

A Bayesian Examination of Anchoring Bias and Cheap Talk in Contingent Valuation Studies

David Aadland, Arthur J. Caplan and Owen R. Phillips*

October 2005

Abstract

We present a theoretical framework for understanding the relationship between anchoring bias, hypothetical bias, and cheap talk in contingent valuation surveys. In our theory, interviewers provide agents with signals such as cheap talk and bid values while eliciting the value for nonmarket goods. In response to these signals, agents revise their prior distributions over the value of the good. Previous empirical studies have failed to account for the interaction between cheap talk and anchoring during this updating process, leading researchers to incorrectly assess the effects of cheap talk in reducing hypothetical bias. In particular, we predict that cheap talk will appear to be more effective for relatively large bids. We test our theory in an experimental setting where agents are asked to make a hypothetical, voluntary contribution to a public good. The experimental results, as well as several recent empirical studies, are consistent with the theory.

JEL Codes: Q51, C11, C91

Keywords: Cheap Talk, Bayesian Updating, Contingent Valuation, Anchoring Bias, Incentive Incompatibility

*Aadland and Phillips are associate and full professors of economics at the University of Wyoming, PO Box 3985, Laramie, WY, 82071-3985, USA; 307-766-4931 (Aadland phone); 307-766-5090 (fax); aadland@uwyo.edu (e-mail). Caplan is an associate professor at Utah State University, 3530 Old Main Hill, Logan, UT 84341. Support from the Paul Lowham Research Fund is gratefully appreciated. We thank Chris McIntosh and Neil Wilmot for their assistance with the experiments.

1 Introduction

The contingent valuation (CV) method, which uses hypothetical market environments to elicit consumers' maximum willingness to pay (WTP), has become a popular method for collecting data on the value of nonmarket goods.¹ A central problem with the CV method, however, is that because agents do not participate in real market environments, they are prone to hypothetical bias. As such, agents will often either knowingly or unknowingly misrepresent their true preferences for the good, i.e., preferences that would be revealed in repeated real-market interactions. In response, researchers have proposed remedies such as combining revealed and stated preference data (Adamowicz, Louviere and Williams (1994)), dichotomous-choice formats for estimating WTP (Cameron and James (1987)), and providing explicit warnings about the problem of hypothetical bias prior to the WTP questions, with the hope that respondents will self correct. This latter method is commonly referred to as “cheap talk” (Cummings and Taylor (1999)).² A common criticism of cheap talk is that it is ad hoc and not well grounded in economic theory.

The primary purpose of this paper is to lay a theoretical foundation for understanding why agents are subject to hypothetical bias and how they might react to information prompts such as cheap talk. It is natural to treat the reaction process as a Bayesian-updating problem, since agents are being provided with new information, which they can use to revise their WTP for the nonmarket good.³ We therefore begin with an abstract theory in which agents are prone to bias associated with formulating their WTP. The bias is modeled as a stochastic component of utility (and thus WTP) over which agents form priors. The priors are updated in a Bayesian manner as the interviewer presents the agent with signals, such as cheap talk and an opening bid for the nonmarket good. The agent

¹For an overview of this literature see Brookshire, Thayer, Schulze and D'Arge (1982), Hausman (1993), Mitchell and Carson (1989), and Cummings, Brookshire and Schulze (1986).

²The term “cheap talk” originates from the game-theory literature, where agents may send non-binding signals prior to commitment.

³Herriges and Shogren (1996) and McLeod and Bergland (1999) also use a Bayesian approach to examine the issues of anchoring bias and incentive incompatibility, respectively. Unlike their studies, however, we focus on the dual issues of cheap talk and anchoring bias.

then forms a rational, updated estimate of the distribution of the stochastic bias term and uses the estimate to calibrate a WTP response. By casting the CV problem in this setting, we are able to sort out previously conflicting empirical results associated with hypothetical bias and cheap talk. We also extend our theory to double-bounded dichotomous-choice (DBDC) formats and discuss the attendant issue of incentive incompatibility.

The key insight from this paper is that agents choose to rationally anchor their WTP estimates to an announced bid for the good in a manner that depends on whether they receive cheap talk. This dependence is important because the effectiveness of cheap talk in reducing hypothetical bias is tested by comparing the actions of those receiving cheap talk (treatment group) with those who do not (control group). Consequently, differences between the treatment and control groups that are attributed solely to cheap talk may instead reflect differences in how agents anchor their WTP estimates to announced bids.

The empirical evidence is mixed on whether cheap talk is an effective means of eliminating hypothetical bias in CV and field experiments. At one end of the spectrum, Cummings and Taylor (1999) find that a long cheap-talk script is effective in eliminating hypothetical bias. List (2001) and Lusk (2003) use a script similar to that of Cummings and Taylor and find that cheap talk only works for inexperienced consumers. This pattern is consistent with a Bayesian updating framework, where experienced consumers have “tightened” their posterior WTP distribution to the point where cheap talk is no longer effective. Poe, Clark, Rondeau and Schulze (2002) report that a shorter cheap-talk script is ineffective in eliminating hypothetical bias, while Loomis, Gonzalez-Caban and Gregory (1994) and Neil (1995) find that reminders about budget constraints and substitutes are also ineffective. Aadland and Caplan (2003) find that, although cheap talk is ineffective overall, it successfully reduces hypothetical bias for certain groups of respondents. On the other end of the spectrum, Cummings, Harrison and Taylor (1995) and Aadland and Caplan (forthcoming) use a shorter script and find that cheap talk may even exacerbate the hypothetical bias.

Three recent papers – Brown, Azjen and Hrubes (2003); Murphy, Stevens and Weatherhead (2005) and Cherry and Whitehead (2004) – find that the effectiveness of cheap talk depends upon the bid level. Indeed, the dependence reported in all three papers is consis-

tent with our theory: cheap talk appears to be effective at relatively high bid levels but ineffective at low bid levels.

In sum, although the pattern of effectiveness for various cheap-talk scripts is unclear, our Bayesian updating theory is capable of explaining several of the apparent anomalies found in the recent literature. In the next section, a theoretical framework for the Bayesian-updating problem is presented. Section 3 describes the experimental design used to test the model. Section 4 presents a series of econometric tests and results. Section 5 extends the theory to a DBDC format, where the issue of incentive incompatibility is explored. Section 6 summarizes the main findings.

2 Theoretical Framework

Assume a continuum of agents indexed on the unit interval. Representative agent $i \in (0, 1)$ maximizes utility

$$u_i = u(z_i, G(\eta_i); \theta_i) \quad (1)$$

by choosing a vector of private goods, z_i . Each agent's valuation of the public good, G , depends on a stochastic component η_i (discussed below). θ_i is a vector of individual-specific characteristics excluding income level. The agent's budget constraint is

$$m_i \geq p'z_i + g_i \quad (2)$$

where m_i is income, p is a vector of prices corresponding to z , and $g_i \geq 0$ is an exogenously determined lump-sum payment toward the provision of $G = \int_i g_i di$.

