# Contingent Valuation of Community Forestry Programs in Ethiopia: Controlling for Preference Anomalies in Double-Bounded CVM[1]

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**Abstract**

This study examines the welfare effects of community plantations in Ethiopia via Contingent Valuation. Both single-bounded and double-bounded survey methods were considered, and, with respect to double-bounded methods, the potential for anomalous response behaviour was also taken into account. The results generally confirm that there are statistically significant welfare benefits to be derived from community forestry; however, the range of the estimated benefits is large. After controlling for anomalous response behaviour, the range of estimated benefits narrows, and our preferred estimates place the welfare gain between Ethiopian Birr (ETB) 20.14 and 30.41 per household, which is much lower than the estimated benefits without controlling for anomalous preference responses.

*Keywords*: Double-bounded contingent valuation, shift bias, anchoring bias

*J.E.L. Classification:* Q26, Q23, Q28

## 1. INTRODUCTION

Deforestation and the attendant scarcity of fuel means increased collection times for gathering fuel and nontimber products and less time households can allocate to other productive activities; thus, there are welfare costs to deforestation (Kohiln and Amacher, 2005). Developing countries have responded to the situation by establishing community forest plantations on village woodland commons (Cooke et al., 2008). The extant literature finds benefits to households (Köhiln and Amacher, 2005; Gelo and Koch, 2012; Gelo, 2011;

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Jagger et al., 2003) and the environment (Tefera et al., 2005; Jagger et al., 2003; Köhlin and Parks, 2001) arising from these programs.[4]

Despite the potential and realized benefits, little is known about local willingness to support community forestry activities. Since these programs require both land and monetary resources, and involve trade-offs – better community plantations in the future at the cost of deterred current resource extraction for the community – knowledge of community perceptions is tantamount to determining whether community forestry is a viable option at the community level. Importantly, if communities do not expect to gain from the program, it is unlikely that the program will be effectively supported at the local level, and the aforementioned benefits may remain elusive.

Unfortunately, the benefits offered by community plantations are not amenable to market valuation.[5] In such circumstances, it is common to evaluate non-market goods via Contingent Valuation (CV). One popular method is the single-bounded dichotomous choice (SBDC) design (Whitehead, 2002; Hanemann, 1994; Köhlin and Parks, 2001; Herriges and Shogren, 1996). Its popularity comes from the U.S National Oceanographic and Atmospheric Administration (NOAA) recommendations (Arrow et al., 1993), and its "take-it-or-leave-it" format, which mimics the decision-making task individuals face in daily market transactions

[4] More often than not, community forest woodlots are established on common land close to a village, serving as a readily available substitute to alternative local sources of fuel, such as that collected in government-managed de facto open access natural forests (Cooke et al., 2007). The relative accessibility of these woodlots has been observed to reduce the time required to collect fuel (Kohiln and Amacher, 2005), freed labour for other productive endeavours, typically in agriculture (Bluffstone, 2008), and may positively impact agriculture productivity through increased access to fertilizers (Mekonnen, 1999). Furthermore, the woodlots could enhance soil and water conservation, positively impact biodiversity (Jagger et al., 2003) and allow for the reclamation of degraded woodlands (Babulo, 2007; Mekuria et al., 2011; Shylendra, 2002; Tefera et al., 2005), as well as regrowth in previously open access forests (Kohlin and Parks, 2001).

[5] In these regions, labour markets are pervasively imperfect (seasonal at best), while biomass fuels, such as dung and manure, are not widely traded in rural areas of developing countries. Thus, evaluating the benefits, such as reduced fuel collection times or soil fertility improvements, through market prices is not possible. Furthermore, the public good nature of environmental benefits of community forest plantations, as alluded to above, means their prices cannot be observed and welfare effect associated with their change are not easily uncovered.

(Herriges and Shogren, 1996; Haab and McConnel, 2002). In its simplest form, a respondent is asked if she is willing to pay a given sum of money in exchange for a specified change in a non-market good; the respondent either agrees to pay or does not.

Due to its acclaimed incentive compatibility property, Carson et al. (2003) recommends SBDC for non-market valuation, and it has been widely applied to evaluate programs (Mekonen, 2000; Carlsson et al., 2004; Köhlin, 2001; Riera and Mogas, 2004; Brey et al., 2007; Wang et al., 2007). Despite its popularity, SBDC provides limited information about an individual's true willingness-to-pay (Whitehead, 2002; Flachaire, 2006; Herriges and Shogren, 1996), and requires large samples to attain a given level of willingness-to-pay (WTP) estimator precision (Hanemann et al., 1991).

Hanemann et al. (1991) first devised the double-bounded dichotomous design (DBDC), which includes two questions. In the first, as in the standard SBDC, an individual can accept or reject a bid. DBDC differs in offering a second bid. If the first bid is rejected, an even lower bid is offered, which the respondent can accept or reject. If the first bid is accepted, an even higher bid is offered, and the respondent can choose to accept or reject that bid. Unlike SBDC, where WTP is known to lie either above or below a specified amount, DBDC provides additional information to improve the estimates: WTP can lie below a specified amount, above a different amount or between the two amounts. Additional take-it-or-leave-it rounds, if included, could have the potential to pinpoint the WTP location more finely.

Although DBDC gained in popularity and has been favoured over SBDC, due to statistical efficiency, DBDC responses may be internally inconsistent (Cooper et al., 2002; Bateman et al., 2008). Reponses to second rounds can also yield a lower WTP (Cameron and Quiggin, 1994; McFadden, 1994; DeShazo, 2002; Bateman et al., 2001, 2008; Burton et al., 2003). Evidence from Cameron and Quiggin (1994) is typical.[6] Although they find that the WTP distributions implied by the first and second bids are highly correlated, the WTP distributions are not identical, because the variance from the second WTP estimate is greater than the first. Key explanations for this inconsistency, each of which are described in detail in Section 2, are shift or cost expectation effects (Carson et al., 1994; Alberni et al., 1997; Whitehead, 2002), framing effects (DeShazo, 2002), yea-saying effects (Flachaire and Hollard, 2006; DeShazo, 2002) and strategic effects (Carson, 1999; DeShazo, 2002). Another, perhaps, more revealing explanation for SBDC-DBDC inconsistency is that respondents are unfamiliar with the institutional design of the DBDC – it does not necessarily match market experiences – thus, they are taken by surprise by the second bid resulting in a variety of strategic responses (Cooper et al., 2002; Bateman et al., 2008).

Implicit in the aforementioned literature is the assumption of a priori well-formed preferences, which are readily deduced through the SBDC format. However, the discovered preference hypothesis (DHP) criticizes this assumption as being simplistic. DHP argues that inconsistency between SBDC and DBDC exists, because people might not have well-formed preferences at the outset, and that consistent preferences are learned through a process of repetition and experience (Bateman et al., 2008; Plott, 1996). In other words, the standard CV may be unfamiliar as an exchange institution for non-traded goods. Thus, the SBDC method is predisposed to the uncertain nature of preferences. Therefore, responses are prone to influence from a variety of choice heuristics and framing effects, resulting in apparently

[6] Cameron and Quiggin, (1994) re-analyse Imber et al.'s (1991) DBDC study of the Kakadu Conservation Zone (KCZ) in Australia. The KZC is an important wilderness region, but also contains significant mineral reserves; thus, determining environmental damage costs in order to make an informed decision related to mining or conservation was important.

anomalous preferences (Tversky and Kahneman, 1974) and less precise WTP estimates (Bateman et al., 2008). However, DBDC formats that involve repeated valuation tasks offer familiarity; the decisions become more coherent, less random and more precise, resulting in attenuation of SBDC-DBDC inconsistency. Seminal empirical work by Bateman et al. (2008) supports this hypothesis. [7]

In addition to being internally inconsistent, there might be dependency between the DBDC's first and second responses, an anomaly referred to as an anchoring effect. Econometric tests in the early literature (Herriges and Shogren, 1996; Flachiare and Hollard, 2006 and Chien et al., 2002) confirmed that, in the DBDC format, responses to the second question are anchored on the value of the first bid. The presence of anchoring corroborates the behavioural hypothesis of "coherent arbitrariness"; preferences are internally coherent, but liable to the dictates of some initial arbitrary anchor (Ariely et al., 2003).

