimation model that does not contain the appropriate dummy variable specification.

IV. Data Simulation

In order to demonstrate the extent of WTP bias in a respondent Bayesian updating context for the two identifiable structural shift models (the traditional model, [13], and our extension of this model, [15]), we simulate respondents updating on the second bid amount only, as well updating on both bid amounts. Faced with a randomly selected bid amount, a CVM respondent will say yes to b_{ij} when WTP_{ij} is greater than b_{ij}, and no when it is less. Therefore, in a DB-DC CVM when respondents are updating on b_{i2} only, yes/no responses are generated according to:

$$yes_{i1} = \begin{cases} 1 & WTP_{i1} = WTP_{i0} > b_{i1} \\ 0 & WTP_{i1} = WTP_{i0} < b_{i1} \end{cases}, \quad \text{yes}_{i2} = \begin{cases} 1 & WTP_{i2} = WTP_{i0} + \frac{(b_{i2} - \alpha_{i2} - \bar{\theta}_i)\cdot \sigma_\theta^2}{(\sigma_\theta^2 + \sigma_{\varepsilon_{i2}}^2)} > b_{i2} \\ 0 & WTP_{i2} = WTP_{i0} + \frac{(b_{i2} - \alpha_{i2} - \bar{\theta}_i)\cdot \sigma_\theta^2}{(\sigma_\theta^2 + \sigma_{\varepsilon_{i2}}^2)} < b_{i2} \end{cases} \quad [19]$$

where $WTP_{i0} = \bar{\theta}_i + \mu_i$. And, when respondents are updating on both b_{i1} and b_{i2}, yes/no responses are generated according to:

$$yes_{i1} = \begin{cases} 1 & WTP_{i1} = WTP_{i0} + \frac{(b_{i1} - \alpha_{i1} - \bar{\theta}_i)\cdot \sigma_\theta^2}{(\sigma_\theta^2 + \sigma_{\varepsilon_{i1}}^2)} > b_{i1} \\ 0 & WTP_{i1} = WTP_{i0} + \frac{(b_{i1} - \alpha_{i1} - \bar{\theta}_i)\cdot \sigma_\theta^2}{(\sigma_\theta^2 + \sigma_{\varepsilon_{i1}}^2)} < b_{i1} \end{cases},$$

$$\text{yes}_{i2} = \begin{cases} 1 & WTP_{i2} = WTP_{i0} + \frac{(b_{i2} - \alpha_{i2} - \bar{\theta}_i)(\sigma_\theta^2)(\sigma_{\varepsilon_{i1}}^2) + (b_{i1} - \alpha_{i1} - \bar{\theta}_i)(\sigma_\theta^2)(\sigma_{\varepsilon_{i2}}^2)}{\sigma_\theta^2(\sigma_{\varepsilon_{i1}}^2 + \sigma_{\varepsilon_{i2}}^2) + (\sigma_{\varepsilon_{i2}}^2)(\sigma_{\varepsilon_{i1}}^2)} > b_{i2} \\ 0 & WTP_{i2} = WTP_{i0} + \frac{(b_{i2} - \alpha_{i2} - \bar{\theta}_i)(\sigma_\theta^2)(\sigma_{\varepsilon_{i1}}^2) + (b_{i1} - \alpha_{i1} - \bar{\theta}_i)(\sigma_\theta^2)(\sigma_{\varepsilon_{i2}}^2)}{\sigma_\theta^2(\sigma_{\varepsilon_{i1}}^2 + \sigma_{\varepsilon_{i2}}^2) + (\sigma_{\varepsilon_{i2}}^2)(\sigma_{\varepsilon_{i1}}^2)} < b_{i2} \end{cases} \quad [20]$$

where $WTP_{i0} = \bar{\theta}_i + \mu_i$.

We specify our values for $\bar{\theta}_i, \mu_i, \sigma_\theta^2, \alpha_{ij}, \sigma_{\varepsilon_{ij}}^2$, and b_{ij} as summarized in Table 1.[5] For each of the eight specified $\sigma_{\varepsilon_{i1}}$ values, per each of the three specified b_{i1} mean values of Table 1,

[5] Typical CVM initial bids are centered around a single value with specified increments (e.g., 25, 50, 75, 100, 125, 150, 200). We have not specified any such increments in drawing our initial bids from a normal distribution. We do not feel this comprises the analysis.

we generate 1000 samples each of sample size 1000. Given the generated sample data, yes/no responses follow from [19] and [20]. Figure 1 provides an example of generated DB-DC yes/no responses for an illustrative respondent that does not Bayesian update on either bid, updates on the second bid only ($\sigma_{\varepsilon_{i2}}{}^2 = 10$), and updates on both bids ($\sigma_{\varepsilon_{i1}}{}^2 = 10,$ and $\sigma_{\varepsilon_{i2}}{}^2 = 10$).

V. Estimation and Results

In addition to the generated DB-DC yes/no responses and associated bid amounts from the data simulation, an intercept (the only independent variable used in order to represent WTP_i) and the appropriate b_{i2} dummy variable(s) from [13] and [15] complete the datasets to be estimated. The introduction of the structural shift dummy variable(s) requires the data to be stacked, and therefore maximum likelihood estimation of WTP follows from the conventional SB-DC model of Cameron and James (1987), but with two observations for each respondent. We perform probit and logit maximum likelihood estimation for the 1000 samples for each specification. Because probit and logit simulations are qualitatively similar, only logit estimation results are presented below.

Structural Shift Model with only the Dummy Variable for the Asking of the Second Bid

Figures 2(a) and 2(b) illustrate the results from [13] for the estimated mean WTP and standard deviation of WTP respectively, when the initial bid value is drawn from a normal distribution that is centered on the true WTP of 100, and the respondents are updating on both bid amounts. Estimates of the 97.5 and 2.5 percentiles of mean WTP and standard deviation of WTP are also illustrated in Figures 2(a) and 2(b) respectively as a measure of the variability of these estimates across the eight specified $\sigma_{\varepsilon_{i1}}$ values[6]. Furthermore, although the results presented are based upon the simulated responses to both bid amounts, for high levels of $\sigma_{\varepsilon_{i1}}$ (denoted sig eps_1 in the figures) along the x-axis, the results can be interpreted as respondents updating only on the second bid amount. In this way, the figures simultaneously present the results for the estimated mean WTP, standard deviation of WTP, and the associated 97.5 and 2.5 percentiles in both of the respondent Bayesian updating contexts.[7]

While Figure 2(a) shows that the results of estimated mean WTP are unbiased[8] vs. the true value of 100, Figure 2(b) indicates that the estimated standard deviation of WTP is biased upward vs. the true value of 20 for all levels of $\sigma_{\varepsilon_{i1}}$. These general bias results hold whether the respondent is updating on either both bid amounts, or only the second bid amount. However, the upward bias of the standard deviation of WTP becomes larger as less updating is occurring on the first bid amount. Additionally, while the variability of the estimates of mean WTP remains relatively constant over the specified levels of $\sigma_{\varepsilon_{i1}}$, the variability of the estimates of standard deviation of WTP increases with higher levels of $\sigma_{\varepsilon_{i1}}$ (i.e., with less updating on the first bid amount). Therefore, in the case where researchers select initial bid amounts from a distribution that is centered on respondent's prior beliefs of true WTP = 100, unbiased estimates of mean WTP with relatively constant variability are generated, although the standard deviation of the these estimates is biased upward with both the bias and the variability of the standard deviation estimates increasing as respondents update less on the first bid amount.

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[6] Results for $\sigma_{\varepsilon_{i1}}$ = 1000 are not shown for aesthetic purposes, but are approximate to the results for $\sigma_{\varepsilon_{i1}}$ = 100.

