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Contingent Valuation of Community Forestry Programs in Ethiopia: Observing Preference Anomalies in Double-Bounded CVM

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Contingent Valuation of Community Forestry Programs in Ethiopia: Observing Preference Anomalies in Double-Bounded CVM

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Abstract

This study examines the potential for anomalous response behaviour effects within the context of double-bounded contingent valuation applied to community forestry programs in rural Ethiopia. Anomalous responses considered include shift effects, framing effects, anchoring effects, and others closely related to these. The results confirmed the presence of anomalous responses, especially shift and framing effects; anchoring effects are not uncovered. After controlling for these biases, the analysed community forestry program is shown to offer a welfare gain ranging from Ethiopian Birr (ETB) 20.14 to 22.80 annually, per household. In addition to uncovering limited welfare benefits, the results raise questions regarding the validity of previous double-bounded contingent valuation welfare estimates in developing countries, suggesting that future studies should control for incentive incompatibility and framing effects bias.

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

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

1 Introduction

The valuation of non-traded goods is complicated, because prices cannot be observed. Therefore, responses to price changes are not revealed by behaviour and welfare effects related to price changes are not easily uncovered. One common response to these difficulties is to evaluate non-market goods via the Contingent Valuation Method (CVM), since it derives its theoretical basis from

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welfare economics. One popular CVM survey is the single-bounded, or dichotomous choice design (Whitehead, 2002, Hanemann, 1994, Herriges and Shogren, 1996). The popularity of this design is due to: U.S National Oceanographic and Atmospheric Administration (NOAA) recommendations (Arrow et al., 1993), its incentive compatibility property (Haab and McConnel, 2002) and its "take-it-or-leave-it" format, which mimics the decision-making task individuals face in daily market transactions (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, and the respondent either agrees to pay or does not.

Despite its popularity, single-bounded CVM (SBCVM) 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 precision (Hanemann et al., 1991). These limitations have led researchers to look for alternative designs that retain incentive compatibility, but are more efficient (Haab and McConnel, 2002). Hanemann et al. (1991) first devised the double-bounded CVM (DBCVM) format, proving its improved efficiency properties over the single-bounded format. Unlike SBCVM, where the willingness-to-pay (WTP) is known to lie either above or below a specified amount, DBCVM provides additional information. Given its structure, in which an individual is first asked to respond based on one value and then asked to respond to a second value, DBCVM avails the researcher with additional WTP intervals.[1] Estimation of the model incorporates the additional information into the likelihood function to improve model precision.

The fundamental assumption of the double-bounded model is that the respondent's preferences remain the same over the two valuation questions, such that observations are independent across the two responses. Under these assumptions, twice as many observations are available per individual, which yields greater estimation precision.[2] Subsequent studies, however, argue that DBCVM suffers from a number of anomalies. Most poignant of these anomalies is that the subject's response to the second question may be influenced by the first value proposed to them in the survey (Alberni et al., 1997, Flachaire, 2006, Herriges and Shogren, 1996). In other words, preferences may not remain constant, implying that it is possible to estimate different WTP values for the same individual, leading to inconclusive results; it is unclear which WTP is correct. Cameron and Quiggin (1994), amongst others, find that independence is violated in their DBCVM survey.

Several hypotheses explaining the dependence between the first and second responses have, since, arisen in the literature. Key, amongst these, is the pres-

[1] In this study, if the respondent initially says no, the second survey value is specified to lie below the first. If the respondent initially says yes, the second survey value is specified to lie above the first

[2] Hahnemann et al. (1991) compare the information matrices across the SBCVM and DBCVM. They show that a well-designed bid vector yields lower variances in the DBCVM relative to the SBCVM, and empirically validate the conclusion. Empirically, they also find lower WTP point estimates in the double-bounded model.

ence of anchoring and shifting in preferences, which are different versions of starting point bias. 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). Therefore, the respondent may anchor her priors on the initial value. 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 opening value, 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, who rejected the first bid, the follow-up value could be interpreted as a lower quality good, leading to WTP reductions (Alberni et al., 1997).

Recent studies have identified additional sources of preference anomalies that may arise in DBCVM,[3] control for these undesirable effects, and empirically examine their validity. Early literature includes Herriges and Shorgen (1996), who test for anchoring, and Alberni et al. (1997), who examine shifting. More recent examples include Whitehead (2002), who tests for both anchoring and shifting, as well as Flachiare and Hollard (2006), who test more generally for any starting point bias. Moreover, Chien et al. (2002) test for the presence of starting point bias along with compliance bias, wherein an individual violates incentive compatibility constraints. However, a consensus about which bias is salient has not been reached.

