Agricultural Water Management 168 (2016) 45–55

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

# Accounting for user expectations in the valuation of reliable irrigation water access in the Ethiopian highlands

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ARTICLE INFO

*Article history:*
Received 4 March 2015
Received in revised form 24 January 2016
Accepted 25 January 2016
Available online 3 February 2016

*Keywords:*
Willingness to pay
Contingent valuation
Hybrid choice model
Integrated choice and latent variable model
Developing countries

ABSTRACT

We estimate the willingness-to-pay (WTP) for reliable access to irrigation water for a sample of farmers in a watershed of the Ethiopian highlands who do not have prior experience with irrigation. To address the lack of previous irrigation experience, we account for underlying expectations of future irrigation productivity using an Integrated Choice and Latent Variable (ICLV) econometric model. We then compare the ICLV estimates with alternative models that do not account for expectations regarding productivity increases with irrigation. Our results indicate that both the ICLV and alternative provide similar conclusions with respect to the mean WTP for reliable irrigation water access. However, ignoring farmers' perceptions would understate the uncertainty of the mean or aggregate WTP.


## 1. Introduction

Reliable access to irrigation water can be defined as adequate and continuous year-round water flow for the purpose of crop production. Reliable irrigation is important in many developing-country settings because it increases agricultural productivity by reducing temporal variability that leads to major crop failure (Araya and Stroosnijder, 2011; Carruthers and Donaldson, 1971; Leite et al., 2015; Nam et al., 2015), increases yields because of more appropriate or timely watering (Valverde et al., 2015) and increases farmers' confidence in investing in higher-yielding technologies (for example improved seeds) that can be constrained by uncertainty of water supply (Perry, 2005).

Given the increased productivity resulting from irrigation, user valuation of reliable access to irrigation water is an important issue that has been addressed in previous literature (Mesa-Jurado et al., 2012; Storm et al., 2011). Valuation is important because it provides a source of information relevant for aggregating costs and benefits of irrigation projects. User valuation of may also be used to facilitate the design of payment for environmental services (PES) schemes in which water users make transfers to others whose actions help support reliable access to irrigation water (Whittington and Pagiola, 2012). The latter need for information motivates and provides a context for our study of irrigation water valuation in the Ethiopian highlands, where in many locations the lack of appropriate soil conservation measures accelerates reservoir siltation and reduces the availability of irrigation water (Ayele et al., 2016; Guzman et al., 2013; Kassahun and Jacobsen, 2015; Kidane and Alemu, 2015).

The problems resulting from the absence of soil conservation in the Ethiopian highlands can be severe: the Borkena Dam in South Wello (Ethiopia) was constructed before adequate soil conservation measures were put in place and complete siltation of the dam occurred within one rainy season (Desta et al., 2005). Maintaining reliable irrigation is also a concern for recently completed large-scale irrigation reservoirs such as the Koga Reservoir in Ethiopia (Assefa et al., 2015). It is estimated that the time during which irrigation water is available would be reduced by one month with an 11% reduction in volume of that reservoir, and that with the current siltation rate, it may lose 30% its volume in 35 years (Reynolds, 2012). Thus, in locations where high soil erosion potential exists,

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http://dx.doi.org/10.1016/j.agwat.2016.01.017
0378-3774/

reliable irrigation often cannot be achieved without continuous appropriate soil conservation practices being implemented.

However, implementation of soil conservation practices that increase irrigation water availability may result in significant time and monetary costs if undertaken by individual (upstream) farm households, and the principal benefits of their implementation may accrue to other (downstream) households (Kassahun and Jacobsen, 2015). Although it is not our objective to analyze potential transfer programs in detail (downstream) user valuation provides information that would be relevant for the design of a programs to effect financial transfers to (upstream) households undertaking soil conservation measures.