[7] This is true for all of the other estimation figures associated with this model, namely Figures 3(a) and 3(b)

[8] T-tests at the 1% level are used to confirm the presence of bias for all estimation results of mean WTP and standard deviation of WTP unless otherwise noted.

But what about the case where researchers prior beliefs of true WTP do not match to those of respondents, a case that seems to be more likely to occur in the implementation of a CVM? Figures 3(a) and 3(b) illustrate the results from [13] for the estimated mean WTP and standard deviation of WTP respectively when the initial bid value is drawn from a normal distribution that is not centered on the true WTP, i.e., 50 < 100, and the respondents are updating on both bid amounts[9]. In this case, both the estimates of the mean WTP and the standard deviation of WTP are biased when respondents are updating on both bid amounts, and also when respondents are updating only on the second bid amount. From Figure 3(a) we see that for strong updating on both bid amounts (low levels of $\sigma_{\varepsilon_{i1}}$), mean WTP is biased downward from true WTP = 100 with little variability in the estimates. In fact, for complete updating on the first bid amount ($\sigma_{\varepsilon_{i1}}$=0), estimated WTP is the mean of the bid distribution = 50. However, with less updating on the first bid amount, estimated mean WTP is biased upward from true WTP = 100 and contains more variability in the estimates. Estimated standard deviation of WTP is again biased upward vs. the true value of 20 for all levels of $\sigma_{\varepsilon_{i1}}$, but in this case the upward bias and variability of the standard deviation estimates are more constant over the specified levels of $\sigma_{\varepsilon_{i1}}$.

To better understand the source of the bias, Table 2 illustrates the shifts in the percentages of Yes-Yes, Yes-No, No-Yes, and No-No responses between respondents not updating on either bid, and those updating on both bids when $\sigma_{\varepsilon_{i1}}$=2 and $\sigma_{\varepsilon_{i2}}$=10. When respondents do not update on either bid presented to them, and given that the presented initial bid value is drawn from a normal distribution that is not centered on the true WTP, i.e., 50 < 100,

[9] The opposite mean WTP graph is produced when the initial bid value is drawn from a normal distribution with mean exceeding the true WTP, i.e., 150 > 100

more than 90% of the DB-DC responses fall into either the Yes-Yes or Yes-No vote categories as would be expected. Due to the high levels of Yes votes in this non-updating scenario, responses primarily fall into bounded intervals only above the initial bid amount = 50, and estimated mean WTP is able to move to the true WTP = 100. However, when respondents are updating (relatively strongly) on both bid amounts, there is a remarkable decrease in Yes-Yes votes and corresponding increase in No-Yes and No-No votes. As can be inferred from the Bayesian updating example of Figure 1, for strong enough updating as well as relatively close true WTP and initial bid amounts, initial yes responses in a non-updating context are easily reversed. Therefore, responses no longer primarily fall into bounded intervals only above the initial bid amount = 50, and estimated mean WTP is not able to approach true WTP = 100.

These overall estimation results for the traditional structural shift model indicate that, in a respondent Bayesian updating context, this model fails to generate unbiased estimates of mean WTP unless the initial bid amount is centered on respondent's prior beliefs. Unfortunately, achieving initial bid amounts that are centered on respondent's prior beliefs is a case that would appear to be seemingly rare in practice, or at the very least places a heavy burden on the typical CVM pre-test. That is, it is reasonable to assume that pre-test respondents would also be Bayesian updating, and therefore results from a pre-test would not provide any further insight into how to adjust the bid amounts to be centered on respondent's prior beliefs of what is true WTP. Moreover, these overall estimation results for the traditional structural shift model indicate that, in a respondent Bayesian updating context, this model always fails to generate unbiased estimates of the standard deviation of WTP.

Structural Shift Model that also Includes a Term that is a Function of the Second Bid

Figures 4(a) and 4(b) illustrate the results from [15] for the estimated mean WTP and standard deviation of WTP respectively when the initial bid value is drawn from a normal distribution that is centered on the true WTP of 100, and the respondents are updating on both bid amounts. Estimates of the 97.5 and 2.5 percentiles of mean WTP and standard deviation of WTP are also illustrated in Figures 4(a) and 4(b) respectively as a measure of the variability of these estimates across the eight specified $\sigma_{\varepsilon_{i1}}$ values[10]. Furthermore, although the results presented are based upon the simulated responses to both bid amounts, for high levels of $\sigma_{\varepsilon_{i1}}$ (denoted sig eps_1 in the figures) along the x-axis, the results can be interpreted as respondents updating only on the second bid amount. In this way, the figures simultaneously present the results for the estimated mean WTP, standard deviation of WTP, and the associated 97.5 and 2.5 percentiles in both of the respondent Bayesian updating contexts.[11]

While Figure 4(a) shows that the results of estimated mean WTP are still unbiased vs. the true value of 100, Figure 4(b) indicates that the previous bias in the standard deviation of WTP = 20 from the traditional structural shift model of Figure 2(b) has dissipated. Furthermore, the variability of both the estimated mean WTP and standard deviation of WTP has decreased significantly as evidenced by the tighter 97.5 and 2.5 percentile lines. However, we do start to see evidence of increased variability of mean WTP estimates, as well as evidence of bias and increased variability of estimates for the standard deviation of WTP for high levels of updating on bid 1 (low levels of $\sigma_{\varepsilon_{i1}}$)[12]. These results at the least therefore indicate that this specification does a better job then the traditional structural shift model in producing unbiased estimates of the

[10] Results for $\sigma_{\varepsilon_{i1}}$ = 1000 are not shown for aesthetic purposes, but are approximate to the results for $\sigma_{\varepsilon_{i1}}$ = 100.

[11] This is true for all of the other estimation figures associated with this model, namely Figures 5(a) and 5(b)

[12] Convergence issues at these low levels (i.e., $\sigma_{\varepsilon_{i1}}$ < 10) prevent us at this time from making a more definitive statement concerning bias and depicting the results graphically.

standard deviation of WTP when it is believed that respondents update only on the second bid amount.

Figures 5(a) and 5(b) illustrate results from [15] for the estimated mean WTP and standard deviation of WTP respectively when the initial bid value is drawn from a normal distribution that is not centered on the true WTP, i.e., 50 < 100, and the respondents are updating on both bid amounts. Contrasting Figures 5(a) and 5(b) with Figures 3(a) and 3(b) we clearly see the improvement in reduced bias over the traditional structural shift model for both the estimates of mean WTP and the standard deviation of WTP. We also see improvements in the variability of both the estimated mean WTP and standard deviation of WTP as evidenced by the tighter 97.5 and 2.5 percentile lines. We again, however, start to see evidence of increased variability of mean WTP estimates, as well as evidence of bias and increased variability of estimates for the standard deviation of WTP for high levels of updating on bid 1 (low levels of $\sigma_{\varepsilon_{i1}}$)[13].

These overall estimation results for the structural shift model we specify that also includes a term that is a function of the 2nd bid amount indicate that in a respondent Bayesian updating context, unbiased and less variable estimates of mean WTP and standard deviation of WTP can be generated. The results certainly hold well for the case where respondents are only updating on the second bid amount as is typically perceived in the DB-DC CVM literature. For the case where respondents are updating on both bids, even though there is some indication of bias for high levels of updating on bid 1, obvious improvement over the traditional structural shift model in terms of reduced bias estimates of mean WTP and standard deviation of WTP is demonstrated.

[13] Convergence issues at these low levels (i.e., $\sigma_{\varepsilon_{i1}} < 10$) prevent us at this time from making a more definitive statement concerning bias and depicting the results graphically.