Herriges and Shogren (1996), for example, find evidence of anchoring. Furthermore, controlling for anchoring in their DBCVM leads to less precision in their WTP estimate, relative to the SBCVM. They conclude that single-bounded models perform better, in the presence of significant anchoring effects. Whitehead (2002) estimates a random effects probit model, allowing for coefficient variation across two sets of take-it-or-leave-it questions to control for anchoring, and includes a dummy variable for the second question to control for shifting. Controlling for these effects, Whitehead (2002) finds a significant improvement in precision in his analysis. However, that gain may not be obtained with another data set. Both Flachaire and Hollard (2006) and Chien et al. (2005) report evidence of anchoring, while only the former analysis also uncovers significant precision improvements in their WTP point estimates.

Overall, the literature does not provide consistent and robust evidence of anchoring, shifting and improved estimate precision. Of greater concern is that the literature related to anchoring and shifting has focused on developed countries, primarily the US. As the double-bounded format has not featured in the developing world literature, it has not been possible to consider the generalizability of these preference anomalies to other countries and cultures. Although there is steady growth in the CVM literature in developing countries, the focus has been on biases related to the CVM scenario and survey administration, rather than anchoring, shifting and related biases. Specific examples include

[3] Via the application of Kahneman and Tversky's (1979) prospect theory, DeShazo (2002) has established that respondents might frame the follow-up offer as a gain or loss compared to the initial offer, which results in a downward bias in the WTP for subsamples subjected to ascending bid sequences.

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 (Lynam et al. 1994; Shyansundar et al. 1995; Mekonnen, 2000 and Köhlin, 2000). While these studies aim to provide useful policy information related to environmental interventions, they do not consider the sorts of biases discussed above, although Köhlin (2001) and Carlsson et al. (2004) control for "yea-saying", which is one form of compliance bias.

Therefore, the main contribution of this research is to provide empirical evidence related to biases that might arise in a developing country DBCVM setting, focussing on community forestry programs in Ethiopia. Our data comes from a contingent valuation study of community plantations in selected rural villages in Ethiopia. In this analysis, we applied a host of empirical strategies including interval censored data models, bivariate probit models and various random effects probit models to examine whether response biases are observed. Moreover, we compared the parameter estimates of the latter models with that of SBCVM model to consider the effect of the biases and the underlying precision of the estimates. The results show that significant biases, especially related to shifting and compliance, arise in our data. However, the hypothesis that peasant households anchor their willingness to pay to starting bids is rejected.

The analysis is laid out in the following way; Section 2 discusses theoretical and empirical specifications. Section 3 describes the design of the contingent valuation experiment and data collection method. Section 4 presents the results of the analysis, along with a short discussion. The analysis concludes with Section 5.

2 Theoretical and Empirical Specifications

Consider an individual, denoted by i, whose WTP for a non-market good, in log form, is w_{it}. In keeping with the potential for preference anomalies in the DBCVM, WTP is allowed to depend on survey timing. Further, assume that the individual faces two take-it-or-leave-it survey questions, related to their WTP, which is in line with the DBCVM. She is offered an initial value, to which she can respond either yes or no. In a follow-up, depending upon the initial answer, she is offered a different value, to which she can also answer either yes or no. These survey values, referred to as bids, will be denoted, in log form, as b_{it}.

The survey structure yields a set of observed outcomes, $Y_i = \{Y_{i1}, Y_{i2}\}$, where $Y_{it} = \{0, 1\} = \{\text{no, yes}\}$ are the outcomes from each survey question. Assuming rationality – an individual does not agree to pay more than she is willing – the set of observed responses yields a set of intervals for estimating WTP. Mathematically, $Y_i = (\text{yes, yes}) \iff w_i \geqslant b_{i2}, Y_i = (\text{yes, no}) \iff b_{i1} \leqslant w_i < b_{i2}, Y_i = (\text{no, yes}) \iff b_{i1} > w_i \geqslant b_{i2}$,and $Y_i = (\text{no, no}) \iff w_i < b_{i2}$. As the purpose of CVM surveys is to elicit WTP, w_{it} is not observed; however, WTP can be constructed from an empirical analysis that potentially includes determinants of WTP, such that $w_{it} = \chi_{it}\beta_t + u_{it}$.

2.1 *Bivariate Probit*

The preceding structure, with a few assumptions, follows a bivariate probit model. Define **I** as an indicator function equal to one if the expression is true, and zero otherwise, such that $Y_{it} = \mathbf{I}(w_{it} > b_{it})$. Further, assume that the unobserved WTP can be written as above, $w_{it} = \chi_{it}\beta_t + u_{it}$, where $u_{it}\tilde{}N(0, (\sigma_1^2\ \rho\sigma_1\sigma_2), (\rho\sigma_1\sigma_2\ \sigma_2^2)))$, is a vector of explanatory variables described further, below, and β_{it} is a vector of parameters to be estimated. Accordingly, if $w_i = w_{i1} = w_{12}$ and $\rho = 1$, 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). It is also possible to restrict the model in other ways. For example, 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.

2.2 *Common Preference Anomalies*

The literature offers several explanations for the divergence between SBCVM and DBCVM, some of which have been described above. These explanations revolve around the proposition that the response to the second bid is not necessarily independent of the initial bid.