Thus, the main objective of this study is to estimate irrigation beneficiary farmers' mean and the aggregate willingness to pay (WTP) for reliable irrigation water access for a specific watershed in the Ethiopian highlands. Although a number of previous studies have analyzed WTP for irrigation water in Africa more generally (Angella et al., 2014; Storm et al., 2011), a key challenge in our study setting is that the majority of farmers in Ethiopia do not have irrigated farming experience (Awulachew et al., 2007). For these farmers, the stated value of reliable irrigation services depends, in part, on their perceptions about future production gains from access to reliable irrigation, rather than on previous irrigated production experience. To accommodate this reliance on perceptions in our WTP estimate, we adapt the Integrated Choice and Latent Variable (ICLV) model (Ben-Akiva et al., 1999; Bolduc et al., 2005; Daly et al., 2012b). We also compare WTP estimates based on the ICLV model results to a standard estimation approach to assess the bias introduced by omitting the latent perceptions about future irrigation production and its impacts on the uncertainty of estimated mean and aggregate WTP. In addition to the practical relevance of our study for one specific watershed, we also contribute to the growing literature on ICLV modeling in environmental valuation. And on the valuation of irrigation water in developing countries.

### 1.1. Accounting user's expectations for a WTP estimates

Most agricultural investment decisions depend on perceptions of future profitability (Cary and Wilkinson, 1997). However, perceptions may not necessarily match reality (Carman and Kooreman, 2014; Glenk and Colombo, 2011; McFadden, 1999). Reviewing several studies in economics and psychology, McFadden (1999) concludes that "it is difficult to exclude failures of perception rationality as sources of many observed anomalies." Thus, recognizing and accounting for this issue is essential in modeling, particularly in a complex dynamic system such as smallholder agriculture, and we should not expect user perceptions to be accurate (Sterman, 2000). Consequently, farm households may over- or under-estimate the value of reliable irrigation.

Omitting perceptions that are likely to be important may result in omitted variable bias inconsistent parameter estimates (Onjala et al., 2014; Whitehead, 2006). Nevertheless, there are a number of challenges to the inclusion of perceptions in WTP estimates. Perception or attitudinal response data cannot be used as a direct measure of an underlying latent attitude or perception in WTP estimates because of potential measurement error (Ashok et al., 2002). In addition, perceived expectation responses from survey questions do not necessarily translate into a causal relationship with WTP (Daly et al., 2012b; Viscusi and Evans, 2006). Finally, the unobservable effect of the response from perceived expectation about future production and the decision to pay for reliable irrigation services may be correlated. This creates a potential endogeneity bias. A method that avoids these potential problems is the integrated choice and latent variable (ICLV) model (Ben-Akiva et al., 1999; Bolduc et al., 2005; Daly et al., 2012b). In this model, the perception or attitudinal response data are used as an indicator of the underlying latent variable. In contrast to previous studies, we use expert knowledge about future expectations regarding irrigation productivity to classify respondents' perceptions. Accordingly, respondents are categorized as either in accordance with experts or placed in different categories. We do so to consider whether individuals underestimate or overestimate future irrigation productivity because an individual's perception may be associated with the under or over estimation of WTP.

The latent variable can include various perceptions, such as expectations regarding average production changes, experience with the method, variability in climate and consequently in output, and uncertainty regarding management and prices. The degree to which beliefs and uncertainties about the future are taken into account is unobserved by the analyst, but will determine a farmer's willingness to pay for reliable irrigation services and his or her latent variable indicator. Capturing the latent variable in the ICLV model improves understanding of the underlying choice process and the heterogeneity in perceptions and the distribution of utility values for reliable irrigation services.

## 2. Material and methods

### 2.1. Integrated choice and latent variable model

Most economic activities including agriculture, environmental management, education, finance, health involve decision making based on the expectation of future outcomes (Andersen et al., 2014; Cary and Wilkinson, 1997; Delavande et al., 2011; Hurd, 2009). However, when there is no revealed data regarding economic decisions and expectations about future outcomes, researchers often use stated preference data to study behavior and motivation that leads to a (stated) particular choice or decision. We consider the stated choice decision regarding WTP for reliable irrigation services and perceptions about the expected productivity of irrigated farming. We hypothesize that both the WTP for reliable irrigation services and the perceptions about irrigated farming (the latent variable indicator) are influenced by an underlying latent variable that represents perceptions about the expected productivity of irrigated farming. To test this hypothesis and to better understand the decision that governs choice behavior, both the choice and perception response data are simultaneously modeled using the ICLV framework (Ben-Akiva et al., 1999; Bolduc et al., 2005; Hess and Beharry-Borg, 2012). The ICLV has three model structures: the latent variable model, the latent variable indicator model and the choice response model.