We invoke the standard assumption that utility is strictly increasing and concave in both the private and public goods. The term η_i reflects the notion that agents are not always capable of accurately assessing the value of the public good due to a lack of experience with the good or potential hypothetical bias associated with nonmarket valuation surveys. In particular, agents with $\eta_i > 0$ tend to overestimate their WTP for G , agents with $\eta_i < 0$ tend to underestimate their WTP for G , while agents with $\eta_i = 0$ accurately assess their

WTP for G . As we show below, although agents attempt to correct for the bias via their interactions with the interviewer, they do not necessarily have adequate information to completely eliminate it.⁴

Let $z_i^* = z(p, m_i - g_i, G(\eta_i); \theta_i)$ represent the agent's optimal choice of the private good vector, implying indirect utility level $u_i^* = u(z_i^*, G(\eta_i); \theta_i)$. The corresponding minimum expenditure function, defined with respect to net income, $m_i - g_i$, is

$$e_i = e(p, G(\eta_i), u_i^*; \theta_i) = m_i - g_i. \quad (3)$$

Using (3), the agent's WTP for G is derived as

$$WTP_i = e(p, G = 0, u_i^*; \theta_i) - e(p, G(\eta_i), u_i^*; \theta_i), \quad (4)$$

which is the difference between the minimum expenditure required to achieve utility level u_i^* without and with the public good. Due to the presence of η_i , (4) reflects the agent's perceived, rather than true, WTP for the public good. Accordingly, we characterize WTP as "true" WTP, $WTP_i(\eta_i = 0)$, plus the term δ_i :

$$WTP_i = WTP_i(\eta_i = 0) + \delta_i, \quad (5)$$

where δ_i has density function $p(\delta_i)$ with population mean

$$\mu = \int \delta_i p(\delta_i) d\delta_i. \quad (6)$$

We assume that δ_i is a random variable that reflects the agent's innate tendency to incorrectly estimate WTP for the public good. While agents do not know $p(\delta_i)$, they do hold prior beliefs regarding the distribution for δ_i . Based on this subjective probability distri-

⁴As is commonly done in the literature, we refer to hypothetical bias in a fairly narrow fashion as the tendency to misstate true WTP when in a hypothetical rather than real market environment. Our theory is general enough to handle related types of biases associated with nonmarket valuation, such as strategic bias, nay-saying, yeah-saying, etc.

bution for δ_i , they form a corresponding expectation denoted by $E_i(\delta_i)$. This expectation represents the agent's initial evaluation of personal bias. For example, if $\delta_i > E_i(\delta_i) = 0$, then the agent does not recognize that he or she is overvaluing the public good and thus a positive bias exists. Another possibility is that $\delta_i > E_i(\delta_i) > 0$, in which case the agent recognizes the public good is overvalued, but only partially corrects for the bias.

We refer to the agent's initial perceived WTP as WTP_i^0 , which is given by (5). However, as the agent receives information from the interviewer, the agent revises WTP_i in an attempt to reduce the influence of δ_i and bring perceived WTP closer to the true WTP. The agent thus forms

$$WTP_i^1 = E(WTP_i | s_i) = WTP_i^0 - E_i(\delta_i | s_i), \quad (7)$$

where $E_i(WTP_i | s_i)$ is agent i 's expectation of WTP_i conditional upon the information contained in the signal vector s_i . From (5) and (7), we see that clear signals provided by the interviewer regarding the population mean of δ_i are, on average, likely to bring perceived WTP closer to the true WTP.

2.1 Eliciting WTP

To elicit WTP_i for the public good in the dichotomous-choice format, the interviewer presents the agent with a hypothetical bid or price for the public good, τ_i . The agent then compares WTP_i^1 to τ_i , and hypothetically accepts if $WTP_i^1 > \tau_i$ and declines otherwise. Prior to offering the bid τ_i , however, the interviewer presents the agent with an additional signal, represented as the draw $c_i \in \{0, \mu\}$. A draw of $c_i = 0$ represents no additional signal, while a draw of $c_i = \mu > 0$ informs the agent of δ_i 's population mean. The latter type of signal is similar in spirit to the cheap talk of Cummings and Taylor (1999).

2.2 Bayesian Updating

Each agent faces a Bayesian-updating problem with a subjective prior distribution for δ_i , $h_i(\delta_i)$. We assume $E_i(\delta_i) = 0$ so that the agent initially perceives no bias in valuing the public good. After receiving the signal $s_i = \{c_i, \tau_i\}$ from the interviewer, the agent then

uses Bayes' formula to form the posterior distribution for δ_i :

$$k_i(\delta_i|s_i) \propto g_i(s_i|\delta_i)h_i(\delta_i), \quad (8)$$

where $g_i(s_i|\delta_i)$ is the distribution for s_i conditional on δ_i . The function $g_i(s_i|\delta_i)$ captures the essence of the revisions to beliefs about δ_i by directly accounting for the interaction between δ_i , c_i and τ_i . Assuming a quadratic loss function, the agent then responds “rationally” to s_i by forming an updated expectation of δ_i using⁵

$$E_i(\delta_i|s_i) = \int_{-\bar{\delta}}^{\bar{\delta}} \delta_i k_i(\delta_i|s_i) d\delta_i. \quad (9)$$

Based on c_i , we therefore have two scenarios to consider.

2.2.1 No Hypothetical-Bias Signal

We begin by considering the case where the agent receives the signal $s_i^0 = \{c_i = 0, \tau_i\}$. Because no signal is sent prior to the bid, revisions to δ_i are exclusively due to information contained in τ_i . For this scenario, we assume

$$E_i(\delta_i|s_i^0) = \alpha(WTP_i^0 - \tau_i) \quad (10)$$

where $0 < \alpha < 1$. Equation (10) states that in revising the bias estimate, the agent considers the bias to be a fraction of the difference between the initial WTP estimate and the bid. Implicit in (10) is the fact that the agent perceives τ_i as a signal that the interviewer has private information regarding the true WTP distribution. Substituting (10) into (7), we obtain an updated WTP (WTP_i^1) via the function

$$WTP_i^1 = (1 - \alpha)WTP_i^0 + \alpha\tau_i. \quad (11)$$

⁵See Hogg and Craig (1978) for a discussion of Bayesian estimation.

This updating function is equivalent to the one presented in Herriges and Shogren (1996).⁶

There is strong evidence to support the notion of anchoring, beginning with Tversky and Kahneman (1974) and discussed more recently by McFadden (2001). To clarify, consider the following. Suppose the agent begins with an initial perceived valuation of the public good, WTP_i^0 , which is based on a noninformative prior and initial expectation of bias $E_i(\delta_i) = 0$. The agent is then confronted with a bid such that $\tau_i > WTP_i^0$. This bid anchors perceptions. The agent interprets this information as indicating that the true WTP value is likely to be somewhere between WTP_i^0 and τ_i . As a result, the agent now places a larger probability on outcomes where $\delta_i < 0$ and infers that the perceived distribution for δ_i needs to be shifted to the left. This implies that the agent revises the perceived WTP upward toward τ_i , resulting in $WTP_i^1 > WTP_i^0$. Conversely, when $\tau_i < WTP_i^0$, the agent assumes it is now more probable that $\delta_i > 0$ and that the initial WTP was biased upward. In this case, the agent revises the perceived WTP downward toward τ_i , resulting in $WTP_i^1 < WTP_i^0$. Finally, when s_i^0 does not reveal any new information (i.e., when $c_i = 0$ and $\tau_i = WTP_i^0$), the agent does not revise the initial expectations and sets $WTP_i^1 = WTP_i^0$.