Few, if any, recent papers have applied CV to the evaluation of community woodlots in developing countries. Those that have primarily follow SBDC (Kohlin, 2001; Carlsson et al., 2004) or open-ended formats (Mekonnen, 2000). As noted above, SBDC and open-ended elicitation formats may be subject to preference uncertainties, and, if not, may still be imprecise. Thus, previous estimates may not be reliable, and, combined with the limited number of studies available, there is a need to uncover newer and, hopefully, better information regarding the perceived value of community woodlots. Although the main contribution of this research is to evaluate the welfare that households associate with community forestry in rural Ethiopia, the research also examines the potential for DBDC

[7] They use a sequence of DBDC (Learning Design Contingent Valuation (LDCV)) formats, and confirm both institutional learning – i.e. increased familiarity with the hypothetical market yielded greater valuation response consistency between the single-bounded and double-bounded formats – and value learning, i.e., anchoring effects die away with repeated valuation tasks.

anomalies to arise in developing country settings. Specifically, we provide evidence related to internal inconsistency, shifting, anchoring and framing effects in a developing country setting, following Whitehead (2002) and Alberini (1997).[8] After revising the structure to incorporate these worries, WTP estimates settle in the range of ETB20-30 (1 USD ≈ Ethiopian Birr 12.615, at the time of the survey). Although these estimates are economically small, they are statistically significant. Furthermore, when spread over a larger population than could be considered in the analysis, the cumulative sum could be large enough to fund additional community forestry projects in the country.

## 2. THEORETICAL AND EMPIRICAL SPECIFICATIONS

Consider an individual, denoted by $i$, whose log WTP for a non-market good is $w_i$. Further, assume that the individual faces two take-it-or-leave-it bids, related to their WTP. She is offered an initial bid, to which she can respond either yes or no. In a follow-up, depending upon the initial response, she is offered a second bid, to which she can also answer either yes or no. The presented survey bids will be denoted, in log form, as $b_{it}$.

The survey yields a set of bid responses, $Y_i = \{Y_{i1}, Y_{i2}\}$, where $Y_{it} = \{0,1\} = \{\text{no}, \text{yes}\}$, and $t = \{1,2\}$ represents the bid timing in the DBDC survey. Assuming rationality – an individual does not agree to pay more than she is willing – the set of observed bid responses yields a set of intervals for estimating WTP; recall that initial rejections are followed by lower second bids, and that initial acceptances are followed by higher second bids. Mathematically, $Y_i$ = (yes, yes) ⇔ $w_i \geq b_{i2}$, $Y_i$ = (yes, no) ⇔ $b_{i1} \leq w_i < b_{i2}$, $Y_i$ = (no, yes) ⇔ $b_{i1} > w_i \geq b_{i2}$,

[8] Alternative approaches to test and mitigate DBDC's internal inconsistency include a one-and-one-half-bound (OOHB) approach by Cooper et al (2002) and Learning Design Contingent Valuation (LDCV) by Bateman et al. (2008). Unfortunately, our CV design didn't allow us to follow these alternative approaches.

and $Y_i$ = (no, no) $\Leftrightarrow w_i < b_{i2}$. Since $w_i$ is not observed, WTP is constructed from an empirical analysis that potentially includes determinants of WTP.

### *2.1. Common Preference Anomalies and potential DBDC biases*

The preceding structure did not allow for differing WTP values across the questions. However, survey respondents might be affected by the information they have received, which could affect their WTP values. It would also imply a violation of the standard assumptions related to consumer behaviour, specifically, the assumption that preferences are stable. Thus, we denote (potentially) time-dependent WTP values, in log form, as $w_{it}$. The literature offers several explanations for the potential divergence between WTP values over the survey. Key, amongst these, is the presence of anchoring and shifting in preferences, which are different versions of starting-point bias. These explanations revolve around the proposition that the response to the second bid is not necessarily independent of the initial bid. Additionally, one might worry about internal consistency, wherein the SBDC WTPs might substantially differ from DBDC WTPs.

2.1.1. Anchoring Effects. The anchoring effect ensues if the respondent, uncertain about the amenity value of the good, assumes the initial value is informative of the true value (Herriges and Shogren, 1996, Whitehead, 2002). Intuitively, anchored preferences are an adjustment of prior beliefs regarding WTP, based on the initially proposed bid, and that adjustment yields a posterior WTP in the Bayesian tradition. That is, the initial bid may serve as an anchor, if the respondent assumes that it conveys information on the true value of the good (DeShazo, 2002).

Following Herriges and Shogren (1996), anchoring allows the individual's stated WTP to change over the survey, and be related to the initial bid.

$$w_{i2} = (1-\gamma)w_{i1} + \gamma b_{i1} \quad (1)$$

In equation (1), the posterior WTP is a weighted average of the prior WTP and the information provided by the initial bid, based on the weighting factor $\gamma \in [0,1]$, assumed constant across participants. Respondents who receive ascending sequences interpret the second bid as being lower than it actually is – it has a lower weighted average – which increases the probability of accepting the second bid. On the other hand, respondents who receive a descending sequence may construe the second bid as having a higher weighted average, which decreases the probability of acceptance (Watson and Ryan, 2007, DeShazo, 2002). Therefore, if anchoring occurs, the middle interval is dependent on the relative strengths of the effects in the upper and lower intervals.

2.1.2. Shifting Effects. Shift effects, on the other hand, arise if a respondent understands the first value as information regarding the true cost of the proposal. Under shifting, an individual willing to pay the first (and thus receives a higher second bid) may perceive the second bid as an unfair request to pay an additional sum; hence, she will undercut her true WTP. In the same vein, for an individual rejecting the first bid (and thus receives a lower second bid), the second bid could be interpreted as a lower quality good, leading to WTP reductions (Alberni et al., 1997). Along these lines, shifting is modelled as a reduction in the WTP that is independent of the initial bid, where $\delta < 0$ is assumed in equation (2).

$$w_{i2} = w_{i1} + \delta \quad (2)$$

In the presence of shifting and anchoring, the posterior WTP is modified to account for the weighted average of the prior and the initial bid and adjusted for the shift.

$$w_{i2} = (1-\gamma)w_{i1} + \gamma b_{i1} + \delta \qquad (3)$$

2.1.3. Implementation. Depending on the assumptions made, the aforementioned outcomes can be modelled in numerous ways. Defining $\mathbb{I}$ as an indicator function equal to one if the expression is true, and zero otherwise, yields $Y_{it} = \mathbb{I}(w_{it} > b_{it})$, where, as above, 1 is associated with "yes" and 0 with "no". Further, assume that latent WTP can be written as a simple linear function, $w_{it} = X_{it}\theta_t + u_{it}$, where $u_{it} \sim N\left(0, \left((\sigma_1^2 \quad \rho\sigma_1\sigma_2), (\rho\sigma_1\sigma_2 \quad \sigma_2^2)\right)\right)$, $X_{it}$ is a vector of explanatory variables described further below, and $\theta_t$ is a vector of parameters to be estimated. Restricting the parameters, such that $w_i = w_{i1} = w_{12}$ and $\rho = 1$, implies that observed differences are due to randomness in the underlying distribution of the WTP. This restricted bivariate probit is equivalent to the interval model applied by Hanneman et al. (1991). Assuming that there is no correlation between the underlying error terms results in probit models that could be estimated either for each survey question, separately, or pooled across all survey questions. Similarly, if data from the second question is ignored, a simple probit model can be used to estimate SBDC WTP values.