#### 2.1.1. The latent variable model

The latent variable models is specified as a linear function of individual characteristics, $f(Z_n|dX_n + \eta_n)$, and is determined through a structural relationship:

$$Z_n = dX_n + \eta_n \tag{1}$$

where $Z_n$ is the value of the latent variable of an individual, $X_n$ is the individual characteristics, $d$ is an unknown parameter and $\eta_n$ is the error in the latent variable equation.

#### 2.1.2. The latent variable indicator model

The response from altitudinal or perceptional questions may come in various forms, which dictates the type of model specification. For example, Bolduc et al. (2005) used a linear specification for the attitudinal response data, whereas Daly et al. (2012b) and Hess and Beharry-Borg (2012) followed an ordered choice approach to account for the ordered nature of the response data. In contrast to these two approaches, we specify a binary choice model for the latent variable indicator model, $I_n$ (Eq. (2)). This is because our latent variable indicator, perceptions about expected productivity of irrigation farming, has two responses (for detail see Section 2.3.2).

$$I_n = \begin{cases} 1, \text{if} I_n^* > 0 \\ 0, \text{if} I_n^* < 0 \end{cases} \tag{2}$$

where $I_n^*$ is the latent construct observing an outcome for $I_n = 0 \text{or} I_n = 1$, which itself is a function of the latent variable, $Z_n$:

$$I_n^* = \lambda Z_n + \upsilon_n \tag{3}$$

Here $\lambda$ is the impact of the latent variable on the latent variable indicator, and $\upsilon_n$ is a random disturbance term.

Thus, conditioning on the latent variable and assuming that $\upsilon_n$ takes the logistic distribution, the probability of the latent variable indicator model, $I_n = 1$ is given by the logit model.

$$P_1(I_n = 1|Z_n) = \frac{1}{1 + \exp(\lambda Z_n)} \tag{4}$$

### 2.1.3. The choice response model

Based on a random utility framework, assuming that utility is linear in parameter and decision makers are utility maximizers, the utility of an individual, $U_n$, for selecting an alternative, $i$, is specified as:

$$U_{ni} = \alpha \text{Price}_{ni} + \beta X_{ni} + b Z_{ni} + \varepsilon_{ni} \tag{5}$$

The alternative is what a farmer obtains from voting to pay for a reliable irrigation service. $\alpha$ is the price coefficient ($\text{Price}_n$), $\beta$ is a parameter to be estimated for the individuals' observed characteristics, $X_{ni}$, $b$ is the impact of the latent variable on choice, $Z_{ni}$, and $\varepsilon_{ni}$ is a stochastic error term. Subsequently, we omit the "$i$" subscript for simplicity.

The choice response model $y$ for two alternatives is expressed as the function of the utility as:

$$y_n = \begin{cases} 1, \text{if} U_n > 0 \\ 0, \text{if} U_n < 0 \end{cases} \tag{6}$$

Assuming that $\varepsilon_n$ is independently and identically distributed (i.i.d.), the probability model conditioning on observed characteristics of the individual's and the latent variable is given by the simple binary logit model:

$$P_2(y_n|Z_n) = \frac{1}{1 + \exp(\alpha \text{Price}_n + \beta X_n + b Z_n)} \tag{7}$$

Because the latent variable is unknown, the unconditional probability of the choice model is given by the integral of the choice response model over the distribution of the latent variable.

$$P_2(y_n) = \int_{Z_n} P_2 \left( \frac{1}{1 + \exp(\alpha \text{Price}_n + \beta X_n + b Z_n} \right) \times f(Z_n | dX_n + \eta_n) dZ_n \tag{8}$$