2.2.2 A Signal About The Mean of Hypothetical Bias

Next, consider the case where the agent receives the sequential signal $s_i^1 = \{c_i = \mu, \tau_i\}$ from the interviewer. In other words, prior to receiving the bid the agent receives the signal that δ_i has population mean μ . Keep in mind, this does not imply that the agent now knows δ_i with certainty, only that it is drawn from a distribution with mean μ .

We assume that in response to the initial signal $c_i = \mu$, the agent revises the estimate of δ_i so that $E_i(\delta_i|c_i = \mu) = \mu$.⁷ The agent therefore estimates that his or her individual

⁶The weighted-average form of the updating function in (11) results if $g_i(s_i|\delta_i)$ is a normal distribution and $\alpha = \sigma_h^2/(\sigma_g^2 + \sigma_h^2)$, where σ_g^2 is the variance of $g_i(s_i|\delta_i)$ and σ_h^2 is the variance of the prior distribution $h_i(\delta_i)$. The formal derivation of (11) is available, upon request, in a technical appendix.

⁷Some may argue that agents are unlikely to adjust their WTP perfectly to the signal $c_i = \mu$. For simplicity, we assume perfect adjustments, however, it is important to recognize that the subsequent results are robust to partial adjustments where $0 < E_i(\delta_i|c_i = \mu) < \mu$.

bias is equal to the average bias in the population. Next, the agent compares the adjusted WTP ($WTP_i^0 - \mu$) to τ_i and uses a variation of equation (10) to update their estimate of δ_i :

$$E_i(\delta_i | s_i^1) = \mu + \gamma(WTP_i^0 - \mu - \tau_i),$$

where $0 < \gamma < 1$. This implies

$$WTP_i^1 = (1 - \gamma)(WTP_i^0 - \mu) + \gamma\tau_i. \quad (12)$$

To test whether the cheap-talk signal $c_i = \mu$ is effective in eliminating hypothetical bias, the relevant measure is

$$\begin{aligned} \Delta_i &\equiv E_i(WTP_i | s_i^1, WTP_i^0) - E_i(WTP_i | s_i^0, WTP_i^0) \\ &= (\alpha - \gamma)(WTP_i^0 - \tau_i) + (\gamma - 1)\mu. \end{aligned} \quad (13)$$

If $\Delta_i = -\mu$, we conclude that cheap talk successfully reduced agent i 's WTP bias by μ . We now discuss several different cases that depend on the relative values of α , γ , WTP_i^0 , and τ_i .

Case 1. Common Anchoring Structure ($\gamma = \alpha$) We begin with the case where $\gamma = \alpha$, that is, the agent anchors to τ_i in the same fashion with or without cheap talk. Equation (13) then collapses to $\Delta_i = (\gamma - 1)\mu$, which implies that even when cheap talk reduces initial WTP by exactly μ , anchoring makes it appear that cheap talk was only partially effective (i.e., $\Delta_i > -\mu$). Furthermore, as $\alpha = \gamma \rightarrow 1$, cheap talk appears to have no effect because the anchoring completely overshadows the cheap-talk adjustment.

Figure 1 depicts the interaction between cheap talk and anchoring bias for Case 1, assuming $WTP_i^0 - \mu > \tau_i$. Panel A shows the prior and posterior distributions for δ_i when the agent receives the signal s_i^1 . The agent begins with the noninformative prior distribution $h_i(\delta_i)$. After receiving the signal $c_i = \mu$, the agent then revises the distribution to $k_i(\delta_i | c_i = \mu)$, leading to a revised WTP equal to $WTP_i^0 - \mu$. Next, the agent receives

the bid τ_i and further revises the distribution to $k_i(\delta_i|s_i^1)$ with conditional mean WTP_i^1 . In Panel B, the agent begins with the same noninformative prior, receives bid τ_i without having been subjected to any cheap talk, and then revises the distribution for δ_i to $k_i(\delta_i|s_i^0)$. In comparing Panels A and B, note that although WTP_i^1 is farther to the left in Panel A than in Panel B, the difference between the two is less than μ . As a result, when testing for cheap talk, we incorrectly conclude that cheap talk only partially eliminates the bias μ .

To clarify, consider the following numerical example. Suppose the agent's $WTP_i^0 = \$10$ and the cheap-talk signal is $c_i = \mu = \$4$. The agent then adjusts initial WTP to be consistent with the first signal (i.e., $WTP_i^0 - \mu = \$6$) and compares this to the bid, which we assume is $\tau_i = \$2$. Letting $\alpha = \gamma = 0.5$, $WTP_i^1 = (0.5 \times 6) + (0.5 \times 2) = \4 with an anchoring effect of $\$4 - \$6 = -\$2$. By comparison, when $c_i = 0$ the agent sets $WTP_i^1 = (0.5 \times 10) + (0.5 \times 2) = \6 , implying an anchoring effect of $\$6 - \$10 = -\$4$. Note that although cheap talk reduces initial WTP exactly as anticipated, because of the interaction with anchoring bias, cheap talk appears to be only partially effective (i.e., $\Delta_i = \$4 - \$6 = -\$2 > -\mu = -\4).

Case 2. Dual Anchoring Structures ($\gamma \neq \alpha$) We now consider the case where the anchoring parameter is different with and without the cheap-talk signal. We assume throughout that $\gamma < \alpha$ so that the anchoring effect associated with τ_i is weakened by the presence of a cheap-talk signal. It is important to recognize that by assuming $\gamma < \alpha$, we are not claiming that the *total* effect of cheap talk and anchoring on WTP is necessarily smaller than without cheap talk, only that the *marginal* contribution of anchoring is weakened by the presence of cheap talk.

Begin by defining a critical bid level

$$\tau_i^* = WTP_i^0 + [\gamma/(\alpha - \gamma)]\mu, \quad (14)$$

which equates the measured cheap-talk effect in (13) to $-\mu$. As a result, for cheap talk to appear fully effective, the bid must equal WTP_i^0 plus a positive constant. Figure 2 depicts

the combination of WTP_i^0 and τ_i values that will result in a measured cheap-talk effect equal to $-\mu$. Using this τ_i^* locus and the 45 degree line from Figure 2, we define three distinct regions and discuss how they relate to Δ_i .

Region 1. Ineffective Cheap Talk ($\tau_i < WTP_i^0$). In this case, the agent receives a *relatively* low bid τ_i , corresponding to the region below the 45 degree line in Figure 2. When $c_i = 0$, the agent then anchors downward toward τ_i . If instead the agent receives the cheap-talk signal $c_i = \mu$ prior to receiving the bid, then depending upon the size of μ , the agent may either anchor downward toward the bid (when $WTP_i^0 - \mu > \tau_i$), anchor upward toward the bid (when $WTP_i^0 - \mu < \tau_i$) or not anchor at all (when $WTP_i^0 - \mu = \tau_i$). Because $\tau_i < \tau_i^*$, the measured cheap-talk effect will be larger than $-\mu$. In fact, we know from (13) that Δ_i will be larger than $(\gamma - 1)\mu$. Therefore, we are likely to mistakenly conclude that cheap talk is ineffective in eliminating the hypothetical bias, or worse yet, that it exacerbates the bias.