Investigating Respondent Strategic Behavior

DB-DC WTP bias from a structural shift model is typically indicated as being downward due to the estimated negative δ coefficient (Alberini et al., 1997; Whitehead, 2002). Furthermore, Carson et al. (2000) have discussed various strategic behavior theories as to how agents may interpret this second price signal in order to explain the WTP downward bias. We show, in fact that it is the asymmetry induced by the standard DB-DC CVM protocol of halving b_{i1} for an initial no response, and doubling b_{i1} for an initial yes response that generates the negative δ coefficient in a respondent Bayesian updating context, not necessarily respondent strategic behavior.

Table 3 presents results from two different estimations of [13] when the initial bid value is drawn from a normal distribution that is centered on the true WTP of 100, and the respondents are updating on both bid amounts with $\sigma_{\varepsilon_{i1}}^{2} = 25$, and $\sigma_{\varepsilon_{i2}}^{2} = 10$. In the first estimation, b_{i2} is generated by halving b_{i1} for an initial no response, and doubling b_{i1} for an initial yes response (the standard DB-DC CVM protocol). In the second estimation, b_{i2} is generated as (b_{i1} – 60) for an initial no response, and (b_{i1} + 60) for an initial yes response. We do generate a (-) δ coefficient in the standard halving/doubling b_{i2} generation, but the (-) δ coefficient disappears in our [b_{i1} (+)/(–) 60] estimation. Clearly, respondent strategic behavior cannot be inferred simply from the generation of a (-) δ coefficient for a DB-DC CVM where b_{i2} is generated by halving b_{i1} for an initial no response, and doubling b_{i1} for an initial yes response and respondents are acting as Bayesian updaters.

Our simulation results already presented in Figures 2(a) – 5(b) have all assumed the respondent's known constant of the signal, α_{ij}, from [2] to equal 0. If believing that respondents are in fact acting strategically similarly to one of the Carson et al. (2000) strategic behavior theories, allowing $\alpha_{ij} \neq 0$ allows for investigation of bias in this strategic behavior context. For example, if respondents feel that the researcher has placed them into a bargaining situation they will feel that the b_{ij} presented to them has been purposefully inflated. In this case, $\alpha_{ij} < 0$ in order to counteract the perceived bid inflation.

Figures 6(a) – 7(b) present mean WTP simulation results[14] with α_{ij} = -20 for both structural shift identifications of [13] and [15], as well as where b_{i1} = true WTP = 100 and where b_{i1} = 50 < true WTP = 100. In this strategic behavior context, we now see upward bias being generated for the case where researcher priors are compatible with respondent priors of true WTP =100 as shown by Figure 6(a). The structural shift specification including the term for b_{i2} still appears to be able to correct for the generated bias as shown by Figure 7(a), although not at as low of levels of $\sigma_{\varepsilon_{i1}}$ as when α_{ij} = 0. These results indicate that the specification of [15] is even more important in a possible strategic behavior Bayesian updating context.

VI. Empirical Application

Carson et al. (1992) conducted a DB-DC CVM for the State of Alaska in order to obtain a WTP value "to prevent another Exxon Valdez type oil spill". Median WTP = $31 was estimated from respondents' answers to both CVM questions using an interval DB-DC model assuming a Weibull distribution. As a check on the sensitivity of the estimated DB-DC median WTP value, median WTP = $41 was also estimated from answers to the first question only using a SB-DC model assuming a log-normal distribution. Given the disparity between the SB-DC and DB-DC WTP estimates, they conclude that a slight downward bias exists between respondents' answers to only the first bid amount and answers to both bid amounts. Indeed, Carson et al. (2003) note

[14] Standard deviation of WTP graphical results are not presented, but are still biased as was the case where α_{ij} = 0.

that the structural shift model of Alberini et al. (1997) could be used to account for this downward bias. We therefore use the *Alaska* dataset to estimate WTP from the two identifiable structural shift models of this paper (the traditional model, [13], and our extension of this model, [15]).

Table 4 presents the maximum likelihood estimates following from the conventional SB-DC model of Cameron and James (1987) using the *Alaska* study responses to the first bid amount only. Additionally, Table 4 presents the maximum likelihood estimates for the two identifiable structural shift models of [13] and [15] using the *Alaska* study responses to both bid amounts with the data being stacked to account for the introduction of the structural shift dummy variable(s). Only an intercept and the appropriate b_{i2} dummy variable(s) from [13] and [15] are used in the estimation, and a log-normal distribution has been assumed in order to follow the results of Carson et al. (1992).

Our SB-DC estimation produces an estimate of 3.73 for the intercept, equating to a median WTP[15] = \$41.58, with the standard deviation of WTP estimated at 3.15. This WTP result closely mirrors the median WTP = \$41.44 of Carson et al. (1992). The traditional structural shift model of [13] produces an estimate of 4.18 for the intercept, equating to median WTP = \$65.54, and 19.73 for the standard deviation of WTP. Also, although a negative coefficient is generated for the 2nd question dummy variable, it is significant only up to the 10% level. The structural shift model of [15] that we specify that also includes a term that is a function of the 2nd bid amount produces an estimate of 3.83 for the intercept, equating to median WTP = \$46.14, and 7.01 for the standard deviation of WTP. Importantly, the additional term that is a function of the 2nd bid amount is significant at the 1% level. A standard likelihood ratio test between [13] and [15] indicates that [15] in fact fits the *Alaska* data better.

[15] Given the log-normal distribution, median WTP = exp(βx') with βx' being the intercept.

This empirical application demonstrates, similar to our simulations, that if one believes respondents are only updating on the second bid amount and hence true WTP is represented by SB-DC estimates, than the structural shift model of [15] does a better job of estimating a less biased true WTP when utilizing a DB-DC CVM approach compared to the traditional structural shift model of [13]. Of course, if respondents are updating on both bid amounts, true WTP may not be identifiable as has been shown.

VII. Conclusions

We have shown why existing structural shift models used to estimate unbiased WTP from a DB-DC CVM are theoretically incapable of doing so in a Bayesian updating context due to misspecification and identification issues. Through our data simulations we have demonstrated the extent of the WTP bias when the identifiable, yet misspecified structural shift model is used. The results are most serious when researcher and respondent prior beliefs of true WTP are not congruent. We suggest a more properly specified structural shift model following from the respondent Bayesian updating behavioral model that includes an additional term that is a function of the second bid amount. Our data simulations show that this specification can correct for much of the potential WTP bias. An empirical application to the *Alaska* Exxon Valdez DB-DC dataset confirms the simulation outcomes, with the key result being that our simple extension of the traditional structural shift model is significantly different from zero.

The results of the paper also offer an alternative to the perception that respondents act strategically in a DB-DC CVM, and that their responses are not incentive compatible between questions. Rather, uncertain respondents act rationally by incorporating information signaled to them through both of the presented bid amounts. Not accounting for this possibility in the structural shift estimation leads to biased estimates of the respondent's true WTP.