For estimation purposes, following Bolduc et al. (2005), the error in the latent variable equation, $\eta_n$, is assumed to be normally distributed with mean 0 and variance of 1.[1] Then, the likelihood of observing $y_n = 1$ can be rewritten as:

$$P_2(y_n) = \int_{Z_n} \left( \frac{1}{1 + \exp(\alpha \text{Price}_n + \beta X_n + b Z_n)} \right) \times \left( \frac{1}{\sigma_{\eta n}} \phi \left[ \frac{Z_n - dX_n}{\sigma_{\eta n}} \right] \right) dZ_n \tag{9}$$

where $\sigma_{\eta_n}$ is standard deviation of $\eta_n$, $\phi[h]$ gives the standard normal (0, 1) density function:

$$\phi[h] = \frac{1}{\sqrt{2}} \exp\left( \frac{-h^2}{2} \right)$$

Eq. (9) can be estimated without incorporating attitudinal or perceptional indicators. However, the accuracy of the latent variable in the choice response model is questionable. Thus, the model should be simultaneously estimated with the latent variable indicator function (Ben-Akiva et al., 1999). Assuming that the errors in Eqs. (1), (2) and (5) are independently distributed, the joint probability of the observable choice response $y_n$ and latent variable indicator response $I_n$, conditional on the observed characteristics of the individual $X_n$, can be obtained by integrating over the distribution of the latent variable $Z_n$:

$$P(y_n, I_n) = \int_{Z_n} \left( \frac{1}{1 + \exp(\alpha \text{Price}_n + \beta X_n + b Z_n)} \right) \times \left( \frac{1}{1 + \exp(\lambda Z_n)} \right) \times \left( \frac{1}{\sigma_{\eta n}} \phi \left[ \frac{Z_n - dX_n}{\sigma_{\eta n}} \right] \right) dZ_n \tag{10}$$

Then, the log likelihood can be obtained from:

$$\text{LL}(y, I) = \sum_{n=1}^{N} \log \int_{Z_n} \left( \frac{1}{1 + \exp(\alpha Price_n + \beta X_n + b Z_n)} \right) \times \left( \frac{1}{1 + \exp(\lambda Z_n)} \right) \times \left( \frac{1}{\sigma_{\eta n}} \phi \left[ \frac{Z_n - dX_n}{\sigma_{\eta n}} \right] \right) dZ_n \tag{11}$$

where $n = 1, , , N$ is index of respondent.

The modeling framework of ICLV is summarized in Fig. 1A. Note that if we exclude the latent variable, $Z_{ni}$, the model structure becomes the familiar utility function (Fig. 1B) and Eq. (5) becomes:

$$U_n = \alpha \text{Price}_n + \beta X_n + \varepsilon_n \tag{12}$$

Eq. (12) can be estimated with a simple binary logit model. Note also that omitting the latent variable (perception of future irrigation productivity) may create additional errors that could be correlated with other explanatory variables. Thus, we define a modified equation:

$$U_n = \alpha \text{Price}_n + \beta X_n + u_n \tag{13}$$

where $u_n$ is a composite error defined as: $u_n = e_n + \varepsilon_n$, $e_n$ is part of the unobservable error and can be correlated with observed explanatory variables.

Here the issue is if $e_n$ is correlated with observed explanatory variables, the estimated parameters from Eq. (13) will be inconsistent. For example, if price and future irrigation productivity (i.e., the omitted variable represented by $e_n$) are correlated, the estimated coefficient for the price, $\alpha$ will be biased downward (Train, 2009). The reason is that the price coefficient carries important information about irrigation productivity.

The specification in Eq. (13) is used as the base model for comparison with the choice response model with the latent variable. Another interesting model to consider is one that considers attitudinal or perceptional questions as a direct measure of underlying perceptions or attitudes (Fig. 1C). McFadden (1999) noted that a large field of literature in non-market valuation study failed to correct several of the issues discussed above by treating perceptional questions as direct measures of underlying perceptions. Here, an

[1] Alternative normalization is also possible through the latent variable indicator model when there are two or more latent variable indicators for a single latent variable (Ben-Akiva et al., 1999).