Region 2. Partially or Fully Effective Cheap Talk ($\tau_i^* \geq \tau_i \geq WTP_i^0$). In this case, the agent receives a bid that is no less than initial WTP but no greater than the critical bid value. This corresponds to the region in Figure 2 between (and including) the 45 degree line and the τ_i^* locus. First, if $\tau_i = WTP_i^0$, anchoring only occurs for those who receive the signal $s_i = \mu$. As in Case 1, (13) simplifies to $\Delta_i = (\gamma - 1)\mu$, implying that cheap talk appears to be only partially effective. On the other hand, if $\tau_i = \tau_i^*$, then by (14), the measured cheap-talk effect equals $-\mu$, and cheap talk appears to be fully effective. In sum, any bid value between τ_i^* and WTP_i^0 leads to a measured cheap-talk effect between $(\gamma - 1)\mu$ and $-\mu$.

Consider another numerical example. Suppose that $WTP_i^0 = \$10$, $c_i = \mu = \$4$, $\alpha = 0.5$ and $\gamma = 0.25$, implying a critical bid value from (14) of $\tau_i^* = 14$. The agent first adjusts the initial WTP to be consistent with the cheap-talk signal (i.e., $WTP_i^0 - \mu = \$6$) and then compares this to an assumed bid of $\tau_i = \$12$. Revised WTP is thus $WTP_i^1 = (0.75 \times 6) + (0.25 \times 12) = \7.5 with an anchoring effect of $\$7.5 - \$6 = \$1.5$. By comparison,

when $c_i = 0$ the agent sets $WTP_i^1 = (0.5 \times 10) + (0.5 \times 12) = \11 , implying an anchoring effect of $\$11 - \$10 = \$1$. As in Case 1, cheap talk reduces initial WTP exactly as anticipated but it appears to be only partially effective (i.e., $\Delta_i = \$7.5 - \$11 = -\$3.5 > -\mu = -\4).

Region 3. Overly Effective Cheap Talk ($\tau_i > \tau_i^*$). In this case, the agent receives a *relatively* high bid τ_i , corresponding to the area above the τ_i^* locus in Figure 2. After receiving the signal s_i^0 , the agent anchors upward toward τ_i . If the agent instead receives the signal $c_i = \mu$ prior to receiving the bid, the agent similarly anchors upward toward the bid (note that $WTP_i^0 < \tau_i$ implies that $WTP_i^0 - \mu < \tau_i$ as well). Because $\tau_i > \tau_i^*$, we know that Δ_i will be smaller (more negative) than $-\mu$. We therefore conclude that although cheap talk corrects for hypothetical bias, it does so by too much.

Returning to our numerical example, we consider a case where $\tau_i = \$18 > \$14 = \tau_i^*$. As in the previous examples, the agent's initial revised WTP with cheap talk is \$6. Again, letting $\alpha = 0.5$ and $\gamma = 0.25$, we see that with cheap talk $WTP_i^1 = (0.75 \times 6) + (0.25 \times 18) = \9 , with an anchoring effect of $\$9 - \$6 = \$3$. With no cheap talk, the agent's $WTP_i^1 = (0.5 \times 10) + (0.5 \times 18) = \14 , with an anchoring effect of $\$14 - \$10 = \$4$. In this case, we mistakenly conclude that cheap talk overcorrects for hypothetical bias (i.e., $\Delta_i = \$9 - \$14 = -\$5 < -\mu = -\4).

3 Experimental Designs

These experiments are designed to capture the influence of valuation uncertainty, hypothetical bias, anchoring, and cheap talk within a controlled laboratory setting. Instructions are available upon request from the authors. Approximately 300 participants were recruited via email using a comprehensive list of students provided by the Registrar's Office at the University of Wyoming. Most subjects were undergraduate business majors. The experiments consisted of three treatments – revealed preference (RP), stated preference with no cheap talk (NCT), and stated preference with cheap talk (CT). The RP treatment was

included to test for hypothetical bias.⁸

Each of the treatments was comprised of three sessions ranging from 20 to 30 students per session. In each treatment, participants were given \$10 to “invest” either for real (in the RP treatment) or hypothetically (in the NCT and CT treatments). As participants entered a classroom, they received \$10 in cash, an instruction page, and a page asking for the first investment decision in a series of two hypothetical or actual investment decisions. The instruction page, along with an example, were read aloud to the participants and any questions regarding the experiment were answered.

The example and actual payout charts used in the experiments are presented below. In the example, five people could invest between \$0 and \$2. Depending on their average investment and the roll of a die, the payout chart shows all the possible returns to an investment. After deciding an amount to invest, which could be \$0 putting the subject in the “No, I won’t invest” section of the chart, a die would be thrown to decide if the payout was the min (1 or 2 on the die), mid (3 or 4), or max (5 or 6). After the example chart was explained subjects were then taken to the actual payout chart.

[Insert Sample and Actual Payout Charts Here]

Focusing on the payout charts, note that while the cooperative outcome to the investment game – everyone investing between \$8 and \$10 in the actual chart – results in the highest expected return for the participants, the noncooperative solution of no investment is the dominant strategy for all individuals. This captures the free-riding problem associated with public goods. Also note that valuation uncertainty (δ) is captured by imposing a random payout range for investment intervals. The actual payout chart uses \$2 intervals.

Participants completed the first page of the experiment (which elicited a continuous measure of their initial WTPs for the actual payout chart) – this page was collected and a second page was distributed. The second page elicited the participants’ dichotomous investment choices. For the RP treatment, each participant’s investment was collected. The

⁸Prior to the actual sessions, a trial version of the RP and CT treatments were run with 10 students per session.

total class contribution was then calculated and “returns on investment” were calculated and announced. Participants in the RP treatment were paid and excused after the results were announced. The entire experiment lasted between 10 and 15 minutes per session. All subjects were asked to complete a brief demographic questionnaire before leaving. In the RP treatment, average earnings (net of the initial \$10 endowment) were approximately \$0.50.

Page 1 of the experiment generates a continuous value for WTP_i^0 ; participants were asked, “As an initial guess, how much of your \$10 do you think you would be willing to invest?” Page 2 then follows-up this question with a referendum, “Would you be willing to make an investment of \$xx?”, where each participant was given a different randomly selected \$xx amount from the set of bids $\{\$1, \$3, \$5, \$7, \$9\}$. In the case of the CT treatment, the referendum was preceded by the following cheap-talk script,

Before answering the next question please note that in previous runs of this experiment we found that people typically overstate their true willingness to invest by approximately \$2.00 when asked to do so in a hypothetical setting like this. Please keep this in mind when answering the next question.

We now turn to the econometric analysis of the experimental data.