The interval data (double-bound) model imposes cross-equation parameter restrictions, such that the mean WTP underlying each response is identical. However, other assumptions are also possible. For example, allowing for inequality in the WTP and for less than perfect correlation between the errors terms results in a bivariate probit model. Therefore, the latter nests the interval data model as special case. The problem with the unrestricted model, however, is that it leads to two different estimates of WTP, and the true value would not be identified, although constraining the bivariate probit model to have equal parameter values solves the identification problem.

On the other hand, since there are multiple responses for each respondent, it is possible to use the panel structure, examining the data through a random effects probit, Whitehead (2002). In the model, two observations – responses to bids offered – are available for each individual, $Y_{it} = \mathbb{I}(X_{it}\theta_t + u_{it} > b_{it})$. The underlying unobserved component can be decomposed into an individual (random) effect $\alpha_i$ and an idiosyncratic effect $\eta_{it}$ giving rise to the general error term $u_{it} = \alpha_i + \eta_{it}$, where $\alpha_i \sim N(0, \sigma_\alpha^2)$, $\eta_{it} \sim N\left(0, \sigma_\eta^2\right)$ and $\mathcal{E}[\alpha_i X_{it}] = 0$, such that the variance of the unobserved error is $Var(u_{it}) = \sigma_\alpha^2 + \sigma_\eta^2$. Due to the common error component for each individual, that remains fixed across valuation questions, but varies across individuals, the underlying unobserved error components are correlated, $\rho = \sigma_\alpha^2 / \left(\sigma_\alpha^2 + \sigma_\eta^2\right)$.

The error-component structure of this model discriminates between models assuming that the WTP remains constant across valuation questions and those that assume otherwise (Haab and McConnel, 2002, Alberini et al., 1997). If the variance attributed to the idiosyncratic effect, $\sigma_\eta^2$ is zero, then correlation between the WTP error terms is one. Error component models, thus, collapse to what is known as interval-censored data models, such that a simple probit model can be estimated over pooled survey responses (Hanneman et al., 1991). However, if the variance attributable to the idiosyncratic component, $\sigma_\eta^2$ is non-zero, i.e. if the correlation parameter, $\rho$, between the two WTP variables is low, either error component models (Alberini et al., 1997) or bivariate probit models (Cameron and Quiggin, 1994) could be used for parameter estimation.

In terms of the random effects probit model, a number of specifications are possible. The most general empirical specification to be considered allows for anchoring and shifting within the random effects specification. In the presence of anchor and shift effects, the WTP is defined as in (4). In equation (4), $z$ represents a vector of individual specific controls and $\Gamma$ represents the vector of parameters to be estimated.

$$w_t = \beta_0 + \Gamma z + \beta_t b_t + \delta(t-1) + \gamma(t-1)b_t \tag{4}$$

For the second survey question, $w_2 = \beta_0 + \Gamma z + (\beta_2 + \gamma)b_2 + \delta$; however, for the first survey question, $w_1 = \beta_0 + \Gamma z + \beta_1 b_1$. When neither shifting nor anchoring are assumed to be present, equation (4) reduces to $w_t = \beta_0 + \Gamma z + \beta_t b_t$.

### *2.2. Additional Preference Anomalies*

In addition to the common anomalies of shifting and anchoring, recent research has offered a more explicit description of effects, most of which relate back to shifting and anchoring.

<u>2.2.1. Framing Effects.</u> From Kahneman and Tversky's (1979) prospect theory, DeShazo (2002) argues that initial approval by respondents can be interpreted as a reference point. Relative to this reference point, the follow-up question is framed negatively, and, thus, respondents are more likely to reject the second bid.  However, respondents rejecting the first bid, such that they are subject to a descending bid sequence, are assumed not to form a reference point, which results in a different behavioural response, compared to respondents subjected to ascending bid sequences.[9] DeShazo (2002), therefore, concludes that response inconsistencies or preference anomalies are only observable for respondents facing ascending iterative questions. This conclusion further suggests that the DBDC model should only include descending follow-up question, in practice.

[9] Flachaire and Hollard (2006) and Watson and Ryan (2007) provide some support for DeShazo's (2002) framing effects.

2.2.2. Strategic Behaviour Effects. With strategic behaviour, respondents may understate their WTP, in an effort to maximize their gain. Strategic behaviour arises, because the presence of a follow-up question signals price flexibility. If respondents understand the double-bounded CVM questionnaire, they may attempt to understate their true WTP, in an effort to game the results (Carson, 1999; DeShazo, 2002). Similarly, the existence of a higher follow-up bid is likely to increase the probability of rejection, thus resulting in downward bias of reported WTP values (Watson and Ryan, 2007).

2.2.3. Cost Expectations Effects. As discussed with shifting, respondents may understand the first bid to be a fair representation of the actual cost of the good in question, such that the follow-up (higher) bid is seen as an attempt to obtain funding beyond what is necessary (Carson et al. 1999; DeShazo, 2002). Under these circumstances, approval, conditional on initial acceptance, is less likely than it otherwise would be (Watson and Ryan, 2007; Flachaire and Hollard, 2006; Alberini, 1997). On the other hand, the first bid could be understood to be information related to the quality of the good in question. Consequently, the respondent is more likely to reject the follow-up bid than she should be, conditional on rejecting the first bid (Alberini, 1997; DeShazo, 2002). Cost expectation effects are, thus, similar to shifting effects, suggesting a downward bias in the WTP (Whitehead, 2002; Flachaire and Hollard, 2006; DeShazo, 2002).

2.2.4. Yea-Saying Effects. Rather than perceiving the bids as information related to the good in question, respondents may, instead, feel that they should attempt to garner approval from the survey enumerator by agreeing. Yea-saying bias describes the tendency for respondents to accept any proposed bid. Under these circumstances, respondents overstate their true WTP in order to acknowledge the interviewer's proposition (Flachaire and Hollard, 2006, DeShazo, 2002), and it is often associated with ascending bid sequences (DeShazo, 2002, Watson and Ryan, 2007) rather than with descending bid sequences. The resulting upward bias in WTP is associated with a shift parameter $\delta$ that is always positive (DeShazo, 2002, Chein et al., 2005 and Watson and Ryan, 2007). In other words, the yea-saying effect is the exact opposite of the cost expectation effect.

2.2.5 Implementation. These preference anomaly effects are considered via random effect probit models using either ascending bid data or descending bid data. As with the general model, discussed in subsection 2.1.4, the analysis is based on equation (4) and assumes that the unobserved component can be split into an individual component, which is normally distributed and independent of the observed covariates, and an idiosyncratic component.