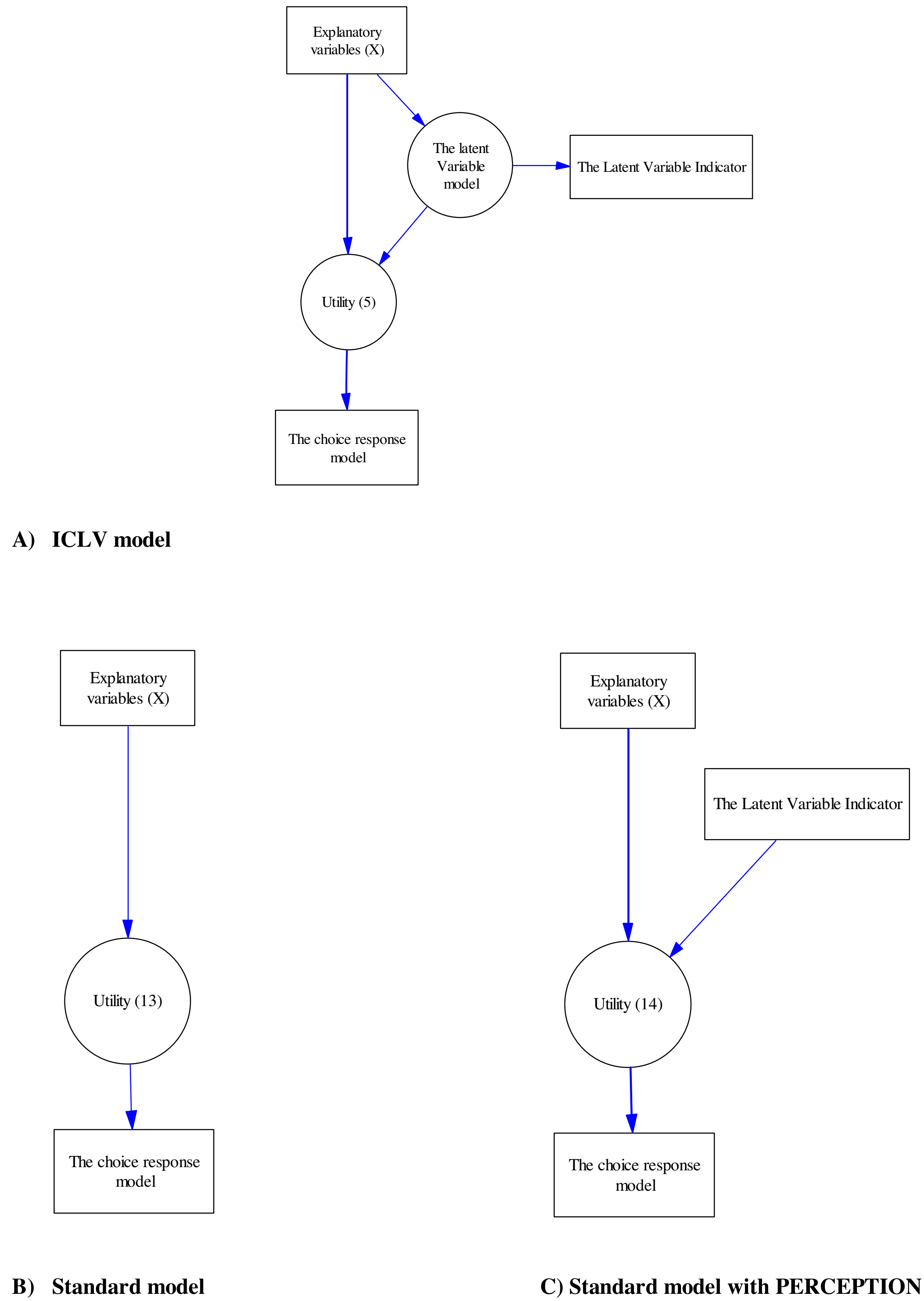


**Fig. 1.** ICLV model structure and Standard models (modified from (Ben-Akiva et al., 1999)). The number in parenthesis represent equation numbers for each model utility specifications. The unobserved variables are shown in the circular shapes and the choice and the latent variable indicators are shown in the rectangular shapes. Arrows show the direction of influence.

interesting issue to explore is how WTP estimate is biased by doing so. The utility for this model is specified as:

$$U_n = \alpha Price_n + \beta X_n + cI_n + w_n \tag{14}$$

Here $c$ is the coefficient of the latent variable indicator, $I_n$. The results of several previous studies that incorporate perception response directly indicate that $c$ is a highly significant determinant of stated choice decisions. This seems the driving force that creates a temptation for researchers to incorporate the face value perception directly into the model. The term $w_n$ is a composite error similar to $u_n$ because of potential endogeneity and measurement error. Eq. (14) can be estimated with a simple binary logit model and we refer to it as "model with perception."