4 Econometric Methods and Results

Selected descriptive statistics are provided in Table 1. These are based in part on the demographic surveys completed by subjects. As Table 1 indicates, the average initial willingness to pay (WTP^0) is \$3.60, while the average bid is \$4.95 with 48% of respondents saying “yes” to the investment question. Across the NCT and RP treatments ($N = 127$), 55% of participants made hypothetical investment decisions while the remaining 45% made real investment decisions. Within the stated preference treatments ($N = 153$), there is also a nearly even split, with 54% receiving cheap talk (CT) and 46% receiving no cheap talk (NCT). Subjects were asked to select from one of four actual income categories, starting

at less than \$10,000 and the largest greater than \$30,000. Risk aversion was measured by asking subjects if they would prefer \$10 with certainty, a 50% chance of \$0 or \$20, or were indifferent between the options.

4.1 Econometric Methods

There are two sources of experimental information on WTP – a continuous initial measure, WTP_i^0 , and a dichotomous-choice response to the investment amount τ_i . Begin with the following model for WTP_i^0 :

$$WTP_i^0 = X_i' \beta + \nu_i \quad (15)$$

where $i = 1, \dots, N$ indexes individual observations, X_i is a vector of demographic characteristics, β is the corresponding vector of coefficients, and ν_i is an i.i.d. normally distributed error term with a zero mean.

As is common in the cheap-talk literature, we specify an empirical model for the (latent) WTP_i^1 variable which allows us to estimate a constant cheap-talk coefficient⁹

$$WTP_i^1 = WTP_i^0 + \Delta C_i + \beta_\tau \tau_i + \epsilon_i \quad (16)$$

where ϵ_i is an i.i.d. normally distributed error term with a zero mean and variance σ_ϵ^2 , C_i is a dummy variable set equal to one if the i^{th} agent receives cheap talk and zero otherwise, and Δ and β_τ are parameters capturing potential cheap-talk and anchoring effects, respectively. Substituting (15) into (16), we arrive at an alternative estimable equation

$$WTP_i^1 = X_i' \beta + \Delta C_i + \beta_\tau \tau_i + (\epsilon_i + \nu_i). \quad (17)$$

⁹Recall that the cheap-talk measure Δ_i in (13) varies across all agents. Here, we are interested in specifying an estimable equation with a constant cheap-talk coefficient, Δ , that is similar to that commonly estimated in the literature and that will enable us to highlight the biases associated with failing to recognize the interaction between cheap talk and anchoring. Also, note that although Δ_i in (13) is defined as the difference of expected values (with and without cheap talk) for the same agent, the econometric analysis will contrast the expected WTP of one set of agents that receive cheap talk (treatment group) with a different set of agents that do not receive cheap talk (control group), holding all other observable factors constant.

We then define the binary variable $ACCEPT_i$, which equals one if the agent invests at his or her given investment level τ_i , and zero otherwise. As is standard in the literature, we assume that $ACCEPT_i = 1$ responses imply $WTP_i^1 > \tau_i$ and $ACCEPT_i = 0$ responses imply $WTP_i^1 \leq \tau_i$.

Next, we define the necessary probabilities for maximum-likelihood estimation. Using (16), the probability that agent i will accept bid τ_i is

$$\begin{aligned}
P_i &= \Pr[ACCEPT_i = 1] \\
&= \Pr[WTP_i^1 > \tau_i] \\
&= \Pr[\epsilon_i > -WTP_i^0 - \Delta C_i + (1 - \beta_\tau)\tau_i] \\
&= \Phi\left(\frac{1}{\sigma_\epsilon}[WTP_i^0 + \Delta C_i - (1 - \beta_\tau)\tau_i]\right)
\end{aligned} \tag{18}$$

for $i = 1, \dots, N$, where Φ is the standard normal cumulative density function. The associated log likelihood function is

$$\log L = \sum_{i=1}^N \{ACCEPT_i \ln(P_i) + (1 - ACCEPT_i) \ln(1 - P_i)\}. \tag{19}$$

As mentioned in the introduction, the existing cheap-talk literature reports mixed results regarding estimates of Δ . Some studies have found that cheap talk is effective (i.e., estimates of Δ are negative and statistically significant), while others have found estimates of Δ that are statistically indistinguishable from zero or possibly even positive. Based on our theory, estimates of Δ from equation (16) or (17) are likely to be biased because they do not account for the interaction of anchoring with cheap talk. As highlighted in Regions 1 and 3 of Figure 2, if $WTP_i^0 < (>)\tau_i$ we expect estimates of Δ will be biased upward (downward) in magnitude.

To explore this possibility, we partition our sample into those who made investment decisions at *relatively* low bid levels ($WTP_i^0 > \tau_i$) and those who made investment decisions at *relatively* high bid levels ($WTP_i^0 \leq \tau_i$). We then estimate equation (16) for these two subsamples. Our theory predicts that the estimate of Δ for the high-bid sample will be

negative and less than the estimate for the low-bid sample.

4.2 Econometric Results

We present econometric results based on two different samples – the full sample (Table 2) and a sample including only upperclassmen – juniors, seniors and graduate students – or those with GPAs higher than 3.5 (Table 3).¹⁰ Begin by focusing on the results from the full sample reported in Table 2. Model 1, which corresponds to equation (15), is estimated using ordinary least squares (OLS). Student characteristics such as rank, GPA, gender, age, income and sensitivity to risk are only able to explain about 7% of the variation in initial WTP. Despite the low overall explanatory power, however, we find that those who are risk averse and upperclass display a significantly lower initial WTP. Model 2 tests for hypothetical bias using a probit model on the RP and NCT treatment data. The coefficient on HYP, although positive, is not statistically different than zero, suggesting that there is no evidence of significant hypothetical bias in the full sample (as we will discuss below, however, there is some evidence of hypothetical bias in Table 3).¹¹

Models 3 through 5 estimate the effect of cheap talk on WTP, again using a probit model. Model 3 does so for the full sample, while models 4 and 5 split the samples into the relatively high-bid and low-bid groups, respectively. To save on degrees of freedom in the partitioned samples, all three models are estimated with initial WTP on the right-hand side, that is, using (16) rather than the full set of demographic variables in (17). The results are qualitatively similar using either approach. Most importantly, note that the cheap-talk dummy variable in model 3, while negative, is not statistically different than zero.¹² This is consistent with much of the recent cheap-talk literature, which finds mixed evidence that cheap talk is effective. However, in model 4 cheap talk is effective for those

¹⁰We consider the latter sample based on the presumption that these participants may have more experience and/or aptitude in dealing with such analytical exercises.

¹¹This result is robust to the type of heteroscedasticity suggested by Haab, Huang and Whitehead (1999).

¹²Because of the possible anchoring effects reflected by the coefficient β_τ in (16), we are not able to identify the parameter σ_ϵ^2 as in Cameron and James (1987). Fortunately, identification of σ_ϵ^2 is not necessary to contrast the estimation results from the relatively high- and low-bid samples.

receiving relatively high bids, while in model 5 it is ineffective (even positive) for those receiving low bids. These results support our hypotheses as shown in Regions 1, 2 and 3 of Figure 1.

Finally, consider the results from Table 3 using the upperclass/high GPA sample. For the most part, the results from Table 3 are similar to those in Table 2, with two primary differences. First, we find significant evidence of hypothetical bias in this sample, indicating that participants are either more likely to (i) overcontribute to the public good in hypothetical settings and/or (ii) not contribute in the real settings. Second, although the ordering of the coefficients on the cheap-talk (C) variable in models 3 through 5 are consistent with our theory, the coefficient in model 4 is not statistically different than zero. In part, this may reflect the smaller sample size as compared with the full sample.