## 3. STUDY AREA, DESIGN AND DATA

For this analysis, a WTP valuation exercise was conducted. The exercise focused on the willingness to monetarily support the establishment of a community forest. The design follows the DBDC, and the survey was conducted in selected sites in Ethiopia. These sites were chosen, because the Ethiopian Federal Ministry of Agriculture, in collaboration with World Bank, selected these sites for sustainable land management interventions. In these sites, as in most parts of rural Ethiopia, communities use common property woodlands for grazing and fuel wood collection. The areas selected are, according to the local Departments of Agriculture, experiencing unprecedented deforestation, as well as increased demand for woody biomass. Households in these areas use cow dung and crop residues, which could be used, respectively, for fertilizer or fodder, as sources of energy, and walk long distances to harvest fuel wood from natural woodlands.

Although Ethiopia has a long history of initiating and implementing community forestry programs, the experience has not generally been successful, and that lack of success is at least partly due to an approach that did not accommodate the preferences of either the local community or the individuals slated for intervention (Gelo and Koch, 2012). Benin et al. (2002), however, outline another approach, emphasizing local community involvement in resource conservation and management. This change in government behaviour has led to the establishment of area enclosures and plantations, and these have been developed in a more participatory fashion than before. Local Departments of Agriculture still identify the area to be enclosed or planted; however, the community members determine the operational rules associated with these community resources (Gebremedhin et al., 2003).

*3.1. Survey and Bid Response*

The CV surveys included questions related to WTP for a proposed community plantation, as well as information on household socio-economic status. For the survey, 15 households from each of 40 sites, a total of 600 households, were randomly selected.[10] A team of trained enumerators conducted face-to-face interviews. However, in order to conduct the CV study, starting bids were necessary. Starting bids were obtained from a pilot study of 60 randomly selected households, in which an open-ended format was used. The result of the pilot study was a vector of five starting bids: ETB10, ETB20, ETB32, ETB50 and ETB80.

The survey targeted household heads to be the respondents. During data collection, the scenario was first described to the respondents. Following the description, value elicitation questions ensued. To make the scenario as realistic as possible, a suitable area of land for the

[10] These sites were drawn from four regions of Ethiopia; Tigray, Amahara, Oromia and Southern Nations, Nationalities and Peoples regions. In the interest of saving space the full list of these 40 sites is not provided here, but is available from the authors upon request.

establishment of the proposed community plantations was identified, and its size specified, for each survey site. Following the description, respondents were initially asked if they were willing to participate in the program.[11] For those willing to participate, they were further asked if they were willing to pay the initial – randomly assigned – bid.[12] Regardless of whether the respondents were willing to pay the initial bid, we also asked a follow-up question.[13] Follow-up bids were either 50% of the initial bid, if the initial response was rejected, or 150% of the initial bid, if the initial response was accepted. Table 1 summarizes the bids and proportion of acceptances for each bid.

**Table 1. Bid Vectors and Acceptance in Double-Bounded CVM**

| *"No" bid follow-up* | *Proportion accepting* | *Initial bid* | *Proportion accepting* | *"Yes" bid follow-up* | *Proportion accepting* |
|---|---|---|---|---|---|
| 5 | 0.50 | 10 | 0.91 | 15 | 0.74 |
| 10 | 0.41 | 20 | 0.76 | 30 | 0.57 |
| 16 | 0.66 | 32 | 0.75 | 48 | 0.55 |
| 25 | 0.43 | 50 | 0.70 | 75 | 0.28 |
| 40 | 0.37 | 80 | 0.57 | 120 | 0.23 |

Initially randomly assigned bids in centre columns. If respondents answered no, they were offered the "No" follow-up bid in the second question. If the respondents answered yes, they were offered the "Yes" follow-up bid in the second question. Therefore, each row refers to DBDC based on the initial bid

In an effort to capture additional inconsistencies, a final open-ended question, regarding the maximum willingness to pay, was asked to participants. In cases where the open-ended value was lower than the approved bid in the follow-up question, respondents were asked to explain

[11] About 6.5% of the respondent protested in the sense that they weren't willing to participate. These responses are not included in the analysis. Although our decision to ignore these respondents raises the spectre of sample selection bias in the analysis, no data is available from the non-participants, so it is not possible to control for the bias that could have arisen in the analysis.
[12] Hypothetical bias is an issue in stated preference surveys. Although we did not include a cheap talk script or budget reminder in our questionnaire, we included a follow-up question to partly control for this issue and caution should thus, be given to absolute numbers.
[13] The design did not consider the possibility that the second bid was a surprise to the respondents (Cooper et al, 2002).

their decision. Following Carlsson et al. (2004), we recoded the inconsistent responses into a "no" response for the second bid. Köhlin (2001) argues that these inconsistencies are obtained when respondents want to conform to social norms, especially in cultures characterized by courtesy, collective decision-making or paternalistic decision-making.

### *3.2. Additional Survey Data*

The survey included questions related to a number of socio-economic variables, including the sex of respondent, the age and education (both in years) of the household head, the size of household, the household's non-food expenditure, the household's ownership of livestock (measured in tropical livestock units, where 1TLU=250kg), a measure of forest access based on a GIS data, distance to the nearest town, land holdings, a measure of wealth (whether a household has corrugated metal on their house or not) and experimentally determined household rates of time preferences.[14] Descriptive statistics of this data are presented in Table 2.[15]

We postulate that the demand for community forestry depends on covariates vindicated by economic theory. These include income and wealth, the price of the good, other prices and other taste shifters. From this list, covariates were sorted into three broad categories: (1)

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[14] A subject was asked the maximum amount he/she would be willing to pay back after one year, assuming he/she had borrowed ETB 100 today. The rate was calculated as $(FV - 100)$, where 100 is the present value and simplifies the calculation, and $FV$ is the (maximum) future value to pay back in one year. The data was generated from the following questions adopted from Andersson and Alemu (2011):

A. If you had to borrow ETB 100 today, how much would you have to pay back after one year on average? ---------------ETB (that is the sum of ETB 100+interest). ?
B. If you have to borrow ETB 100 today, what will be the maximum sum that you will be willing to pay back in a year from now? ---------------ETB (that is the sum of ETB 100+interest). ?

[15] The underlying sample is a randomly drawn sample of 15 households from a randomly selected 40 villages located in regions identified to be included in the World Bank-funded Sustainable Land Management Project. See http://www.worldbank.org/projects/P107139/sustainable-land-management-project?lang=en for more information on the program.

wealth and income – ownership of a house with corrugated roofing, land holdings and non-food expenditure; (2) the price of the good – livestock ownership, rate of time preference and

**Table 2. Descriptive Statistics of survey data**

| *Variable* | *Description* | *Mean* | *Std. Dev.* | *Minimum* | *Maximum* |
|---|---|---|---|---|---|
| Forest Density | Per-hectare biomass per-capita | 0.25 | 0.50 | 0 | 3 |
| Tropical Livestoch Units | Animal holdings (TLUs) | 8.64 | 6.53 | 0 | 42 |
| Sex of Respondent | =1 if respondent is male | 0.89 | 0.30 | 0 | 1 |
| Age of Household Head | Household head age | 45.43 | 12.74 | 23 | 90 |
| Household Size | Household size | 6.48 | 2.42 | 1 | 15 |
| Education of HH Head | Household head education | 5.50 | 2.94 | 0 | 14 |
| Total Expenditure | Non-food expenditure/year | 4184.10 | 5402.80 | 122 | 36500 |
| Wealth Indicator | Corrugated house | 0.40 | 0.49 | 0 | 1 |
| Land Holdings | Land holding per capita in hectare | 0.82 | 0.97 | 0 | 5 |
| Rate of Time Preference | Rate of time preference | 0.25 | 0.28 | 0 | 2 |
| WTP - Open | Open-ended WTP | 38.80 | 24.86 | 10 | 80 |
| WTP - Ascending | Open-ended WTP (Ascending Bid Sequence Only) | 55.13 | 40.16 | 10 | 240 |
| WTP – Descending | Open-ended WTP (Descending Bid Sequence Only) | 8.88 | 5.68 | 1 | 20 |

WTPa and WTPd, respectively, refer to open-ended willingness to pay for ascending bid and descending bid subsamples of doubled bounded CVM questions.

education; (3) other taste shifters – access to alternative forests, household size, and the distance to town.