For model comparison purposes, the log likelihood for the choice response model (Eq. (9)) is computed from the parameter estimates of the ICLV model in Eq. (11) as in Hess and Beharry-Borg (2012). We do not use the direct model fit of the ICLV model because the model statistics for the ICLV model (Eq. (11)) indicate the results for observing the sequence of the choice response model and the latent variable indicator model, and therefore it is not comparable to the base model that excludes that latent variable. Unknown parameters (Eq. (11)) are estimated using the maximum likelihood technique with numerical integration methods. All models are estimated using Python Biogeme 2.3 application software (Bierlaire and Fetiarison, 2009).

### 2.2. Mean WTP estimates

Once the models are estimated, it is possible to calculate the mean WTP and investigate the uncertainty surrounding its estimated value. More importantly in this study, we are interested in determining how accounting for future expectations regarding irrigation productivity via an ICLV model differs from models that ignore this (Eq. (13)) and models that incorporate perception as a direct measure of the underlying latent variable (Eq. (14)). The mean WTP can be calculated as in Hanemann (1989):

$$\text{MeanWTP} = \left(\frac{1}{\alpha}\right) \ln\left(1 + \exp(\beta X + bZ + cI\right) \tag{15}$$

where $X$, $Z$ and $I$ are the average value of $X_n$, $Z_n$ and $I_n$, respectively.

Then, the standard error of the mean WTP is estimated using the delta method. Recently, Daly et al. (2012a) showed that in many circumstances the delta method provides an exact value for the standard error used to construct the confidence interval. By this method, the variance of WTP for any of the explanatory variables ($X_n$, $Z_n$ or $I_n$), given the coefficient of price, $\alpha$, and any of the parameters of explanatory variables, $\theta$, is given by taking a first-order Taylor expansion around the mean value of the variables:

$$var(\text{WTP}_X) = \left[\left(-\frac{1}{\alpha}\right)^2 var\left(\theta\right) + \left(\frac{\theta}{\alpha^2}\right)^2 var\left(\alpha\right) + 2\left(-\frac{1}{\alpha}\right)\left(\frac{\theta}{\alpha^2}\right) cov\left(\theta, \alpha\right)\right] \tag{16}$$

Here var(.) and cov(.) is variance and covariance respectively. Then, the confidence interval of the mean WTP for $X$, $\text{CIWTP}_x$, can be obtained using the familiar formula:

$$\text{CIWTP}_x = \text{MeanWTP}_X \pm z_{a/2}\sqrt{var(\text{WTP}_X)} \tag{17}$$

where $z_{a/2} = \Phi^{-}\left(1 - (a/2)\right)$, $\Phi^{-}$ is the inverse of the cumulative standard normal distribution and the confidence level is $100\left(1 - (a/2)\right)$ %, where $a$ is the critical level.

In the delta method, we assume WTP to be normally distributed, but this may not always be the case. However, having the same number of observations across the three models and given the estimated parameters, the standard error of each parameter and the covariance of the price and other explanatory variables (Eq. (16)), the delta method provides us with a relatively accurate magnitude of bias from both models with omitted variable and endogenous variable. It is also intuitively much easier to understand. We can rewrite Eq. (16) and inspect the component of variance:

$$var(\text{WTP}_X) = H + K \tag{18}$$

where $H = \left(-\frac{1}{\alpha}\right)^2 var\left(\theta\right) + \left(\frac{\theta}{\alpha^2}\right)^2 var\left(\alpha\right)$, $K = 2\left(-\frac{1}{\alpha}\right)\left(\frac{\theta}{\alpha^2}\right) cov\left(\theta, \alpha\right)$.

The component of the variance explained by $H$ is always positive. Any factor that lowers the magnitude of price or increases the variance of individual parameter estimates can inflate the variance of WTP, but the final magnitude of variance is determined by both the sign and the magnitude of $K$. We know that both endogeneity and omitted variable bias can affect the sign and the magnitude of covariance between the two parameters and the parameter estimate. Thus, in Appendix A, we report the covariance between price and other explanatory variables for the three models used for estimating the variance of WTP to see the effect of handling both omitted variable bias and endogeneity.