Table 1. Specified Values for $\bar{\theta}_i, \mu_i, \sigma_\theta^{\ 2}, \alpha_{ij}, \sigma_{\varepsilon_{ij}}^{\ 2},$ and b_{ij} Used In the Data Simulation

Category	Variable	SpecifiedValue
WTP_{i0}	$\bar{\theta}_i$	100 $\forall$ *i*
	μ_i	~N(0,σ) and σ=20
Standard Deviation of Prior Beliefs	σ_θ	20
Signal known constant	α_{ij}	0
Strength of Updating	$\sigma_{\varepsilon_{i1}}$	1000, 100, 50, 25, 10, 5, 2, 0
	$\sigma_{\varepsilon_{i2}}$	10
Bids	b_{i1}	~N(100,σ), ~N(50,σ), ~N(150,σ) and σ=30
	b_{i2}	(b_{i1})*2, or (b_{i1})*1/2 for yes or no to b_{i1} respectively

Table 2. % of YY, YN, NY, NN Responses for $WTP_{i2} = WTP_{i0} + \delta I_2 + \eta_{i2}$

DB-DC Response	No Updating	Updating on Both Bids
YY	50%	8%
YN	42%	43%
NY	8%	34%
NN	0%	15%

Table 3. δ Coefficient Results For Halving/Doubling, And (+)/(-) 60 b_{i2} Generation

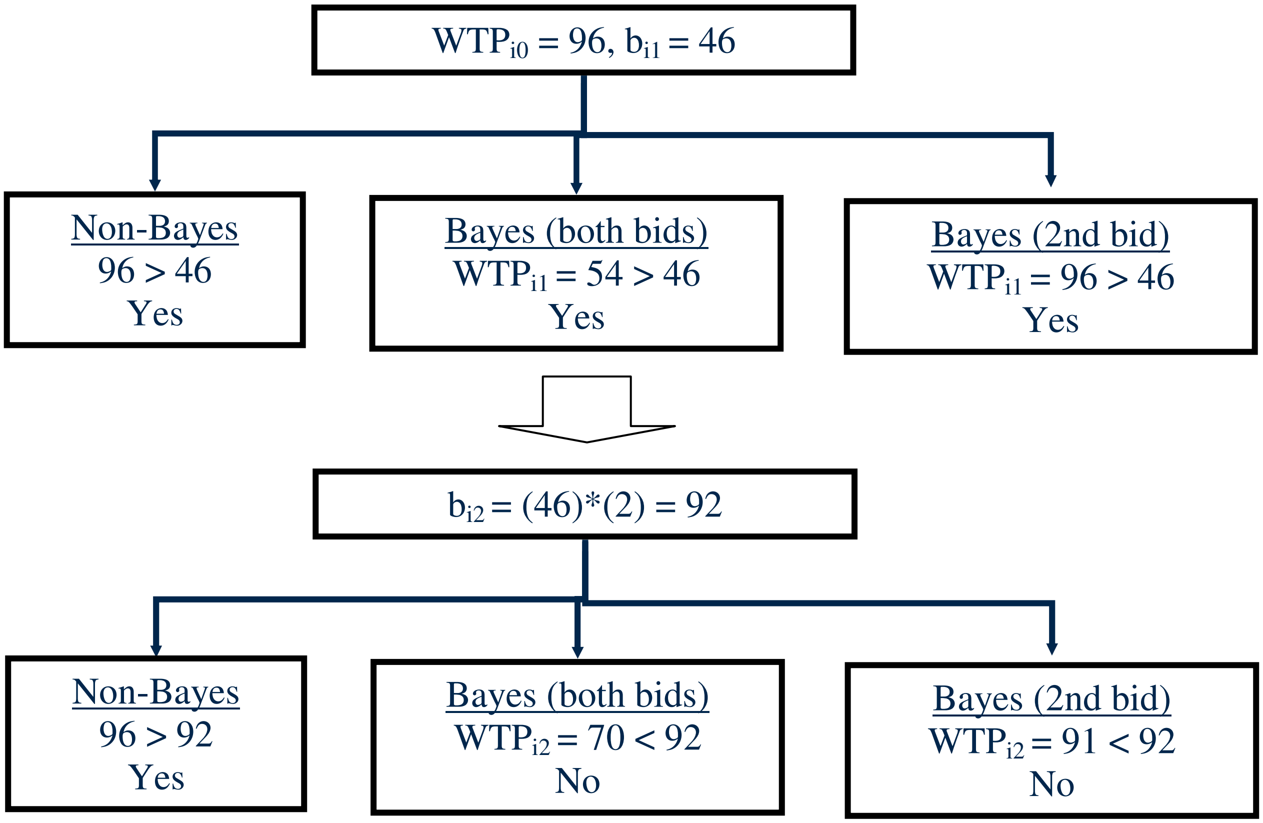
	Estimates halving/doubling	Estimates (+)/(-) 60
WTP	100.1	100.0
δ	-18.9	0.2
σ	93.7	135.3

Table 4: *Alaska* Study Maximum Likelihood Estimates

Parameter	SB-DC	Traditional Structural Shift	Structural Shift with Bid Interaction
intercept	3.7276 (29.91)	4.1827 (5.064)	3.8316 (13.784)
δ^0		-7.7975 (-1.723)	-4.1345 (-4.232)
δ^1			0.0216 (4.606)
σ	3.1493 (7.293)	19.7323 (1.785)	7.0067 (3.886)
log *L*	-695.52	-1400.00	-1392.07
n	1043	2086	2086

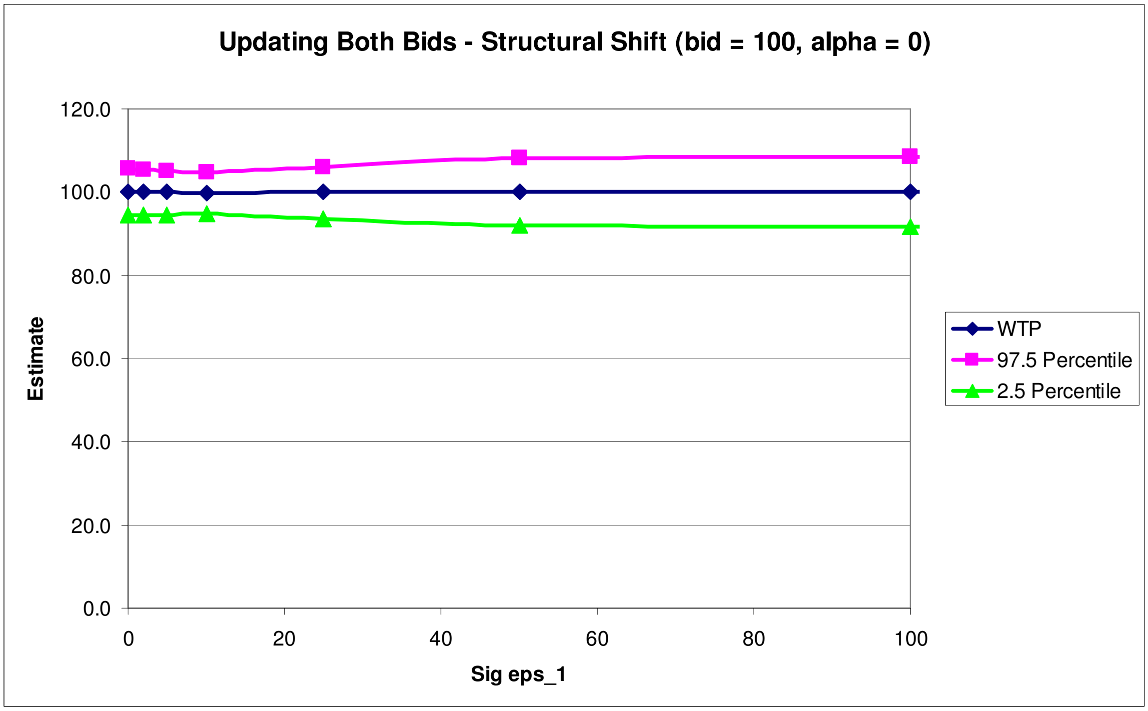
Note: t-statistics are in parenthesis

Figure 1. An Example of Generated Yes/No Responses Based Upon No Bayesian Updating, Updating on the Second Bid Only, and Updating on Both Bids for a Single Respondent



Yes/No Results:	Bid 1	Bid 2
Non-Bayes	1	1
Bayes (both)	1	0
Bayes (2^{nd})	1	0

Figure 2. Simulation results for $WTP_{i2} = WTP_{i0} + \delta I_2 + \eta_{i2}$, where $E(b_{i1})=E(WTP_{i0})=100$.
(a) Mean WTP, (b) Standard Deviation of WTP