2.2.1 Anchoring Effects

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 offer may serve as an anchor, if the respondent assumes that the initial offer conveys information on the true value of the good (DeShazo, 2002). Respondents who are assigned ascending sequences interpret the follow-up bid as a lower weighted average bid, which increases the probability of accepting the follow-up bid. On the other hand, respondents who are assigned a descending sequence may construe the follow-up bid as a higher weighted average bid, 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 effects in the upper and lower intervals.

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

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

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 $\gamma \in [0, 1]$, which is assumed constant. If the individual held (very) loose priors regarding her own WTP, the posterior WTP would be relatively more dependent upon the initial bid, and, vice versa.

2.2.2 Shifting Effects

Under shifting, an individual willing to pay the opening 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, who rejected the first bid, the follow-up value could be interpreted as a lower quality good, leading to WTP reductions (Alberini et al., 1997). Along these lines, shifting is modelled as a change in the WTP that is independent of the initial bid.

$$w_{i2} = w_{i1} + \delta \tag{2}$$

2.2.3 Anchoring and Shifting Effects

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.

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

Therefore, in the second stage, $Y_{i2} = \mathbf{I}((1 - \gamma)w_{i1} + \gamma b_{i1} + \delta + u_{i2} > b_{i2})$, and, in the first stage, $Y_{i2} = \mathbf{I}(w_{i1} + u_{i1} > b_{i1})$.

2.3 *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.

2.3.1 Framing Effect

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.[4] 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 DBCVM model should only include descending follow-up questions, in practice.

[4] Flachaire and Hollard (2006) and Watson and Ryan (2007) provide some evidence of DeShazo's (2002) framing effects.

2.3.2 Strategic Behaviour Effects

Similar to framing effects are strategic behaviour effects, in the sense that they are both related to anchoring. 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).

2.3.3 Cost Expectations Effects

In addition to anomalies related to anchoring, there are at least two associated with shifting. One such example is the cost expectations effect. Specifically, 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, except that the shift parameter δ is always negative, suggesting a downward bias in the WTP (Whitehead, 2002, Flachaire and Hollard, 2006, DeShazo, 2002).

2.3.4 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 δ 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.

2.4 *Implementation*

The primary empirical strategy follows Whitehead (2002), whereby random effects probit models, exploiting the panel structure of DBCVM data, are implemented. In the model, two observations are available for each individual, $Y_{it} = \mathbf{I}(\chi_{it}\beta_t + u_{it} > b_{it})$. The underlying unobserved component can be decomposed into an individual (random) effect α_i and an idiosyncratic effect, η_{it} giving rise to the general error term $u_{it} = \alpha_i + \eta_{it}$, where $\alpha_i \tilde{} N(0, \sigma_\alpha^2), \eta_{it} \tilde{} N(0, \sigma_\eta^2)$ and $\varepsilon[\alpha_i \chi_{it}] = 0$, 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, $\rho_\alpha = \sigma_\alpha^2/(\sigma_\alpha^2 + \sigma_\eta^2)$, which is defined as a fraction of the variance attributed to the individual specific effect, α_i.

This structure helps us discriminate 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 a fraction of the variance attributed to the individual specific component, ρ_α, is zero then correlation between the WTP error terms is one.[5] The difference between WTPs is, thus, due to the random component, η_{it}. Error component models, thus, collapse to what is known as interval-censored data models, a simple probit model estimated over pooled survey responses (Hanneman et al., 1991). However, if a fraction of the variance attributable to the individual specific component is non-zero, either error component models (Alberini, 1997) or bivariate probit models (Cameron and Quiggin, 1994) could be used for parameter estimation. The problem with the latter is that it leads to two different estimates of WTP, and the true value would not be identified.

As alluded to in the preceding subsections, we implemented a range of empirical models in the analysis: unrestricted bivariate probit, restricted bivariate probit, an interval data model, probit models for SBCVM response and random effects probit models. The restricted bivariate probit model imposes cross-equation parameter restrictions, such that the mean WTP underlying each response is identical ($\beta_0 = \beta_1$). However, unlike the interval data model, which assumes identical mean WTP as well as dispersion parameters ($\beta_0 = \beta_1, \sigma_0 = \sigma_1$), the restricted bivariate probit model doesn't impose equality of the WTP dispersion parameter ($\sigma_0 \neq \sigma_1$). Therefore, the unrestricted bivariate probit model nests both the interval data model and the restricted bivariate probit model as special cases. 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).

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

In equation (4), z represents a vector of individual specific controls and Γ represents the vector of parameters to be estimated. For the second survey question, $w_2 = \beta_0 + \Gamma z + \beta_2 b_2 + \delta + \gamma b_2$; however, for the first survey question,

[5] Note that the fraction of the variance attributable to randomness in the WTP, η_{it}, could be expressed as $\rho_\eta = \frac{\sigma_\eta^2}{(\sigma_\alpha^2+\sigma_\eta^2)} = 1 - \frac{\sigma_\alpha^2}{(\sigma_\alpha^2+\sigma_\eta^2)}$. It then follows that there is no individual specific component, equivalently, $\sigma_\alpha^2 = 0$, implies that $\rho_\eta = 1$.