Whereas proxies for wealth and income are relatively clear, variables used as price proxies merit further explanation. With regard to the price of the good, community forestry involves both temporal and intertemporal trade-offs. Specifically, the establishment of community forestry on grazing land implies a potential income loss from livestock production, as grazing land is a major input for production. Moreover, given that community forestry establishment and management requires labour, income from alternative employment may have to be sacrificed, the value of which depends on the level of education. Therefore, such opportunity costs should be construed as part of the cost of establishing the community forest, in addition to the direct contribution suggested by the proposed bids. We, therefore, hypothesize that both the level of education and the ownership of livestock are expected to reduce the demand for community forestry. Likewise, community forestry involves an intertemporal trade-off; the benefits given up today to establish the programme must be weighed against benefits that accrue at later dates. We capture these intertemporal trade-offs through the household head's rate of time preference, assuming that this rate is inversely related to the demand for community forestry.

With regard to proxies for other taste shifters, recall that both access to alternative forests, typically open access natural forests, and the opportunity to buy from markets, as measured by the distance to town, are potential community forestry substitutes. We, therefore, argue that better access to alternative forests and shorter distances to town will lower forest product prices. Subsequently, these measures are expected to be associated with reduced demand for community forestry. Moreover, the size of the household is likely to reduce WTP, partly because a larger household increases the supply of labour available for collecting forest products from open access forests. However, all else equal, larger households require more biomass (increased WTP). The net effect of household's size on WTP, thus, depends on the relative strength of either influence.

## 4. EMPIRICAL RESULTS

In this section, we present the results of the empirical analysis, focussing on estimated WTP and outlining possible inconsistencies. The primary empirical results are available in Tables 3-5, while specific preference anomaly effects are presented in Tables A1-A2.

### *4.1 Base WTP Estimates*

The bid-response data conform to a priori expectations, as informed by economic theory; the share of acceptances generally falls as the bid rises (see Table 1). Moreover, from an analysis of the raw data, we found that some households chose to give lower WTP values in the open ended follow-up question, than was uncovered from the closed-end questions; 14.7% of respondents were inconsistent in this way. Köhlin (2001) offers several explanations: yea-saying (or compliance bias), strategic behaviour and cultural bargaining experiences that might be triggered by the preference elicitation format. In our case, when asked to explain responses that were inconsistent, 2.5% of the subjects reported that they wanted to please the enumerator, 42.5% thought it was obligatory to report, 52.5% felt they were too poor and could not afford to pay, while 2.5% gave other reasons.

Making use of only the initial response questions in our DBDC provides a comparison with the extant literature, which primarily includes SBDC; see the first column of Table 3. The SBDC results suggest, as expected, both negative price effects and positive income effects, both of which are statistically significant. Under the SBDC, mean WTP is estimated to be ETB80.52; the ratio of the 95% confidence interval to the mean is 0.43.[16] In the final two columns of Table 3, bid response behaviour is no longer required to be equivalent across the

**Table 3. Parameter estimates of simple probit model and bivariate model**

| *VARIABLES* | *Single Bound Dichotomous Choice* | *Unconstrained Bivariate Probit* | |
|---|---|---|---|
| | | *Initial Bid Model* | *Follow-up Bid Model* |
| Log Initial Bid | -0.023*** | -0.529*** | |
| | (0.003) | (0.086) | |
| Log Follow-up Bid | | 0.002* | 0.002* |
| | | (0.001) | (0.001) |
| Log Total Expenditure | 0.0037* | 0.002* | 0.009** |
| | (0.002) | (0.001) | (0.004) |
| Correlation (Rho) | | 0.528*** | |
| | | (0.077) | |
| Constant | 1.823*** | 0.834 | 1.635*** |
| | (0.450) | (0.512) | (0.440) |
| WTP in ETB | 14.69*** | 25.71*** | 20.14*** |
| | (0.95) | (6.31) | (4.05) |
| Log-Likelihood | -298.8 | -646.0 | |
| Observations | 550 | 550 | |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

two survey questions, which results in two different WTP estimates: ETB 84.04, for the first question, and ETB69.62; their confidence interval to mean ratios are 0.42 and 0.36. Similarly, the results support the contention that, although bid response behaviour across the survey questions is correlated, that correlation is not perfect, as $\rho$ is estimated to be significantly different from unity.

[16] Mean WTP is calculated from regression coefficients at the mean of the regressors (see Whitehead, 2002). Standard errors are obtained from the asymptotic covariance matrix, following the delta method (Cameron 1991; Greene 1997), and the ratio is computed as the upper bound minus lower bound (from the 95% confidence interval) divided by the mean WTP estimate.

To test DBDC internal inconsistency, we estimated the difference between the first response WTP mean, $\mu_{SBi}$, and that obtained from the second response, $\mu_{DBi}$ (i.e. $\Delta_i = \mu_{SBi} - \mu_{DBi}$); see Bateman et al. (2008). Standard errors were obtained via bootstrapping, controlling for the sample design. The estimated difference is statistically significant ($\Delta_i = ETB15.03$, $SE = ETB3.72$); thus, we cannot reject the hypothesis that our DBDC is internally inconsistent. The resulting positive difference estimate is consistent with Carson, Groves and Machina's (2007) claim that willingness to pay (WTP) estimates decrease; the first-only bid WTP exceeds the second-only bid WTP. Furthermore, there is an efficiency gain from the second question; the second-only bid WTP standard error is below that of the first-only bid WTP standard error.[17]

*4.2. Examining Inconsistent Preference Behaviour*

Given the preference anomalies observed in the preceding analysis, we implement a series of random effect probit models accounting for individual heterogeneity and preference variation within the DBDC. The base random effects probit model is denoted as the naïve model, as it assumes equal WTP values across bid questions; hence, we do not account for anchoring effects, shift effects or both in the naïve model; the results are available in Table 4. In addition to the naïve model, shifting, anchoring, and a combination of the two were also considered. For comparison, an interval data model is also included in this table. The resulting WTP values range from a low of ETB14.69 to a high of ETB30.41. In all cases, the resulting WTP estimates are lower, compared to the SDBC and DBDC WTP estimates

[17] To test, broadly, whether consistency relates to experience, the analysis was repeated with split subsamples: experienced and inexperienced. Here, experience implies that the respondent prior knowledge about community forest plantation programs, either through participation in the program or via information. For the inexperienced, WTP estimates are ETB100.13 (SE=ETB14.29) for the first response and ETB83.88 (SE=ETB8.68) for the second response; there is a statistically significant difference of ETB18.71 (SE=ETB4.20). For the experienced, the estimates are, respectively, ETB65.04 and ETB49.18; the difference is estimated to be statistically significant: ETB 13.88 (SE=ETB4.26). Thus, there is a suggestion that experience attenuates internal inconsistency.