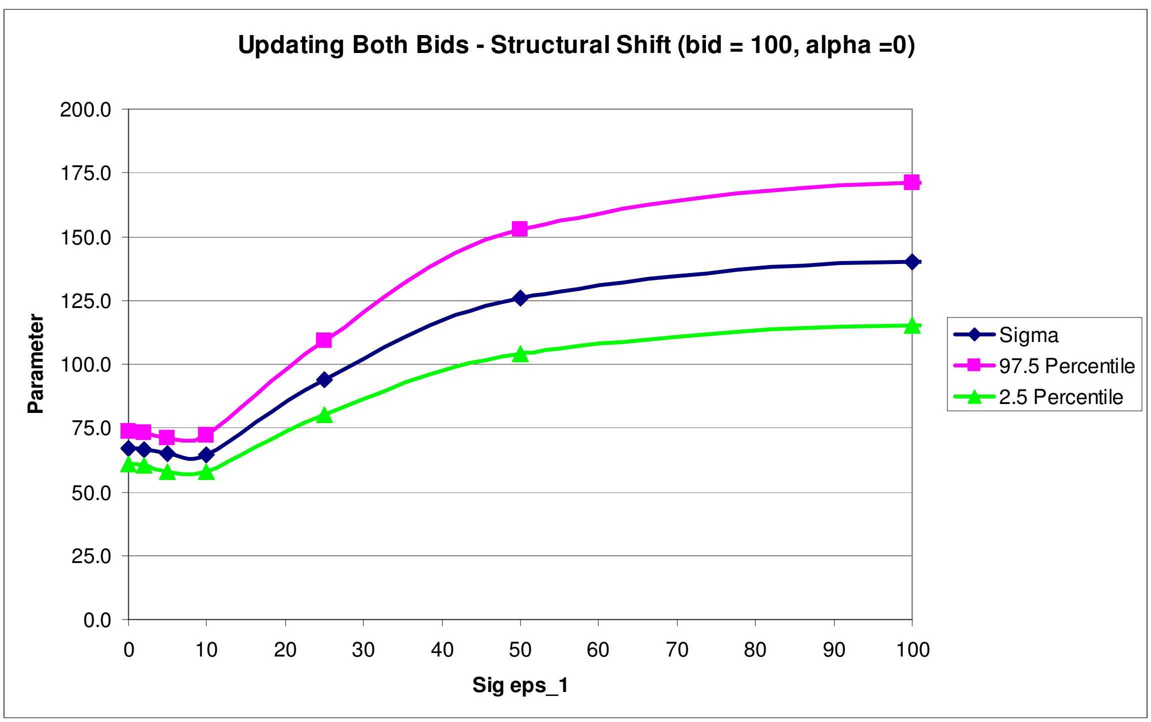
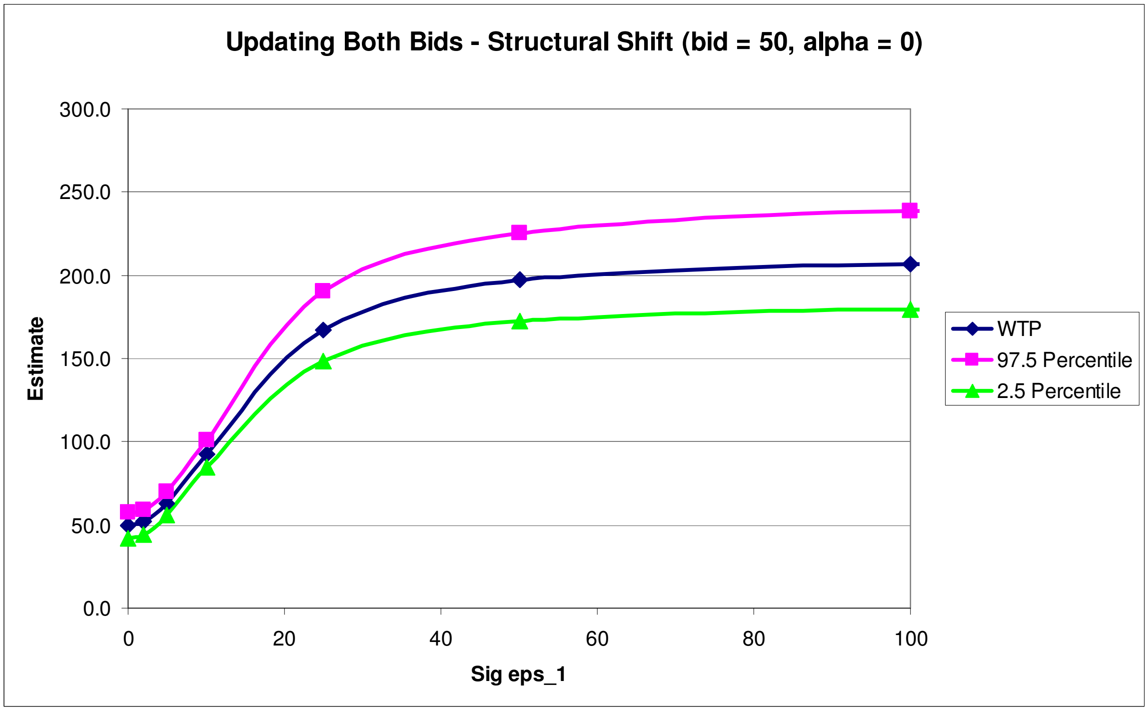


Figure 3. Simulation results for $WTP_{i2} = WTP_{i0} + \delta I_2 + \eta_{i2}$, where $E(b_{i1})$=50 < $E(WTP_{i0})$=100
(a) Mean WTP, (b) Standard Deviation of WTP