$w_1 = \beta_0 + \Gamma z + \beta_1 b_1$. When neither shifting nor anchoring are assumed to be present, equation (4) reduces to $w_t = \beta_0 + \Gamma z + \beta_t b_t$.

3 Study area, Design and Data

For this analysis, a valuation exercise for WTP elicitation, related to the establishment of a community forest program, was conducted. The design follows the DBCVM, 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 didn't accommodate the preferences of either the local community or the individuals slated for intervention (Gelo and Koch, 2012). Benin et al. (2002), however, outline a more recent approach, emphasizing local community involvement in resource conservation and management, which forms part of the incumbent government's rural development polices. 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, Fekadu, 2008).

3.1 *Survey and Bid Response*

The CVM 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. A team of trained enumerators conducted the interviews. However, in order to conduct the CVM study, starting bids were necessary. Starting bids were obtained from a pilot study of 60 randomly selected households, in which an open-ended CVM question format was used. The result of the pilot study was a vector of five starting bids: 10, 20, 32, 50 and 80.

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 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.[6] For those willing to participate, they were further asked if they were willing to pay the initial – randomly assigned – bid. Regardless of whether the respondents were willing to pay the initial bid, a follow-up question was also asked of the respondent. 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 acceptance for each bid.

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

As noted above, 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 the 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 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.[7] Descriptive statistics of this data are presented in Table 2.

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) 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 education; (3) other prices – 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.

[6] 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.

[7] A subject was asked the maximum sum that he/she would be willing pay one year from now, if he/she had borrowed ETB 100 today. The rate of time preference was calculated from this value using the net present value formula. The question was adopted from Andersson et al. (2011).

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. Moreover, we presume that time preferences are dependent on household wealth measures (education, landholding and ownership of corrugated house etc.) and household head characteristics, such as age and sex.

With regard to proxies for other prices, 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 larger households have less discretionary income per capita and partly because a larger household increases the supply of labour available for collecting forest products from open access forests.

4 Empirical Results

In this section, we present the results of the empirical analysis, including tests for preference anomalies. Following these tests, we present the welfare analysis. Specifically, we present the valuation of the program's perceived welfare benefits, based on a host of empirical strategies that include determinants of household WTP.

4.1 *Testing for Preferences Anomalies*

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 raw data, we found that some households chose to give lower WTP values in the open ended follow-up question than wase uncovered from the closed-end questions; 14.7% of respondents were inconsistent in this way. Köhlin (2001) offers several explanations regarding the sources of this inconsistency, which include 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. According to these responses, 45% of the inconsistencies arose from "yea-saying" or compliance bias.

In what follows, we test for a number of bias effects by employing a range of empirical models. To that effect, we first fit restricted bivariate models, an interval data model and unrestricted bivariate probit models (see Table 3). The likelihood ratio test supports the hypothesis that the unrestricted bivariate probit models and restricted bivariate probit model fit the data better than the interval data model, $\chi^2 = 61.54$, $p = 0.00$ and $\chi^2 = 77.56, p = 0.001$, respectively. However, the unrestricted bivariate probit model is not an improvement over the restricted bivariate probit model, $\chi^2 = 16.04, p = 1$. In addition to these tests, we find that the error correlation deviates significantly from unity, $p = 0.528$ for the unrestricted bivariate probit and $p = 0.553$ for the restricted bivariate probit, supporting the hypothesis that WTP varies across the valuation questions. Equivalently, the results lend support to the claim that preference anomalies are present in the responses and that parameter estimates from standard double-bounded models are not appropriate for inference.

Moreover, via a likelihood ratio test, as was done in DeShazo (2002), we test whether parameter consistency holds across the two WTP equations for the ascending bid sequence subsample and descending bid sequence subsample. The results revealed 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 ($\chi^2 = 769.75, p = 0.00$). When combined, these results lead us to reject the null hypothesis that there are no framing effects within the survey.[8]

4.2 *Controlling for Preferences Anomalies*

Given the preference anomalies observed in the preceding analysis, we also implement a series of random effect probit models accounting for WTP variation and compare those results with that of a single-bound probit model and a random effects probit model. The random effects probit model is denoted as the naïve model, as it assumes equal WTP values across bid questions; hence, we don't account for anchoring or incentive effects or both. Comparing the single-bound and random effects probit model, we see that the latter yields lower WTP point estimates, as well as lower standard errors. This finding supports Hanemann et al. (1991), who conclude that double-bounded models yield both lower point estimates and improved efficiency.

[8] 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.