**Table 4. Parameter estimates of random-effect probit models without covariates**

| *VARIABLES* | *Interval Data* | *Naïve* | *Shift* | *Anchoring* | *Shift-anchoring* |
|---|---|---|---|---|---|
| Log Current Bid | -0.381*** | -0.579*** | -0.575*** | -0.591*** | -0.578*** |
| | (0.054) | (0.092) | (0.093) | (0.093) | (0.093) |
| Log Total Expenditure | 0.013*** | 0.002* | 0.002* | 0.002* | 0.002* |
| | (0.037) | (0.001) | (0.001) | (0.001) | (0.001) |
| $(t-1)$ Indicator | | | -0.479*** | | -0.358* |
| | | | (0.134) | | (0.193) |
| Log Initial Bid | | | | -0.080*** | |
| | | | | (0.004) | |
| Constant | 0.782** | 2.701*** | 2.930*** | 2.898*** | 2.942*** |
| | (0.331) | (0.374) | (0.345) | (0.344) | (0.346) |
| WTP in ETB | 14.69*** | 25.71*** | 20.14*** | 30.41*** | 22.82*** |
| | (0.95) | (6.31) | (4.05) | (6.05) | (6.57) |
| Log-Likelihood | -668.7 | -656.9 | -654.1 | -655.4 | -653.7 |
| Observations | 1086 | 1086 | 1086 | 1086 | 1086 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

described above. Thus, at the very least, ignoring individual heterogeneity, as was done in the initial analysis, biases the WTP estimates.[18] If we compare WTP differences between the shift, anchoring and shift-anchoring models – standard errors are again bootstrapped – the WTP estimates are not statistically significant. However, when compared to the naïve model WTP, the differences are statistically significant. Those differences are, respectively, 6.82 (SE=2.62), -4.95 (SE=2.72) and -7.03 (SE=2.75) compared to the shift, anchoring and shift-anchor WTPs. Moreover, compared to the simple probit and bivariate probit results reported in Table 3, these model estimates were more precisely estimated, suggesting an improvement in statistical efficiency. The interval-data model WTP standard error (ETB0.95) was lower than the WTP standard error from the DBDC (ETB9.53), corroborating Hanemman et al. (1991) and Alberini (1995).

[18] The WTP estimates here are generally larger than ETB10.42 and ETB2.63 found in Fredrik et al. (2004) and Mekonnen (2000), based on SBDC and open-ended CVM, respectively.

In terms of possible preference anomalies, we begin by considering shift-effects and starting point biases. The shift effect is introduced as a dummy variable, $t-1$, and is referred to as the shift effect model, hereafter.[19] The results point to both negative and statistically significant shift effects, which is in line with Alberini et al. (1997) and Whitehead (2002). The negative sign implies that there is a downward shift in WTP, sometimes referred to as nay-saying (Chien et al., 2005) as opposed to yea-saying, although yea-saying was assumed away in the analysis, since those responses were removed from the analysis; see subsection 3.1. In effect, the result corroborates our earlier finding of internal inconsistency of DBDC that the WTP values from the first and second valuation question differs substantially and that difference is positive.

The shift effect model was then altered to, instead, allow for anchoring. In the anchoring effect model, $b_{it}(t-1)$ is introduced to capture potential starting point bias, i.e., the possibility that the response in the second question depends on the initial bid. The results point to negative and significant anchoring effects, which violates the assumptions of the standard anchoring effect model.[20] Consequently, we cannot conclude that anchoring effects are present; rather, something else is likely to be at work. Possibly, since the starting point bid is interacted with the shift dummy, the negative anchoring effect is more likely a result of model misspecification, as was noted by Whitehead (2002). Although our result is consistent with Whitehead's (2002) evidence, it is contrary to Chien et al. (2005) and Flachaire and Hollard (2006); the latter two found evidence of anchoring bias in their data.

In case the anchoring effect was inappropriately capturing other effects, the simultaneous presence of both shift effects and anchoring effects was also considered. This model is

[19] See equation (4). Note that $t = \{1,2\}$, and, therefore, $t - 1 = \{0,1\}$.
[20] See equation (1). Recall $\gamma \in [0,1]$.

referred to as the shift-anchor model, hereafter. As with the shift model, the estimated shift effect is negative, implying a downward shift in WTP. Similarly, as with the anchor effect model, the anchoring coefficient remains negative but not statistically significant.[21]

Finally, the preceding random effects probit models were implemented for both the ascending bid sequence subsample and the descending bid sequence subsample, separately. In each of these subsamples, the shift effect is present in the shift and shift-anchor models. As before, we fail to detect evidence of anchoring effects in either of the subsamples for either the anchor-effect or the shift-anchor effects model; see Appendix Table A1. Via a likelihood ratio test, as was done in DeShazo (2002), parameter consistency tests across the two WTP equations for the ascending bid sequence subsample and descending bid sequence subsample are conducted. The results reveal that the null hypothesis of parameter consistency for descending bid sequence subsample could not be rejected ($\chi^2 = 1.54, p = 0.67$). In contrast, the null hypothesis of parameter consistency for the ascending bid subsample is rejected ($x^2$ =769.75, $p = 0.00$). When combined, these results lead us to reject the null hypothesis that there are no framing effects within the survey.[22]

*4.3. Welfare Determinants*

Further analysis of the bid function allows for the identification of salient determinants of WTP. In the analysis, the parameters, which capture the link between socio-economic covariates and WTP, for the most part, accord with our a priori expectations. The results are

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[21] Bayesian model selection analysis, not reported here, suggests that the shift model is superior to all of the models. Moreover, likelihood ratio test results for model selection support the choice of the shift and shift-anchor models, even though the shift-anchor effects model yields an inconsistent, with respect to theory, negative anchor effect.

[22] Note that these results also point to the presences of a yea-saying effect. However, as we have controlled for yea-saying problems, by discarding responses, as discussed earlier, the test points to the presences of framing effects.

**Table 5. Parameter estimates from random-effect probit model with covariates**

| *VARIABLES* | *Naïve* | *Shift* | *Anchor* | *Shift-anchor* |
|---|---|---|---|---|
| $(t-1)$ Indicator | | -0.545** | | -0.711** |
| | | (0.226) | | (0.315) |
| Log Initial Bid | | | -0.0065 | 0.0045 |
| | | | (0.008) | (0.006) |
| Log Total Expenditure | 0.292** | 0.294** | 0.292** | 0.295** |
| | (0.130) | (0.131) | (0.130) | (0.131) |
| Log Current Bid | -0.648*** | -0.633*** | -0.647*** | -0.643*** |
| | (0.166) | (0.166) | (0.167) | (0.167) |
| Total Livestock Units | -0.0114** | -0.0115** | -0.0115** | -0.0111* |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Household Size | 0.108** | 0.109** | 0.109** | 0.108** |
| | (0.055) | (0.055) | (0.054) | (0.055) |
| Distance to Town | 0.0002 | 0.0002 | 0.0002 | 0.0002 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Forest Density | 0.0043 | 0.0044 | 0.0044 | 0.0041 |
| | (0.288) | (0.289) | (0.288) | (0.289) |
| Rate of Time Preference | 0.403 | 0.406 | 0.400 | 0.424 |
| | (0.375) | (0.376) | (0.376) | (0.377) |
| Age of Household Head | -0.0214 | -0.0217 | -0.0216 | -0.0208 |
| | (0.014) | (0.014) | (0.014) | (0.014) |
| Education of HH Head | 0.0166 | 0.0164 | 0.0164 | 0.0180 |
| | (0.042) | (0.042) | (0.042) | (0.042) |
| Constant | 0.890 | 1.104 | 0.908 | 1.563 |
| | (1.354) | (1.345) | (1.370) | (1.200) |
| Log-likelihood | -246.9 | -244.8 | -246.9 | -244.5 |
| Observations | 928 | 928 | 928 | 928 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

reported in Table 5, focussing on the bias-corrected models, while subsample estimates are available in Table A2. As can be seen in Table 5, the results are fairly consistent. Mean WTP increases with total expenditure and household size, but decreases in the price of the community forestry program. In other words, community forestry is seen as a normal good. Furthermore, the demand for community forestry corresponds to the law of demand: increases in contributions reduce the willingness-to-pay. The only significant demand shifter uncovered, other than income, is household size. These results suggest that larger households perceive greater community forestry benefits. Two explanations are plausible. Either larger households demand more biomass or community forestry has the potential to unleash labour from collection activities or both, which may offset the negative effect on labour supply. Overall, the result does not support either Mekonnen (2000), who found that household size is negatively associated with the demand for community forestry, or Carlsson (2004), who reports that household size does not affect the demand for community forestry.