5 DBDC Formats and Incentive Incompatibility

Although the Bayesian-updating process described in Section 2.2 is based on the single-bounded dichotomous choice format, our framework naturally extends to multiple-bounded dichotomous-choice formats. For example, in a double-bounded format the agent receives the signal $s_i = \{c_i, \tau_{1i}, \tau_{2i}\}$ sequentially from the interviewer, where τ_{1i} and τ_{2i} represent the initial and follow-up bids, respectively. In this case, the agent uses Bayes' formula twice to update beliefs regarding the distribution of δ_i – first using (8) based solely on c_i and τ_{1i} , followed by a revision of beliefs again using (8) but based instead on c_i , τ_{1i} and τ_{2i} . The agent then forms sequentially updated expectations of δ_i using (9). In a technical appendix, we form a measure of cheap-talk effectiveness similar to that presented in Section 2.2, and distinguish the cases based on the relative values of the anchoring parameters, WTP_i^0 , τ_{1i} and τ_{2i} .¹³

In the context of the DBDC format, the question of incentive incompatibility arises.¹⁴

¹³The technical appendix is available upon request from the authors.

¹⁴The early literature on incentive incompatibility in CV studies (Cummings, Elliot, Harrison and Murphy (1997); Cummings, Harrison and Rutstrom (1995)) appears to characterize incentive incompatibility more broadly than some of the more recent studies. For example, Cummings, Harrison and Rutstrom (1995)

Do the follow-up bids induce a “structural shift” in the agent’s stated WTP away from the underlying true WTP (in either the positive or negative direction)? Previous studies laying out the theoretical underpinnings of this question include Alberini, Kanninen and Carson (1997) and Carson, Groves and Machina (1999). Whitehead (2002) finds empirical evidence in support of the existence of incentive incompatibility in the double-bounded format.¹⁵ Whitehead presumes that the agent’s initial WTP represents the true underlying WTP. As a result, any shift away from initial WTP induced through the iterative bidding process represents perforce incentive incompatibility. However, for most goods in which CV analysis is applied, agents are unlikely to know their true WTP with certainty. Recall from (5) that WTP_i^0 represents the agent’s perception of the true WTP rather than true WTP itself. Therefore, the shift from WTP_i^0 to WTP_i^1 represents the agent’s rational updating of the uncertainty associated with what is believed to be the true WTP. In an environment of uncertainty, it is possible that the follow-up referenda in DBDC formats provide valuable information for agents who are rationally seeking their true WTP. Whether this updating brings the agent closer to the true WTP or not depends on the information contained in the signal. Once this Bayesian perspective of WTP formation is taken, the recent discussion of the incentive incompatibility of DBDC formats changes markedly.

6 Summary

In this paper, we develop a Bayesian approach to model the elicitation of WTP for nonmarket goods and services. Many individuals have limited experience in trying to formulate a precise value for the types of public and environmental goods often examined under non-market valuation studies. In these situations, it seems more natural to model WTP as

on page 260 state that incentive compatibility “implies that subjects will answer the CVM’s *hypothetical* question in the same way as they would answer an identical question asking for a *real* commitment.” While Whitehead (2002) in a more recent study states on page 287 that in DBDC formats “if the follow-up questions are not incentive compatible, stated willingness to pay will be based on true willingness to pay with a shift parameter.”

¹⁵In a subsequent article, Aadland and Caplan (2004) find that the incentive incompatibility shift parameter will be inconsistently estimated if certain restrictions associated with the nature of starting-point bias are not incorporated.

being derived from a Bayesian-updating process rather than from a deterministic process. In a Bayesian framework, agents begin with a prior distribution over their uncertain WTP and use this distribution to form an initial WTP estimate. Agents are then provided with signals from the interviewer such as bids amounts and cheap-talk scripts. This information is used by agents to update their priors as they “grope” for their true WTP. One important implication of this process is that from an econometric standpoint, previous tests for the effectiveness of cheap talk are likely to be biased. In dichotomous-choice formats, the direction and magnitude of the bias depends on the distribution of initial WTPs relative to the opening bids. If a bid is high relative to an agent’s initial WTP, then standard econometric methods are likely to find a significant or exacerbated cheap-talk effect. A bid that is low relative to an agent’s initial WTP leads to a measured cheap-talk effect that is mitigated, non-existent, or even counterintuitive. Because agents’ initial WTPs are typically unknown in nonmarket valuation studies, it is difficult *a priori* to predict the direction and magnitude of the potential bias.

We present two sources of information to test our theory. First, we highlight three recent papers that find weak overall cheap-talk effects, but as predicted by our theory show that cheap talk appears effective for those receiving relatively high bids and ineffective for those receiving relatively low bids. We interpret this evidence as being consistent with the interaction between anchoring and cheap talk in a Bayesian updating framework. Second, we present evidence that the same phenomena occurs in an experimental setting, where we are better able to control for external influences. When taken together, neither of the two sets of evidence allow us to reject our theory. Consequently, our Bayesian interpretation of the valuation for goods with substantial nonmarket components remains a plausible interpretation for the mixed empirical results in the cheap-talk literature.

References

Aadland, D. and Caplan, A. J.: 2003, Willingness to pay for curbside recycling with detection and mitigation of hypothetical bias, *American Journal of Agricultural Economics*

85(2), 492–502.

Aadland, D. and Caplan, A. J.: 2004, Incentive incompatibility and starting-point bias in iterative valuation questions: comment, *Land Economics* **80**, 312–315.

Aadland, D. and Caplan, A. J.: forthcoming, Cheap talk reconsidered: Evidence from cvm, *Journal of Economics and Behavioral Organization* .

Adamowicz, W., Louviere, J. and Williams, M.: 1994, Combining revealed and stated preference methods for valuing enviromental amenities, *Journal of Environmental Economics and Management* **26**, 271–292.

Alberini, A., Kanninen, B. and Carson, R. T.: 1997, Modeling response incentive effects in dichotomous choice contingent valuation data, *Land Economics* **73**(3), 309–324.

Brookshire, D. S., Thayer, M. A., Schulze, W. D. and D’Arge, R. C.: 1982, Valuing public goods: a comparison of survey and hedonic approaches, *American Economic Review* **72**(1), 165–177.

Brown, T. C., Azjen, I. and Hrubes, D.: 2003, Further tests of entreaties to avoid hypothetical bias in referendum contingent valuation, *Journal of Environmental Economics and Management* **46**, 353–361.

Cameron, T. A. and James, M. D.: 1987, Efficient estimation methods for close-ended contingent valuation surveys, *Review of Economics and Statistics* **69**, 269–276.

Carson, R. T., Groves, T. and Machina, M. J.: 1999, Incentive and informational properties of preference questions. Plenary address, European Association of Environmental and Resoruce Economists, Oslo, Norway.

Cherry, T. L. and Whitehead, J.: 2004, The cheap-talk protocol and the estimation of the benefits of wind power. unpublished manuscript, Department of Economics, Appalachian State Universtity.