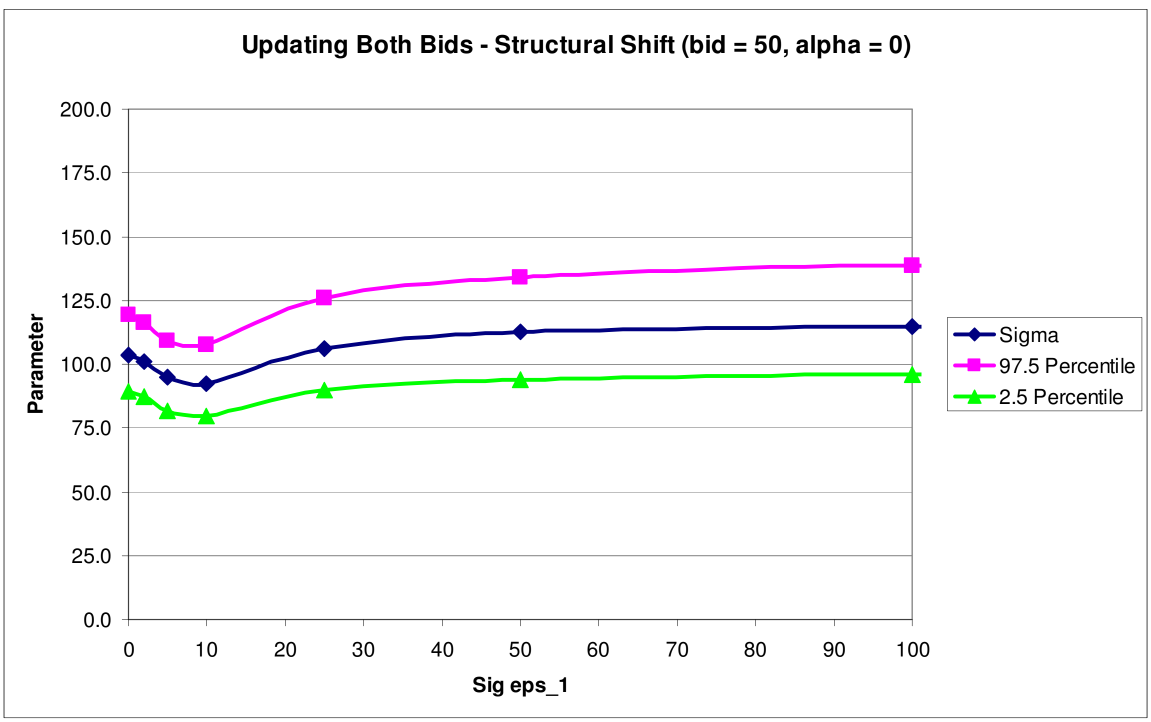
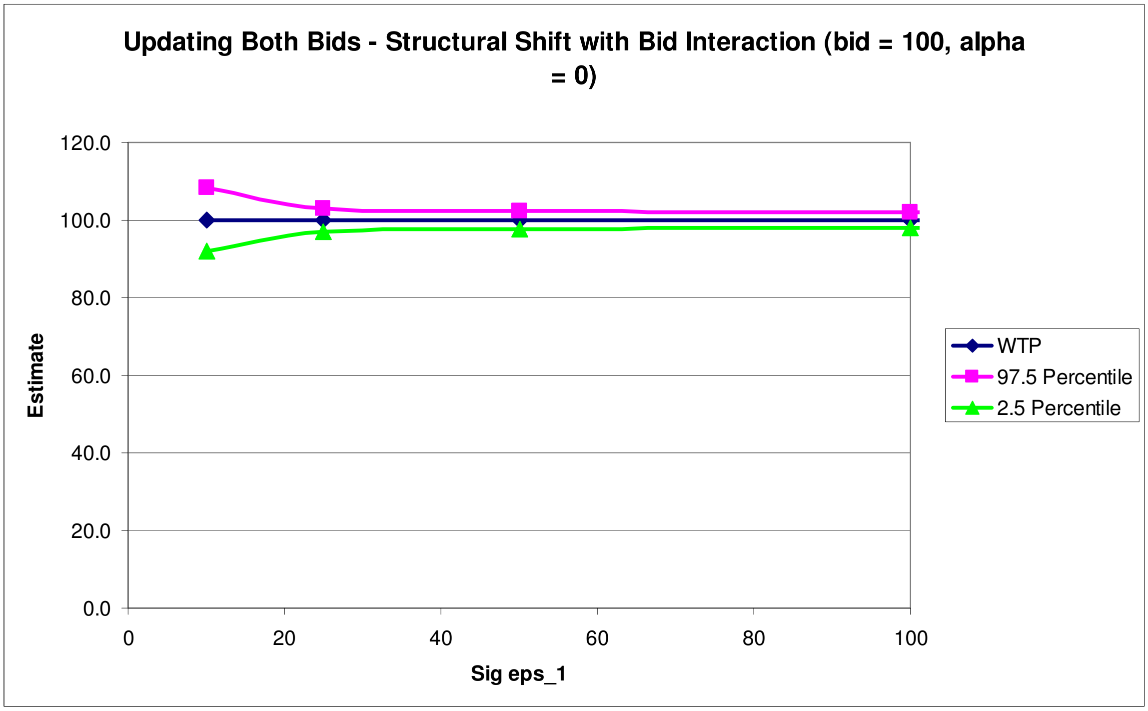


Figure 4. Simulation results for $WTP_{i2} = WTP_{i0} + \delta^0 I_2 + \delta^1 I_2 \left(b_{i2}\right) + \eta_{i2}$, $E(b_{i1})=E(WTP_{i0})=100$.
(a) Mean WTP, (b) Standard Deviation of WTP



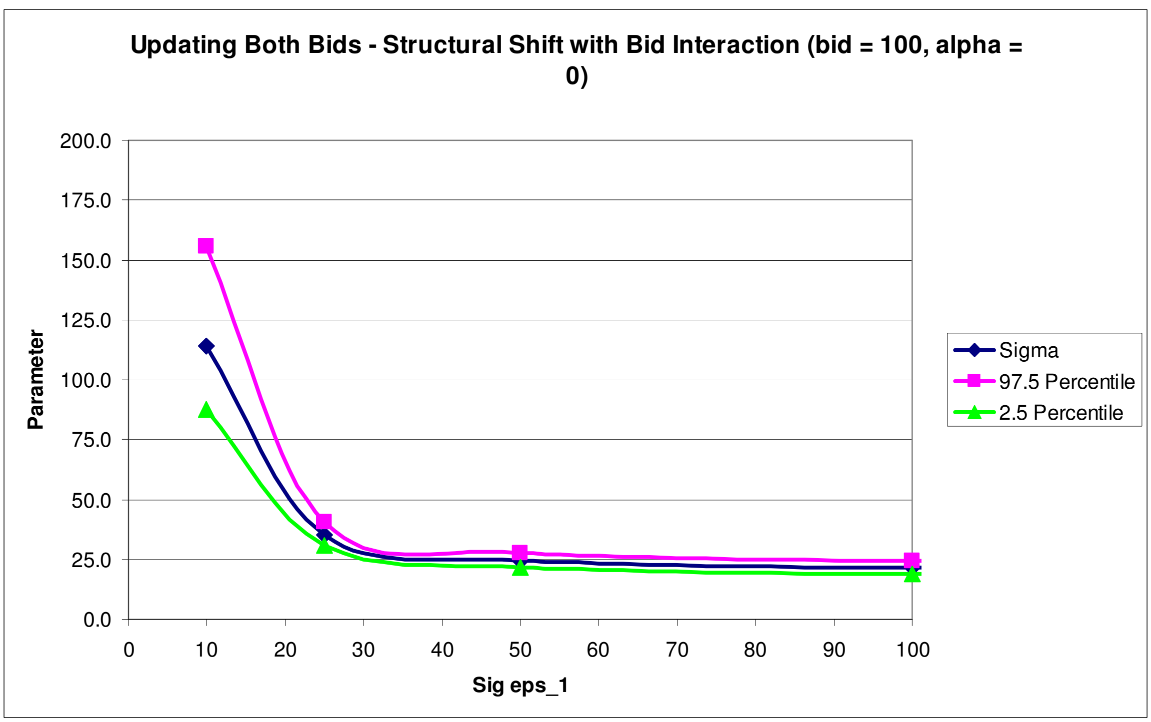
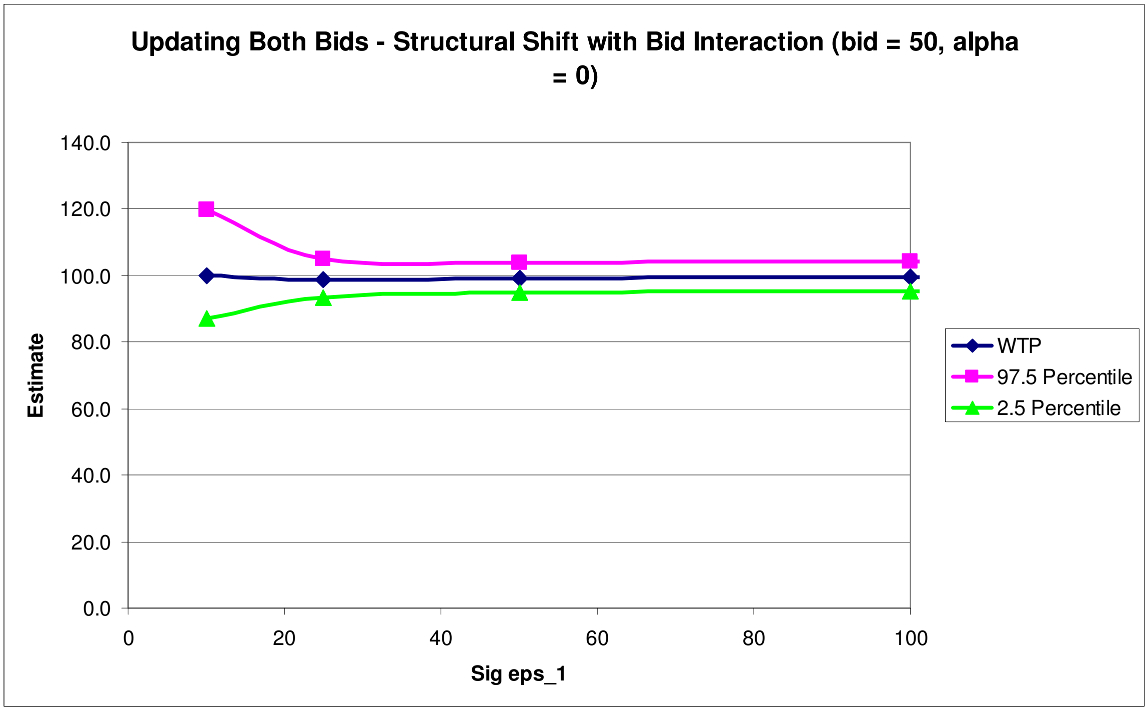