*4.4. Discussion*

The underlying assumption of preference elicitation in the literature is well-formed stable preferences, which is readily deduced through a single incentive compatible survey question, when real financial incentives are in place. The results from the preceding analysis, however, suggest that these survey respondents do not have stable preferences. Given the SBDC standard, and the fact that the DBDC model is expected only to affect model efficiency (Hanneman et al., 1991), one might wonder why the bias-corrected DBDC and interval-data results differ so markedly from both the SBDC and uncorrected DBDC models. Although the difference could simply be driven by statistical artefact – that individual heterogeneity is very important in rural settings – it is useful to examine the reasons for its importance. Recent research in behavioural economics provides a potential clue, based on the need for learning the market, or non-market institutions (Plott, 1996). Plott (1996) conjectures in DHP that respondents will experience uncertainty, when faced with new decisions, such that systematic response bias could obtain. However, if faced with repeated decisions over alternatives and able to observe or internalize the consequences of these decisions, institutional knowledge can be acquired.

The market provides an ideal milieu for such learning. Individuals can discover how best to achieve their goals within market institutions and discover their own preferences (Braga and Starmer, 2005). Practice and repetition takes place in markets; therefore, goods traded in it are high-experience goods, which lay the foundations for well-formed preferences (List, 2003). However, unfamiliarity with exchange institutions (which is true for persons not exposed to markets, as well as for persons dealing for the first time with non-market goods, such as environmental externalities and public health services) is likely to be the rule in rural Ethiopia. Therefore, one explanation for the observed preference anomalies in this study is a lack of experience with markets for non-traded goods, or, perhaps, any markets. Furthermore, the observed preference heterogeneity could be due to differences in opportunities to learn about market institutions for either traded or non-traded goods. In other words, the uncertain nature of preferences in a setting of inexperienced market participants, as was the case in this analysis, could account for systematic WTP bias (Carlsson, 2010). Bateman et al. (2008) provide additional support for that conclusion. In their repeated DBDC survey, institutional and value learning were confirmed; there is no significant difference between SBDC and DBDC estimates, while the anchoring effect progressively died out with repeated DBDC tasks.

## 5. CONCLUSION

SBDC is generally rather easy to implement, and has received growing attention in the literature.[23] The focus of that growing literature has been on biases related to the CV scenario and survey administration, rather than preference anomalies, such as anchoring and shifting. Generally, this literature does not consider the sorts of biases uncovered in this analysis, although Köhlin (2001) and Carlsson et al. (2004) control for “yea-saying”. Unfortunately, there are considerable empirical uncertainties surrounding the reliability and accuracy of CV survey results in developing countries (Whittington, 2002). Furthermore, there are reasons to believe that preference anomalies are likely to be at least as important in developing countries as in developed countries, due to the lack of familiarity with both real and hypothetical

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[23] Specific examples include the valuation of water quality and sanitation improvements (Whittington al., 1988, 1990, 1993, Altaf et al., 1993; Singh et al., 1993), biodiversity and recreation (Sattout et al., 2007; Navrud and Mungatana, 1994 and Moran, 1994), health (Cahn et al., 2006; Cropper et al. 2004 and Whittington et al., 2003) and forestry (; Shyansundar et al. 1995; Mekonnen, 2000 and Köhlin, 2000).

markets. However, those living in developing countries, to a large extent, depend on environmental goods and services – markets for which often fail – hence, developing country welfare has been the subject of a growing number of CV studies. It follows that policy mistakes arising from inaccurate CV results could entail considerable welfare costs in developing countries.

Therefore, the research undertaken in this study focussed on the examination of WTP estimates that accounted for the aforementioned biases, using data from a contingent valuation survey of community plantations in selected rural villages in Ethiopia. The analysis revealed that there are significant preference anomalies in our data. In particular, we found that WTP estimates based upon the first question exceeds that from the second question, suggesting internal inconsistency. Thus, respondents do not follow the same decision rule, when answering the first and follow-up valuation questions. The analysis also confirmed the presence of shift effects, which corroborates the internal inconsistency. However, the hypothesis that peasant households anchor their WTP to the starting bid was rejected. Estimation of compensated variation, after controlling for the preference anomalies, found welfare gains of approximately ETB20-30 for this study's households.After controlling for shift effects and anchoring effects, the statistical precision of the welfare estimates improved, a result confirming a number of developed country studies.

Analysis of the estimated bid functions found that household income, household size, program establishment costs and livestock holdings were important determinants of WTP. The income result suggests that community forestry is a normal good, while the effect of program establishment costs is consistent with the expectation that increased prices reduce demand. The effect of household size is consistent with the notion that community forestry has the potential to free labour time; rather than using time to walk to open access forests and extract resources from far away, household labour supply can be redirected to extraction from closer community forests. The last of these results points to opportunity costs related to foregone grazing land, land that would be required to establish the community forest. This result also implies that the establishment of community forestry, in livestock dependent and land-poor villages could be a welfare-reducing proposition, especially if implementation costs are high.

Overall, the results provide support to the furtherance of community forestry programs, as they offer significant, but economically small, welfare benefits to rural Ethiopian households, at least for the households in this study. Two caveats are in order, though. First, our design did not involve repetition of valuation tasks, precluding a thorough examination of DPH. Second, the study design could not mitigate inconsistencies that could arise from the possibility that the second survey question was a surprise to the respondents. Additional research in this area should address these shortcomings.