- Cummings, R. G., Brookshire, D. S. and Schulze, W. D. (eds): 1986, *Valuing Environmental Goods: A State of the Arts Assessment of the Contingent Valuation Method*, Rowman and Allanheld.
- Cummings, R. G., Elliot, S., Harrison, G. W. and Murphy, J.: 1997, Are hypothetical referenda incentive compatible?, *Journal of Political Economy* **105**(3), 609–621.
- Cummings, R. G., Harrison, G. W. and Rutstrom, E. E.: 1995, Homegrown values and hypothetical surveys: is the dichotomous choice approach incentive compatible?, *American Economic Review* **85**(1), 260–266.
- Cummings, R. G., Harrison, G. W. and Taylor, L. O.: 1995, Can the bias of contingent valuation surveys be reduced? evidence from the laboratory. unpublished manuscript, Division of Research, College of Business Administration, University of South Carolina.
- Cummings, R. G. and Taylor, L. O.: 1999, Unbiased value estimates for environmental goods: A cheap talk design for the contingent valuation method, *American Economic Review* **89**(3), 649–666.
- Haab, T. C., Huang, J.-C. and Whitehead, J. C.: 1999, Are hypothetical referenda incentive compatible? a comment, *Journal of Political Economy* **107**(1), 186–196.
- Hausman, J. A.: 1993, *Contingent Valuation: A Critical Assessment*, North Holland; Amsterdam.
- Herriges, J. A. and Shogren, J. F.: 1996, Starting point bias in dichotomous choice valuation with follow-up questioning, *Journal of Environmental Economics and Management* **30**, 112–131.
- Hogg, R. V. and Craig, A. T.: 1978, *Introduction to Mathematical Statistics*, MacMillan Publishing, New York, New York.

- List, J. A.: 2001, Do explicit warnings eliminate the hypothetical bias in elicitation procedures? evidence from field auction experiments, *American Economic Review* **91**(5), 1498–1507.
- Loomis, J. B., Gonzalez-Caban, A. and Gregory, R.: 1994, Do reminders of substitutes and budget constraints influence contingent valuation estimates?, *Land Economics* **70**(4), 499–506.
- Lusk, J. L.: 2003, Effects of cheap talk on consumer willingness-to-pay for golden rice, *American Journal of Agricultural Economics* **85**(4), 840–856.
- McFadden, D.: 2001, Economic choices, *American Economic Review* **91**(3), 351–378.
- McLeod, D. M. and Bergland, O.: 1999, Willingness-to-pay estimates using double-bounded dichotomous-choice contingent valuation format: A test for validity and precision in a bayesian framework, *Land Economics* **75**(1), 115–125.
- Mitchell, R. C. and Carson, R. T.: 1989, Using surveys to value public goods: The contingent valuation method.
- Murphy, J. J., Stevens, T. and Weatherhead, D.: 2005, Is cheap talk effective at eliminating hypothetical bias in a provision point mechanism?, *Environmental and Resource Economics* **30**(3), 327–343.
- Neil, H.: 1995, The context for substitutes in cvm studies: some empirical observations, *Journal of Environmental Economics and Management* **29**, 393–397.
- Poe, G. L., Clark, J. E., Rondeau, D. and Schulze, W. D.: 2002, Provision point mechanisms and field validity tests of contingent valuation, *Environmental and Resource Economics* **23**, 105–131.
- Tversky, A. and Kahneman, D.: 1974, Judgement under uncertainty, *Science* **185**, 1122–1131.

Whitehead, J. C.: 2002, Incentive incompatibility and starting-point bias in iterative valuation questions, *Land Economics* **78**(2), 285–297.

Table 1. Variable Names, Definitions and Descriptive Statistics

Variable	Definition	Descriptive Statistics		
		Sample Size	Mean	SD
WTP ⁰	Initial WTP	286	3.60	2.89
WTP ¹	Yes to Investment = 1; No to Investment = 0	153	0.48	0.50
τ	Investment Amount	153	4.95	2.84
C	Cheap Talk = 1; No Cheap Talk = 0	153	0.54	0.50
Hyp	Stated Preference = 1, Revealed Preference = 0	127	0.55	0.50
Female	Female = 1, Male = 0	286	0.53	0.50
Old	(Age $\geq$ 22) = 1, Otherwise = 0	286	0.47	0.50
Upperclass	Junior/Senior/Grad = 1, Otherwise = 0	286	0.63	0.48
GPA	Cumulative College GPA	286	3.27	0.50
GPA ²	--	286	10.92	3.17
High Income	(Inc. > \$20K) = 1, Otherwise = 0	286	0.08	0.27
Risk Averse	Risk Averse = 1, Otherwise = 0	286	0.56	0.50

Notes. SD = Standard Deviation. Varying sample sizes reflect different models where the variables are used.

Table 2. Econometric Results

Variables	WTP ⁰ Dependent (OLS)		WTP ¹ Dependent (Probit)											
	Model #1 Demographics		Model #2 Hypothetical Bias			Model #3 Cheap-Talk Effect			Model #4 High-Bid Sample CT Effect			Model #5 Low-Bid Sample CT Effect		
	Coef	SE	Coef	SE	ME	Coef	SE	ME	Coef	SE	ME	Coef	SE	ME
WTP ⁰						0.16***	0.03	0.06	0.50***	0.10	0.16	-0.06	0.06	-0.02
τ			-0.12***	0.04	-0.05	-0.11***	0.03	-0.04	-0.27***	0.06	-0.09	0.23**	0.16	0.08
C						-0.22	0.20	-0.05	-0.52**	0.28	-0.09	0.33	0.35	0.07
Hyp	0.27	0.42	0.19	0.27	0.04									
Constant	-3.56	5.21	-3.38	3.85	--									
Upperclass	-0.78*	0.44	-0.24	0.30	-0.06									
GPA	5.26	3.35	2.53	2.44	0.71									
GPA ²	-0.83	0.53	-0.37	0.39	--									
Female	-0.00	0.34	-0.01	0.23	-0.00									
Old	-0.23	0.44	-0.11	0.30	-0.02									
High Income	-0.05	0.64	0.89**	0.53	0.03									
Risk Averse	-0.96***	0.34	-0.32*	0.24	-0.07									
Summary Statistics	R ² = 0.07 N = 286		Log L = -79.37 N = 127			Log L = -91.63 N = 153			Log L = -40.36 N = 104			Log L = -28.27 N = 49		

Notes. SE = Standard Error. ME = Marginal Effect. CT = Cheap Talk. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

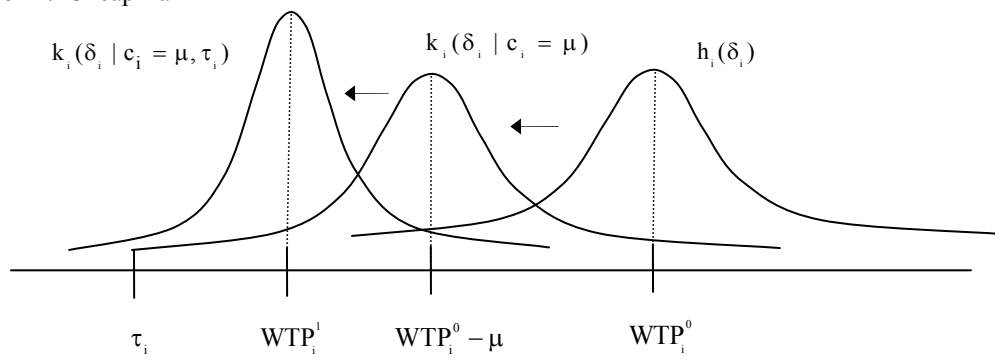
Table 3. Econometric Results (High GPA/Upperclass Sample)