In what follows, we return to models that account for differences in WTP. In other words, we control for shift-effects and starting point biases (see Table 4). The shift effect is introduced as a dummy variable, A, to test whether willingness to pay differs across the valuation questions. This model is referred to as the shift effect model, hereafter. Our results point to both negative and statistically significant shift effects, suggesting that there is a negative shift effect following the first valuation question. The result 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. Equivalently, the result confirms that there is no yea-saying bias, partly because it has been controlled for in the analysis – inconsistent responses to open-ended follow-up questions were discarded.

The shift effect model was then altered to, instead, allow for anchoring. In the anchoring effect model, A_n is introduced to capture potential starting point bias. The results point to negative and significant anchoring effects. Although the absolute value of the coefficient lies in the unit interval, it implies a negative starting point effect, which violates the assumptions of the standard anchoring effect model. Consequently, we cannot conclude that anchoring effects are present. Our conclusion is contrary to Chien et al. (2005), Whitehead (2002) and Flachaire and Hollard (2006), all of which found evidence of anchoring bias in their data.

In case the anchoring effect was inappropriately capturing other effects, we accounted for the simultaneous presence of both shift effects and anchoring effects. This model is 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. Moreover, the likelihood ratio test indicates that this model is not an improvement over the shift-effect model, $\chi^2 = 0.78, p = 0.382$. However, the likelihood ratio test also confirmed that all of these models outperform the random effects probit model and anchor model. Generally, the WTP point estimate is lower in all of the bias corrected models (shift-effect, anchoring effect and shift-anchor effect models) compared to the single-bound estimate.

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 shifting 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.

4.3 *Welfare and Estimation Efficiency*

Although the existence of preference anomalies is interesting, on its own, the primary purpose of CVM is the elicitation of preferences. Preference anomalies should be controlled in the analysis, such that appropriate welfare estimates can be obtained. Upon calculation of the welfare effects, we found that the shift-effect model yielded the lowest median willingness to pay, ETB 20.14, whereas the anchor-effect model and the shift-anchor model yielded slightly higher WTP estimates, ETB 22.80 and ETB 30.41, respectively. However, WTP values for either the ascending or descending bid sequence subsamples were generally lower than for the full sample. As elucidated earlier, the likelihood ratio test results for model selection support the choice of the shift-effect and shift-anchor random effects probit models, although the shift-anchor effects model yields an inconsistent, with respect to theory, negative anchor effect. As such, we report the willingness to pay estimate for these models as our measure of the community forestry welfare impact, which ranged between ETB20.14 and ETB22.80. However, our preferred estimate is the lower estimate of ETB20.14, as the higher estimate includes the inconsistent negative anchoring effect.

In addition to examining the welfare effect, estimated efficiency is also relevant, given the fact that the double-bounded model has been shown to be more efficient. The welfare estimate, median WTP, is computed from the model parameters, and, hence its distribution depends on the distribution of the parameters. The Delta method is used to derive the standard errors of the welfare estimates (Greene 1997). On the basis of efficiency, as measured by the relative standard errors, all of the random-effects probit models (naïve, shift, anchoring, and shift and anchoring models) outperform the single-bounded models. Amongst, the random-effects probit models, the shift-effect model yielded the lowest standard error estimate.

4.4 *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. However, some do not, which led to additional investigation, discussed below. The results are reported in Table 5 and Table 6. In Table 5, the random-effects probit models with selected covariates are presented. One concern that arises in an analysis of this nature is that the model could suffer from endogeneity, arising, especially, from the relationship between the rate of time preference and the error term.

Along those lines, Davidson and MacKinnon's (1993) test rejected the hypothesis that the rate of time preference is exogenous ($\chi^2 = 05.31, p = 0.02$). Therefore, the models were extended to include IV methods. The rate of time preference was instrumented by household head age, gender, land holdings per capita and wealth variables. Following Davis and Kim (2002), instrument relevance based on Shea's (1997) partial r^2, revealed that the null hypothesis of no instrument relevance is rejected ($r^2 = eigenvalue = 0.027$). Therefore, IV results are further discussed. Once IV methods were applied, previously inconsistent, with expectations, parameter estimates were found to conform to our *a priori* expectations. For example, initially, the rate of time preference estimate and the estimate for the measure of access to alternative forests were counterintuitive – they were positive – in the uncorrected random effects model. Following correction, the signs changed, yielding results that were consistent with our expectations.

As expected, the parameter on (logged) bids is negative and significant, supporting the claim that respondents are rational, when faced with increasing cost. In addition, the (logged) income effect is also positive and significant, implying that community forestry is a normal good. Livestock ownership effects were estimated to be negative and significant, suggesting that rural Ethiopian farmers believe there are significant opportunity costs, mostly in the form of reduced grazing land, associated with community forestry. Household size, although not significant, is found to be positive, which was not expected. Possibly, larger households require more biomass, which may offset the effect of increased labour supply. Similarly, other price proxies – access to alternative forests and the distance to town, carry the expected signs, but are not significant. Finally, the rate of time preference is found to be an insignificant, but negative, determinant of WTP, as expected.