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Table A1. Parameter estimates of random-effect probit models without covariates

| VARIABLES | Naïve | | shift | | Anchoring | | Shift-anchoring | |
|---|---|---|---|---|---|---|---|---|
| | ascending | descending | ascending | descending | ascending | descending | ascending | descending |
| Log Current Bid | -0.262*** | -0.973*** | -0.260*** | -0.976*** | -0.264*** | -0.977*** | -0.261*** | -0.979*** |
| | (0.088) | (0.120) | (0.088) | (0.120) | (0.088) | (0.120) | (0.088) | (0.121) |
| Log Tot Exp | 0.002 | 0.004* | 0.002 | 0.003* | 0.002 | 0.003* | 0.002 | 0.003* |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) |
| $(t-1)$ Indicator | | | -0.976*** | -3.190*** | | | -0.953*** | -3.022*** |
| | | | (0.130) | (0.179) | | | (0.186) | (0.270) |
| Initial Bid | | | | | -0.0016 | -0.0052 | -0.0006 | -0.0045 |
| | | | | | (0.004) | (0.006) | (0.003) | (0.006) |
| Constant | 1.368*** | 2.741** | 1.851*** | 4.343*** | 1.404*** | 2.853** | 1.853*** | 4.356*** |
| | (0.463) | (1.202) | (0.320) | (0.449) | (0.454) | (1.143) | (0.321) | (0.449) |
| Observations | 1,086 | 1,086 | 1,086 | 1,086 | 1,086 | 1,086 | 1,086 | 1,086 |
| Log-likelihood | -689.8 | -483.4 | -685.5 | -477.2 | -689.7 | -482.9 | -685.5 | -476.8 |
| WTP | 14.98*** | 15.93 | 9.21*** | 3.24*** | 15.42*** | 17.65 | 9.42*** | 3.86** |
| | (5.26) | (18.57) | (0.98) | (0.95) | (5.17) | (19.50) | (1.57) | (1.39) |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A2. Additional Random-effect Probit Model Estimates

| *VARIABLES* | *Shift-ascending* | *Shift-descending* | *Anchor-ascending* | *Anchor-descending* | *Shift-anchor ascending* | *Shift-anchor descending* |
|---|---|---|---|---|---|---|
| $(t-1)$ Indic | -0.992*** | -3.926*** | | | -1.066*** | -4.163*** |
| | (0.220) | (0.314) | | | (0.304) | (0.500) |
| Initial Bid | | | -0.000442 | 0.00444 | 0.00201 | 0.00626 |
| | | | (0.00601) | (0.00997) | (0.00572) | (0.00987) |
| Log Tot Exp | 0.356*** | 0.172 | 0.355*** | 0.169 | 0.357*** | 0.170 |
| | (0.127) | (0.158) | (0.126) | (0.157) | (0.127) | (0.158) |
| Log Current Bid | -0.360** | -0.968*** | -0.366** | -0.970*** | -0.364** | -0.979*** |
| | (0.155) | (0.220) | (0.155) | (0.220) | (0.155) | (0.221) |
| Total Livestock | -0.0101* | -0.0112 | -0.0101* | -0.0109 | -0.00996 | -0.0108 |
| | (0.006) | (0.012) | (0.006) | (0.012) | (0.006) | (0.012) |
| Household Size | 0.116** | 0.0381 | 0.116** | 0.0375 | 0.116** | 0.0375 |
| | (0.052) | (0.066) | (0.052) | (0.066) | (0.052) | (0.066) |
| Distance Town | -0.0002 | 0.0004 | -0.0002 | 0.0004 | -0.0002 | 0.0004 |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) |
| Forest Density | 0.1320 | 0.0618 | 0.1320 | 0.0597 | 0.1320 | 0.0589 |
| | (0.284) | (0.361) | (0.283) | (0.360) | (0.284) | (0.361) |
| Rate Time Pref | 0.1620 | 0.5600 | 0.1590 | 0.5630 | 0.1690 | 0.5710 |
| | (0.352) | (0.481) | (0.352) | (0.481) | (0.353) | (0.485) |
| Age HH Head | -0.0248* | -0.0084 | -0.0248* | -0.0080 | -0.0245* | -0.0079 |
| | (0.013) | (0.017) | (0.013) | (0.017) | (0.013) | (0.017) |
| Education Head | -0.0088 | 0.0531 | -0.0088 | 0.0540 | -0.0079 | 0.0549 |
| | (0.0399) | (0.0528) | (0.0399) | (0.0527) | (0.0400) | (0.0530) |
| | (0.118) | (0.151) | (0.118) | (0.151) | (0.118) | (0.151) |
| Constant | 0.0499 | 3.007* | -0.406 | 0.969 | 0.0403 | 3.030* |
| | (1.284) | (1.690) | (1.332) | (2.216) | (1.284) | (1.690) |
| | | | | | | |
| Log-likelihood | -258.1 | -170.5 | -261.4 | -176.0 | -258.0 | -170.3 |
| Observation | 928 | 928 | 928 | 928 | 928 | 928 |

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

**Appendix B. CVM questionnaire**

Suppose that the *got* (village) development committee (GDC) proposes to establish a new community forest plantation on communal grazing land. Also suppose that this plan is endorsed by the kebele administration and district office of agriculture.

The community forest plantation offers you the following benefits:

You are able to access fuel wood, and it reduces the household time required to collect fuel wood from distant woodlands and/or other forests. The time saved can be used for agricultural activities, marketing or social activities. You can also use leaves from the plantation for medicinal purposes. When the plantation reaches harvesting age, you can share timber products from the plantation for construction material and agricultural implements. You can either use these products for yourself or sell them to generate cash, depending on your need. However, you should note that the communal grazing land used for the forest plantation is not going to be used for grazing any longer for many years to come.

The proposed woodlot has the following characteristics:

species mix: Eucalyptus

harvest quota: __30____meter cube

type of place: x grazing land

Also note that the government doesn't have access to sufficient funds to finance the project. Therefore, the plantation can only be established if the *got* community contributes money towards the establishment of the forest and the management thereof.

The contribution is required from the community for:

- establishing a community nursery and/or purchasing seedlings;
- site preparation: clearing the site, digging holes and fencing the site; and
- employing guards to protect against theft.

It is also important to note that the control and the management of the contributed funds are to be entrusted to the development committee. By law, the committee cannot divert these funds to any other purpose. Note that the money will be collected by the committee after the main crop harvest each year. The contribution will be made annually for five consecutive years.

When we talked to other people in your village, we have found people who would be willing to vote in favour of the project and those who would not be in favour. Each group has many reasons to vote either for or against, and neither group is wrong.

Those in favour of the project say that:

- Increased forest product availability is worth some cost;
- They are tired of walking long distances to fetch fire wood and other forest products;
- They want to reduce their farm fertility loss through the application of manure (dung) and crop residues, rather than using these products for fuel;
- Timber products for construction and farm implements are becoming scarcer.

Those not in favour of the project say that:

- A new community forest plantation would reduce available grazing land for their animals;
- They would rather use their money for other purposes;
- They own private woodlots or have other alternatives forestry access, such that they do not need a community forest;
- They cannot afford the time required to attend a series of meetings related to the management of the community forest plantation.

Now that we have explained the purposes of this project, and provided you with information from other potential participants in the community. We would now like you to consider this project for yourself. Given the information that we have provided in relation to the establishment of a new community forest plantation, could you answer the following questions?

1. Before proceeding, do you have any questions about the establishment of a community forest plantation, as outlined above?

Yes………………1,

No… ……………2 (go to 2)

1.1 What would you like to know?

*If the respondent asks about costs, tick here and say: "we will come to that in a moment."*

2. Do you want to contribute for the community forest?

Yes………………1, No………………2

2.1 If no, why? Use code A

3. As we said earlier the actual cost of the project is not known. However, if you are a decision maker in your household and asked to contribute Birr __________ annually for five consecutive years, would your household be willing to contribute that amount?

1. Yes ➔ Go to 4
2. No ➔ Go to 5

4. What if you are asked, instead, to contribute Birr_________ annually for five consecutive years, would your household be willing to contribute that amount?

1. Yes 2. No

5. What if you are asked, instead, to contribute Birr_________ annually for five consecutive years, would your household be willing to contribute that amount?

6. What would be the maximum annual amount that your household would be willing to contribute? Birr___________

6.1 To enumerators: *probe if the answer is yes to 4 or 5 and the maximum willingness to pay in 6 is less than the amount agreed to pay in 4 or 5* as follows;

- Why is it that the maximum annual amount that your household would be willing to contribute is less than the amount you initially agreed to contribute? Use code B