Variables	WTP ⁰ Dependent (OLS)		WTP ¹ Dependent (Probit)											
	Model #1 Demographics		Model #2 Hypothetical Bias			Model #3 Cheap-Talk Effect			Model #4 High-Bid Sample CT Effect			Model #5 Low-Bid Sample CT Effect		
	Coef	SE	Coef	SE	ME	Coef	SE	ME	Coef	SE	ME	Coef	SE	ME
WTP ⁰						0.21***	0.04	0.08	0.55***	0.12	0.15	0.02	0.07	0.01
τ			-0.19***	0.05	-0.07	-0.15***	0.03	-0.06	-0.32***	0.07	-0.09	0.17	0.13	0.06
C						-0.28	0.23	-0.06	-0.36	0.33	-0.06	0.03	0.39	0.01
Hyp	0.71	0.51	0.39*	0.29	0.09									
Constant	3.68***	0.61	0.98***	0.46	--									
Female	-0.18	0.40	0.14	0.29	0.03									
Old	-0.31	0.41	-0.32	0.30	-0.08									
High Income	-0.20	0.73	0.91*	0.57	0.03									
Risk Averse	-1.09***	0.40	-0.48***	0.29	-0.10									
Summary Statistics	R ² = 0.05 N = 210		Log L = -52.35 N = 90			Log L = -63.50 N = 118			Log L = -30.26 N = 77			Log L = -23.31 N = 41		

Notes. SE = Standard Error. ME = Marginal Effect. CT = Cheap Talk. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Figure 1. Stylized Representation of Case 1

Panel A. Cheap Talk



Panel B. No Cheap Talk

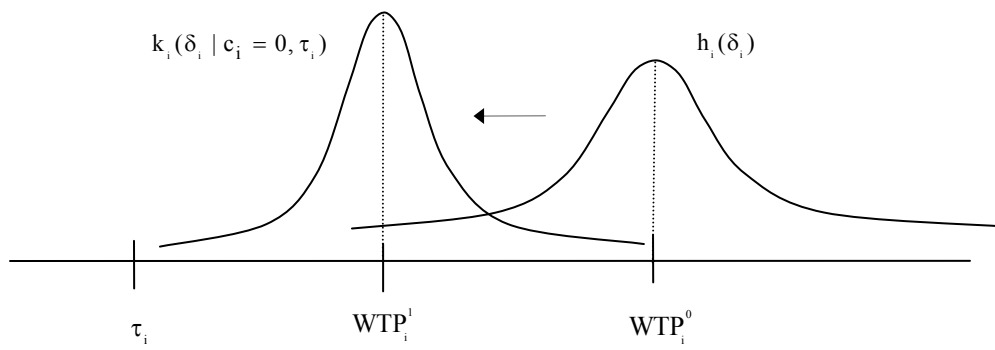
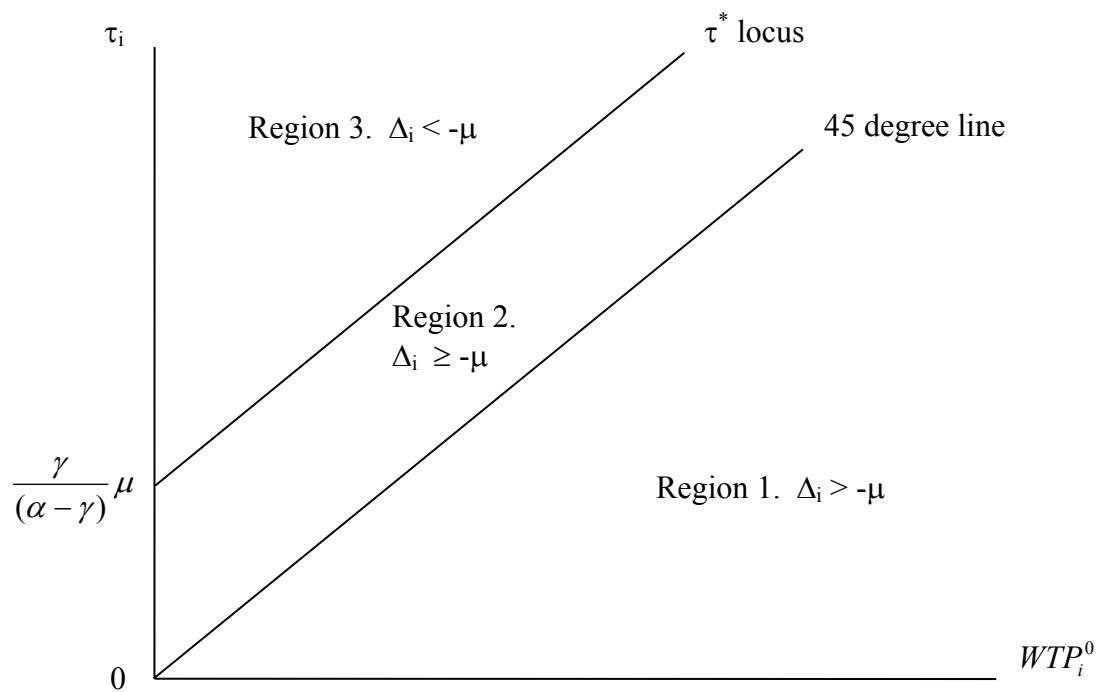


Figure 2. Relationship Between WTP_i^0 , τ and Δ



Sample Payout Chart

Average Group Investment	Range of Payouts Based on Your Investment Choice					
	“YES, I’ll invest”			“NO, I won’t invest”		
	Min Payout	Mid Payout	Max Payout	Min Payout	Mid Payout	Max Payout
Greater than \$0; Less than or equal to \$1	\$0	\$1	\$2	\$1	\$2	\$3
Greater than \$1; Less than or equal to \$2	\$1	\$2	\$3	\$2	\$3	\$4

Actual Payout Chart

Average Group Investment	Range of Payouts Based on Your Investment Choice					
	“YES, I’ll invest”			“NO, I won’t invest”		
	Min Payout	Mid Payout	Max Payout	Min Payout	Mid Payout	Max Payout
Greater than \$0; Less than or equal to \$2	\$0	\$1	\$2	\$1	\$2	\$3
Greater than \$2; Less than or equal to \$4	\$3	\$4	\$5	\$4	\$5	\$6
Greater than \$4; Less than or equal to \$6	\$6	\$7	\$8	\$7	\$8	\$9
Greater than \$6; Less than or equal to \$8	\$9	\$10	\$11	\$10	\$11	\$12
Greater than \$8; Less than or equal to \$10	\$12	\$13	\$14	\$13	\$14	\$15