Figure 5. Simulation results for $WTP_{i2} = WTP_{i0} + \delta^0 I_2 + \delta^1 I_2 \left(b_{i2}\right) + \eta_{i2}$, where $E(b_{i1})$=50 < $E(WTP_{i0})$=100. (a) Mean WTP, (b) Standard Deviation of WTP



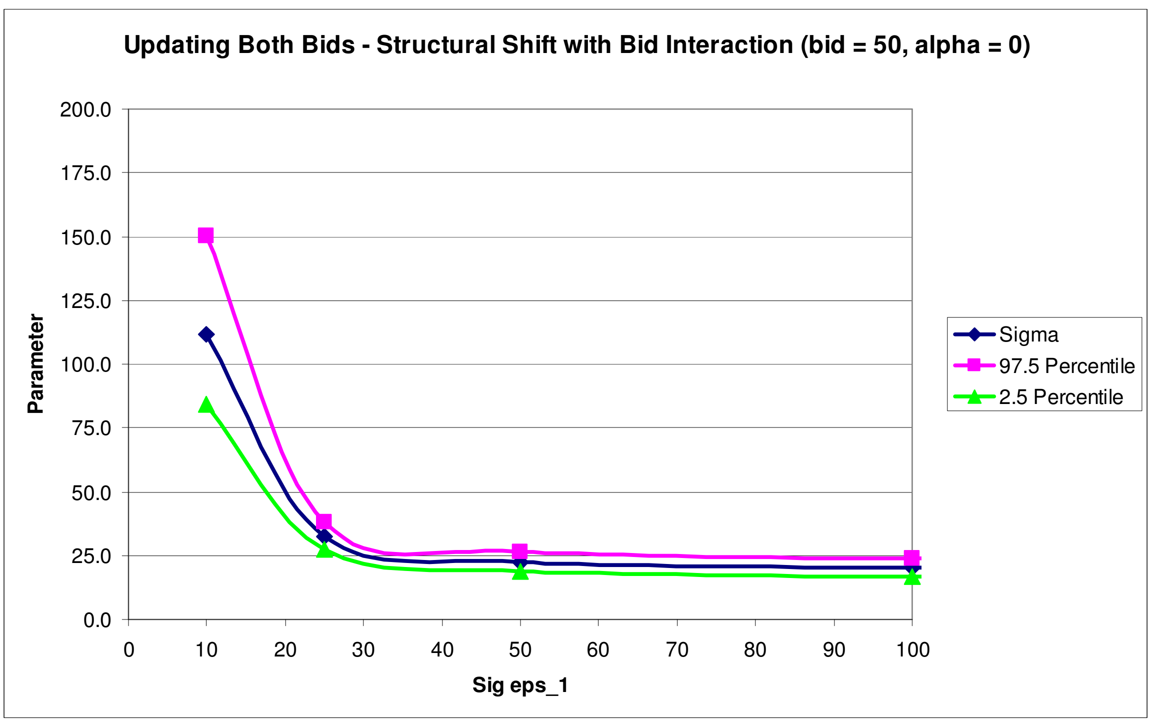
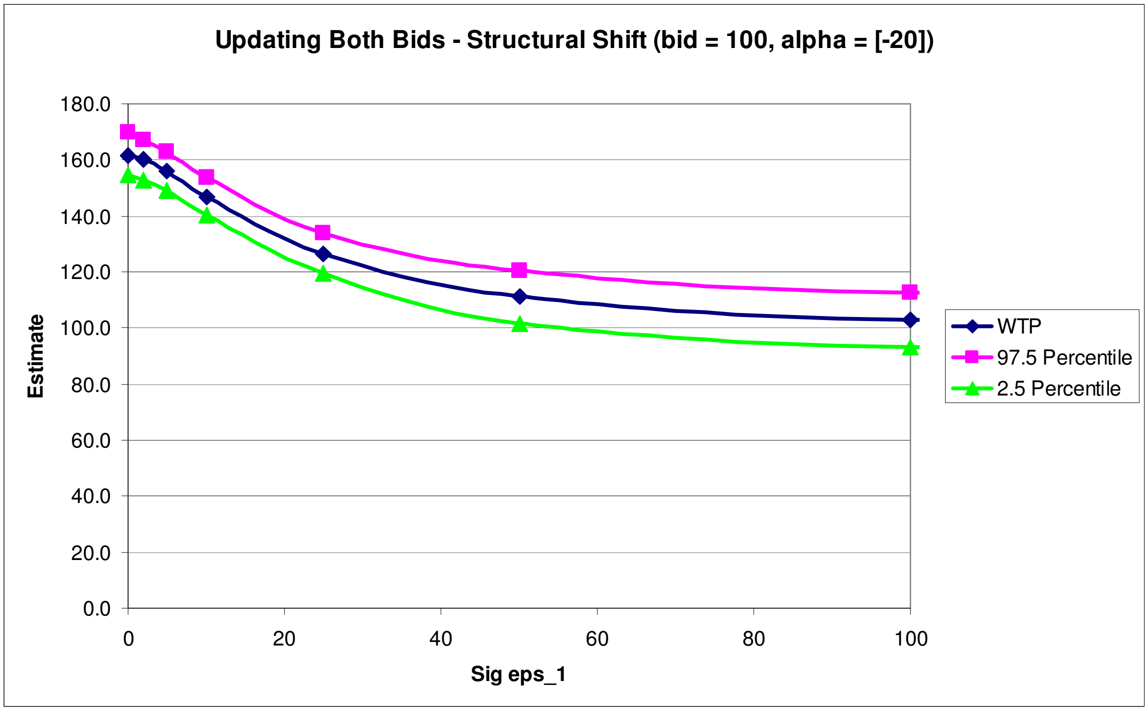


Figure 6. Mean WTP Simulation results for $WTP_{i2} = WTP_{i0} + \delta I_2 + \eta_{i2}$, and α_{ij} = - 20 .
(a) $E(b_{i1})=E(WTP_{i0})=100$, (b) $E(b_{i1})=50 < E(WTP_{i0})=100$