5 Conclusion

SBCVM has desirable properties, such as incentive compatibility and survey implementation benefits; however, proper implementation requires a relatively large sample. The DBCVM has been employed as an alternative method to improve efficiency, i.e., requires fewer survey respondents. However, it also suffers from biases resulting from a range of preference anomalies, including anchoring effects, shift effects and other biases. Although several studies have tested for these biases, the majority of these studies have been undertaken in developed countries.

In this study, we applied a DBCVM format and tested for the aforementioned biases, employing a host of empirical strategies. Our data comes 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. However, the hypothesis that peasant households anchor their WTP to the starting bid is rejected. Estimation of compensated variation, as a welfare measure, after controlling for the preference anomalies, showed that community forestry programs offer welfare gains of approximately ETB20.14 for this study's peasant households. Furthermore, controlling for shift effects and anchoring effects improved the statistical precision of the welfare estimate, a result that confirms a number of the developed country studies.

Moreover, analysis of bid functions found that household income, program establishment costs and livestock holdings are important determinants of WTP. The first of these suggests that community forestry is a normal good, while the effect of program establishment costs are consistent with the expectation that increased prices reduce demand. 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 will 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. Additionally, the failure to account for shift-effect bias and other biases yields an inconsistent welfare estimate within the DBCVM. Therefore, although such methods improve relative precision, care must be taken in their use in developing countries, as well as developed countries.

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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

Note: 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 DBCVM based on the initial bid.

Table 2. Descriptive Statistics of survey data

Variable	*Description*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
density	Per-hectare biomass per-capita	0.25	0.50	0	3
tlu	Animal holdings (TLUs)	8.64	6.53	0	42
sex	=1 if respondent is male	0.89	0.30	0	1
age	Household head age	45.43	12.74	23	90
hhsize	Household size	6.48	2.42	1	15
yrsschool	Household head education	5.50	2.94	0	14
expenditure	Non-food expenditure/year	4184.10	5402.80	122	36500
wealth	Corrugated house	0.40	0.49	0	1
lndszpc	Land holding per capita in hectare	0.82	0.97	0	5
rtp	Rate of time preference	0.25	0.28	0	2
WTP	Open-ended WTP	38.80	24.86	10	80
WTPa	Open-ended WTPa	55.13	40.16	10	240
WTPd	Open-ended WTPd	8.88	5.68	1	20

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

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

VARIABLES	Single-bounded CVM model	Constrained biprobit model (β_1=β_2) (all observation)	Unconstrained bivariate probit (all observation)		Constrained biprobit model β_1=β_2 ascending- bid subsample	Unconstrained bivariate probit (ascending-bid subsample)		Constrained biprobit model β_1=β_2 descending bid subsample	Unconstrained bivariate probit (descending-bid subsample)	
Ln(b1)	-0.023*** (0. 003)	-0.012*** (0.0541)	-0.529*** (0.0857)		-0.501*** (0.0916)	-0.109 (0.273)		-0.132 (0.150)	-0.245 (0.430)	
Ln(income)	0.00037* (0.00217)	0.013 (0.0374)	0.002* (0.006)	0.009 (0.004)	0.006 (0.006)	0.021 (0.161)	0.004 (0.006)	0.171* (0.099)	0.035 (0.256)	0.215* (0.110)
Ln(b2)				-0.573*** (0.0814)						
Ln(b)							-0.540** (0.0953)			-0.208 (0.166)
Constant	1.823*** (0. 45)	1.091*** (0.331)	0.834 (0.512)	1.635*** (0.044)	4.257*** (0.398)	2.985*** (0.968)	2.577*** (0.372)	-1.692*** (0.598)	-2.881* (1.682)	0.316 (0.510)
Ln(Likelihood)	-298.75	-637.942	-645.952	-645.952	. -630.579	-245.703	-245.703	-114.252	-113.483	-113.483
rho		0.553	0.528	0.528	0.616	0.139	0.132	0.114	-0.047	-0.047
Observations		550	550	550	408	408	408	145	145	145
WTP	80.52*** (8.65)	89.296*** (8.28)	84.043*** (9.53)	69.621*** (6.74)	285.004*** (47.25)	1023.83** (423.73)	106.26*** (12.15)	210.53 (181.55)	152.641 (111.40)	2.349 (21.16)