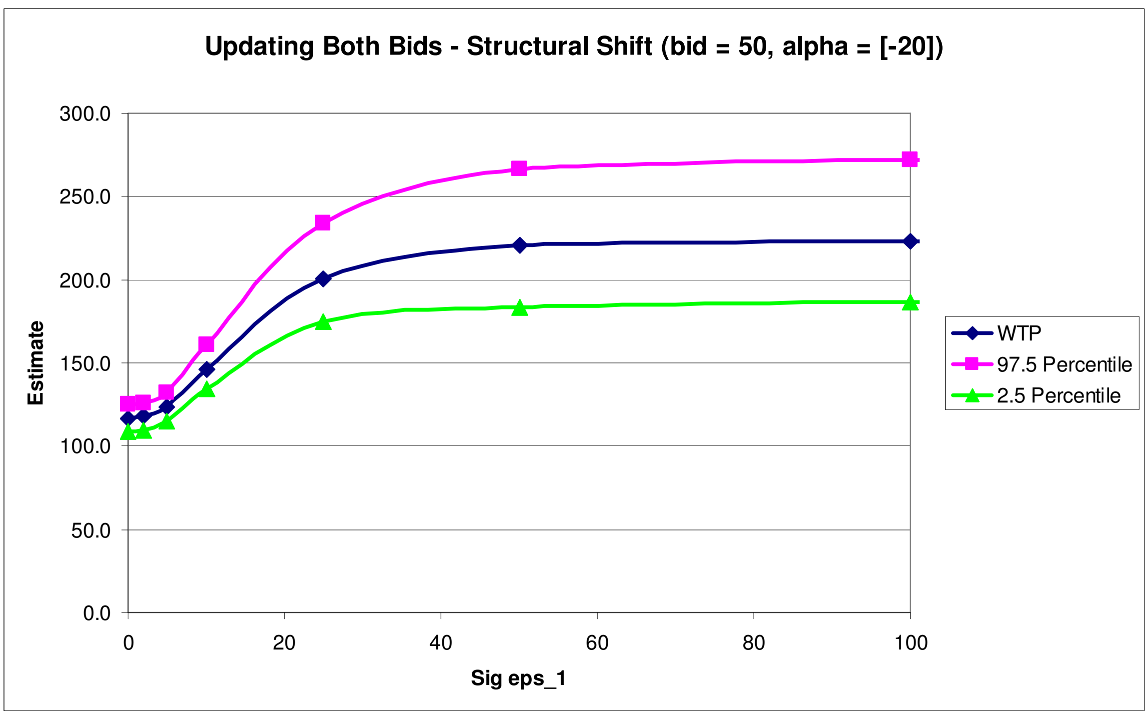
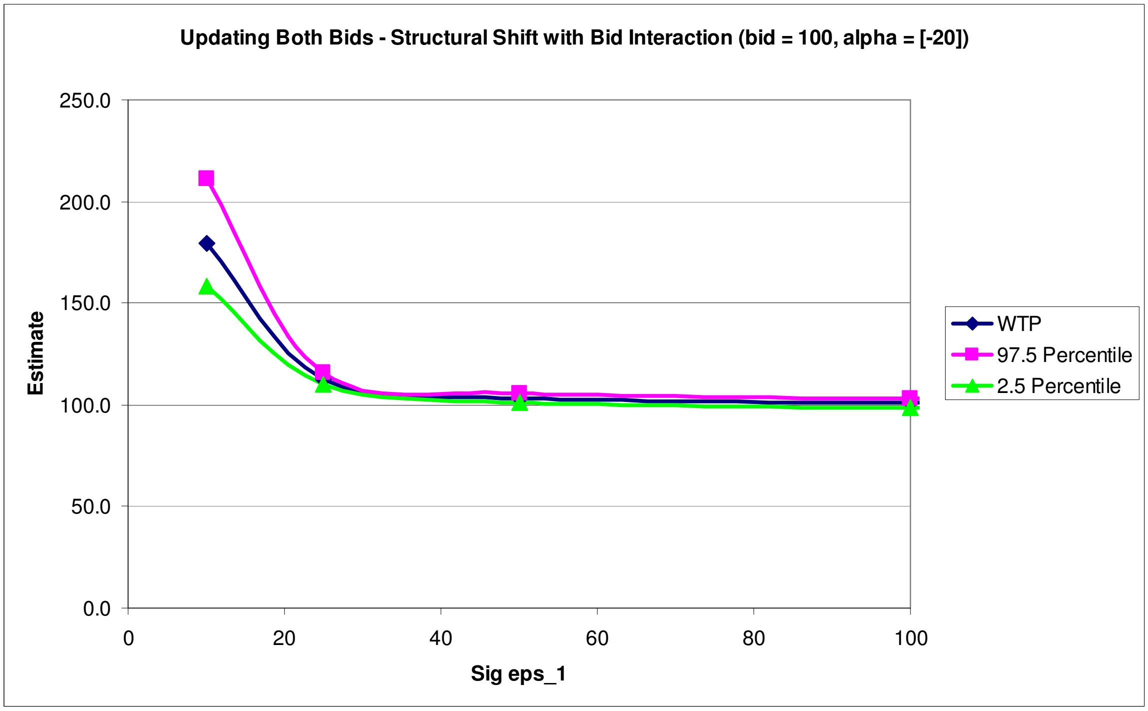
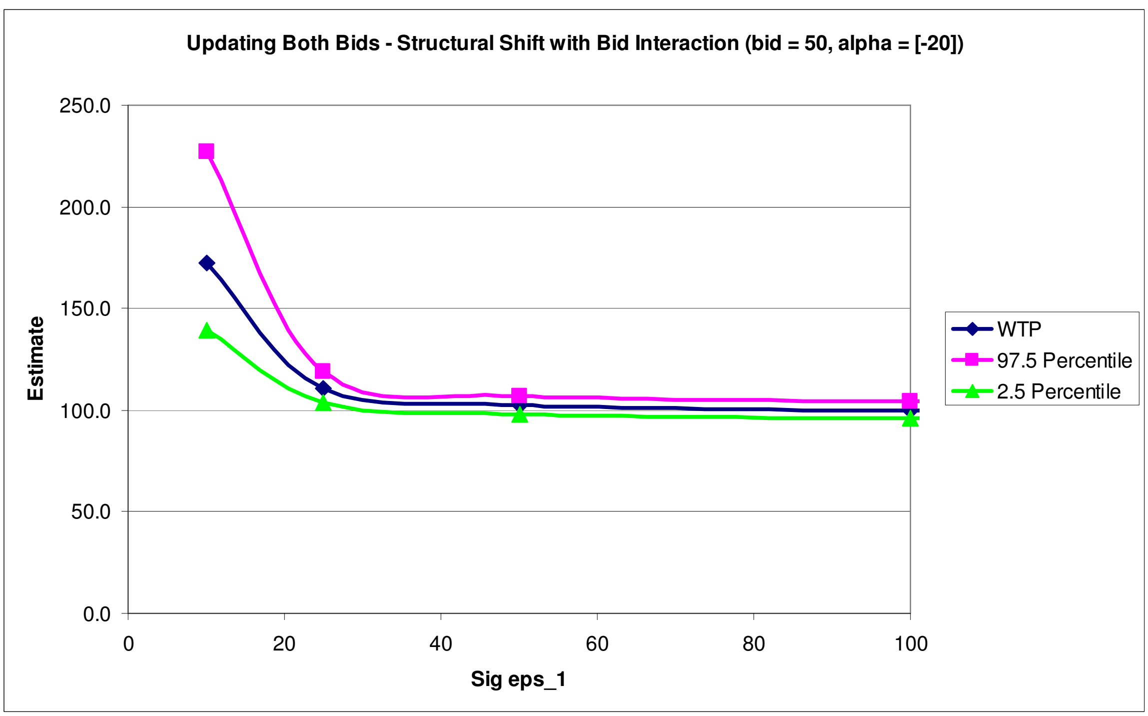


Figure 7. Mean WTP Simulation results for $WTP_{i2} = WTP_{i0} + \delta^0 I_2 + \delta^1 I_2 (b_{i2}) + \eta_{i2}$, and α_{ij} = - 20
(a) $E(b_{i1})=E(WTP_{i0})=100$, (b) $E(b_{i1})=50 < E(WTP_{i0})=100$





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