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

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

VARIABLES	Interval-data	Naïve	Shift	Anchoring	Shift-anchoring	Naïve		shift		Anchoring		Shift-anchoring	
						ascending	descending	ascending	descending	ascending	descending	ascending	descending
lnbid	-0.381***	-0.579***	-0.575***	-0.591***	-0.578***	-0.262***	-0.973***	-0.260***	-0.976***	-0.264***	-0.977***	-0.261***	-0.979***
	(0.0544)	(0.0920)	(0.0930)	(0.0928)	(0.0932)	(0.0875)	(0.120)	(0.0875)	(0.120)	(0.0875)	(0.120)	(0.0876)	(0.121)
lnincome	0.013***	0. 002*	0. 002*	0.002*	0.002	0.002	0.004*	0.002	0.003*	0.002	0.003*	0.002	0.003*
	(0.0372)	(0. 0014)	(0. 0014)	(0. 0014)	(0. 0014)	(0.0013)	(0.0017)	(0.0013)	(0.0017)	(0.0013)	(0.0017)	(0.0014)	(0.0017)
A			-0.479***		-0.358*			-0.976***	-3.190***			-0.953***	-3.022***
			(0.1340)		(0.1930)			(0.130)	(0.179)			(0.186)	(0.270)
An				-0.080***	-0.003					-0.00163	-0.00523	-0.000616	-0.00448
				(0.0048)	(0.0036)					(0.00355)	(0.00555)	(0.00347)	(0.00552)
Constant	0.782**	2.701***	2.930***	2.898***	2.942***	1.368***	2.741**	1.851***	4.343***	1.404***	2.853**	1.853***	4.356***
	(0.3315)	(0.374)	(0.345)	(0.344)	(0.346)	(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	1,086	1,086	1,086	1,086
Log-likelihood		-656.91	-654.05	-655.40	-653.66	-689.81	-483.39	-685.47	-477.16	-689.71	-482.93	-685.45	-476.83
WTP		25.71***	20.14***	30.41***	22.82***	14.98***	15.93	9.21***	3.24***	15.42***	17.65	9.42***	3.86**
		(6.31)	(4.053)	(6.054)	(6.57)	(5.26)	(18.57)	(0.98)	(0.95)	(5.17)	(19.50)	(1.57)	(1.39)

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

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

VARIABLE	*Naïve*	*shift*	*Anchor*	*Shift-anchor*	*Shift-ascending*	*Shift-descending*	*Anchor-ascending*	*Anchor-descending*	*Shift-anchor ascending*	*Shift-anchor descending*
A		-0.545**			-0.992***	-3.926***			-1.066***	-4.163***
		(0.226)		-0.711**	(0.220)	(0.314)			(0.304)	(0.500)
An			-0.00651	(0.0417)			-0.000442	0.00444	0.00201	0.00626
			(0.00771)	0.260**			(0.00601)	(0.00997)	(0.00572)	(0.00987)
lntotexp	0.292**	0.294**	0.292**	(0.315)	0.356***	0.172	0.355***	0.169	0.357***	0.170
	(0.130)	(0.131)	(0.130)	0.00452	(0.127)	(0.158)	(0.126)	(0.157)	(0.127)	(0.158)
lnbid	-0.648***	-0.633***	0.647***	(0.00604)	-0.360**	-0.968***	-0.366**	-0.970***	-0.364**	-0.979***
	(0.166)	(0.166)	(0.167)	0.295**	(0.155)	(0.220)	(0.155)	(0.220)	(0.155)	(0.221)
tlu	-0.0114	-0.0115	-0.0115	(0.131)	-0.0101	-0.0112	-0.0101	-0.0109	-0.00996	-0.0108
	(0.00730)	(0.00731)	(0.00734)	-0.643***	(0.00626)	(0.0119)	(0.00627)	(0.0116)	(0.00624)	(0.0116)
hhsz	0.108**	0.109**	0.109**	(0.167)	0.116**	0.0381	0.116**	0.0375	0.116**	0.0375
	(0.0544)	(0.0545)	(0.0544)	-0.0111	(0.0523)	(0.0662)	(0.0522)	(0.0659)	(0.0524)	(0.0662)
dstwn	0.000154	0.000152	0.000153	(0.0546)	-0.000246	0.000416	-0.000245	0.000432	-0.000239	0.000446
	(0.00145)	(0.00145)	(0.00145)	0.241	(0.00143)	(0.00184)	(0.00143)	(0.00184)	(0.00143)	(0.00184)
fdensity	0.00431	0.00444	0.00435	(0.249)	0.132	0.0618	0.132	0.0597	0.132	0.0589
	(0.288)	(0.289)	(0.288)	0.000164	(0.284)	(0.361)	(0.283)	(0.360)	(0.284)	(0.361)
rtp	0.403	0.406	0.400	(0.00145)	0.162	0.560	0.159	0.563	0.169	0.571
	(0.375)	(0.376)	(0.376)	0.00408	(0.352)	(0.481)	(0.352)	(0.481)	(0.353)	(0.485)
age	-0.0214	-0.0217	-0.0216	(0.289)	-0.0248*	-0.00838	-0.0248*	-0.00804	-0.0245*	-0.00798
	(0.0137)	(0.0137)	(0.0138)	0.424	(0.0133)	(0.0172)	(0.0133)	(0.0172)	(0.0133)	(0.0172)
edu	0.0166	0.0164	0.0164	(0.377)	-0.00879	0.0531	-0.00877	0.0540	-0.00798	0.0549
	(0.0415)	(0.0416)	(0.0416)	-0.0208	(0.0399)	(0.0528)	(0.0399)	(0.0527)	(0.0400)	(0.0530)
	(0.121)	(0.121)	(0.121)	0.0180	(0.118)	(0.151)	(0.118)	(0.151)	(0.118)	(0.151)
Constant	0.890	1.104	0.908	(0.121)	0.0499	3.007*	-0.406	0.969	0.0403	3.030*
	(1.354)	(1.345)	(1.370)	1.081	(1.284)	(1.690)	(1.332)	(2.216)	(1.284)	(1.690)
				(1.346)						
Log-likelihood	-246.893	-244.797	-246.889	-244.515	-258.081	-170.503	-261.439	-175.960	-258.019	-170.306
Observation	928	928	928	928	928	928	928	928	928	928

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

Table 6. Parameter estimates of random-effect IV-probit model with covariates

VARIABLE	*Naïve*	*Shift*	*Anchoring Random effect*	*Anchoring Fixed effect*	*Shift-anchoring*	*Shift-ascending*	*Shift-descending*	*Anchoring-ascending*	*Anchoring-descending*	*Shift-anchor-ascending*	*Shift-anchor-descending*
rtp	-1.294	-1.319	-1.373	-1.349	-1.349	-2.034	-0.0126	-2.145	-0.238	-2.099	-0.0231
	(1.098)	(1.106)	(1.151)	(1.156)	(1.156)	(1.406)	(0.632)	(1.488)	(0.808)	(1.484)	(0.654)
A		-0.0963*			-0.0792	-0.192***	-0.690***			-0.135	-0.707***
		(0.0559)			(0.0911)	(0.0711)	(0.0320)			(0.117)	(0.0515)
An			-0.00161	-0.000466	-0.000466			-0.00351**	-0.00981***	-0.00155	0.000458
			(0.00126)	(0.00198)	(0.00198)			(0.00163)	(0.000884)	(0.00254)	(0.00112)
lntotexp	0.0584*	0.0582*	0.0586*	0.0584*	0.0584*	0.0743*	0.0237	0.0750*	0.0257	0.0746*	0.0237
	(0.0315)	(0.0317)	(0.0323)	(0.0321)	(0.0321)	(0.0403)	(0.0181)	(0.0418)	(0.0227)	(0.0412)	(0.0181)
lnbid	-0.109***	-0.0996**	-0.1000**	-0.0985**	-0.0985**	-0.0539	-0.103***	-0.0532	-0.116***	-0.0507	-0.104***
	(0.0394)	(0.0401)	(0.0418)	(0.0412)	(0.0412)	(0.0510)	(0.0229)	(0.0540)	(0.0293)	(0.0530)	(0.0233)
tlu	-0.00277*	-0.00280*	-0.00292*	-0.00285*	-0.00285*	-0.00300	-0.00117	-0.00327	-0.00185	-0.00314	-0.00113
	(0.00156)	(0.00157)	(0.00162)	(0.00163)	(0.00163)	(0.00199)	(0.000896)	(0.00210)	(0.00114)	(0.00210)	(0.000923)
hhsz	0.0130	0.0131	0.0133	0.0131	0.0131	0.0138	0.00313	0.0143	0.00434	0.0140	0.00307
	(0.0125)	(0.0125)	(0.0128)	(0.0127)	(0.0127)	(0.0160)	(0.00717)	(0.0165)	(0.00898)	(0.0163)	(0.00717)
dstwn	0.000318	0.000321	0.000328	0.000326	0.000326	0.000383	7.81e-05	0.000396	0.000106	0.000392	7.76e-05
	(0.000453)	(0.000456)	(0.000467)	(0.000464)	(0.000464)	(0.000580)	(0.000261)	(0.000604)	(0.000328)	(0.000596)	(0.000262)
fdensity	-0.0677	-0.0696	-0.0722	-0.0714	-0.0714	-0.0837	-0.00349	-0.0888	-0.00635	-0.0872	-0.00385
	(0.106)	(0.107)	(0.110)	(0.110)	(0.110)	(0.136)	(0.0612)	(0.142)	(0.0772)	(0.141)	(0.0619)
Constant	0.732**	0.751**	0.744**	0.712**	0.752**	0.594	0.909***	0.582	0.844***	0.595	0.909***
	(0.325)	(0.327)	(0.334)	(0.338)	(0.331)	(0.416)	(0.187)	(0.432)	(0.235)	(0.425)	(0.187)
Observations	928	928	928	928	928	928	928	928	928	928	928

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

Appendix A. CVM questionnaire

Suppose that the *got* 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. Moreover, it allows you to use crop-residue and animal dung for soil management instead of using them for fuel. In addition, it provides animal feed (fodder), particularly during the dry season, when fodder from communal woodland is rarely available. 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 is to be paid from each community member household, 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;
- They need supplemental feed sources for their cattle, particularly during the dry season;
- Timber products for construction and farm implements are becoming more scarce.

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. Might you be willing to contribute help establish a 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