Finally, the aggregate WTP is obtained by multiplying the mean WTP by the total irrigation command area, which is equal to 28,000 Kada[2] (Gebre et al., 2008). This is because our valuation question is based on per Kada of irrigable land. The confidence interval of the mean aggregate WTP is calculated accordingly.

### 2.3. Data for empirical analysis

#### 2.3.1. Sampling

The Koga Irrigation Project is the first attempt by the Government of Ethiopia to develop a large-scale irrigation scheme for rural farmers. The project covers about 7000 ha of downstream irrigable land and 22,000 ha of upstream watershed area (Gebre et al., 2008). The irrigation command area encompasses seven administrative districts (*Kebeles*), but it occupies a smaller area than the administrative districts. A two-stage random sampling method was employed for the selection of the respondents for the study. First, from a total of seven administrative districts under the irrigation command area, two districts, Enguti and Ambo-Mesk, were randomly selected to represent the total irrigation command areas. Together, the two districts represent about 30% (1727) of households benefiting from irrigation. In each district area, farmers benefiting from irrigation are organized into farmer development groups. Group membership is based on spatial proximity, and groups consist of 20–30 household heads. Accordingly, to make our sample spatially representative, 2 or 3 household heads[3] were randomly selected based on group size from each farmer development group. Farmer development groups are considered homogeneous (Kassahun and Jacobsen, 2015). Using a latent class model posterior probability function, Kassahun and Jacobsen (2015) showed that the preferences of farmers for integrated watershed management activities and economic and institutional incentives within the same spatial-social group (farmer development group) are highly homogeneous. They also recommend a sampling strategy that covers geographical area instead of increasing sample size within the same farmer development group. Accordingly, a total of 210 respondents were selected and surveyed using in-person

[2] Kada is the local land measurement unit. 1 Kada = 0.25 ha.

[3] We select household heads because we assumed that she or he was the ultimate decision-maker with respect to financial matters. If both the husband and the wife were available, the husband was asked to take part in the interview.

interviews from July to October 2008. The identities of households benefiting from irrigation and group membership were obtained from the Agricultural Development office of each district.

Although our survey data were collected in 2008, the issues addressed by this study remain relevant seven years later. Due to the delay in the construction of the canal system, in 2014 only 76% of the infrastructure for irrigation had been completed. As a result, a substantial segment of farmers still did not have access to irrigation water (Agro-BIG, 2014). Moreover, concerns regarding siltation of the Koga reservoirs has increased since we administered our survey (Assefa et al., 2015; Reynolds, 2012).

### 2.3.2. Survey instrument and data preparation for analysis

The survey questionnaire[4] included a brief introduction and initial background questions, followed by a presentation of the contingent valuation scenario. In the valuation scenario, respondents were informed about the potential threat of reservoir sedimentation for reliable irrigation services and the need for appropriate soil and water conservation measures in the upstream part of the watershed. Respondents were also informed that upstream land users are not responsible for the consequences of their land use decisions for downstream water users. Thus, in order to encourage the adoption of appropriate soil conservation measure by upstream land users, the respondents were informed about the need for a monetary contribution from all households benefiting from irrigation. Then, respondents were asked to pay a specified amount of cash per year for access to reliable irrigation services per Kada of irrigable land. The wording of the question is as follows:

> If you are provided access to irrigation water,[5] will you vote for irrigation cooperative[6] rules and regulation that will create a fund, even if its passage would require all irrigation users to contribute (___) ETB[7]/household/Year/Kada of land to maintain the health of the dam and common irrigation channels to ensure reliable year-round irrigation water supply?

For the elicitation format, we adapted a single-bounded dichotomous choice (DC) approach with an open-ended follow-up question. The bid price values were identified during the repeated pretest and focus group discussion. These included the values 25, 31, 37, 43, 49, 58 and 70 ETB. We used the responses from the open-ended valuation question to identify inconsistent responses. We consider a response inconsistent when the respondent agrees to pay for a randomly-assigned bid price in response to the DC valuation question, but states a lower bid in the subsequent follow up open-ended valuation question.[8] Nevertheless, the value from the follow-up open-ended valuation question was not used to estimate the mean WTP as this approach tends to underestimate the value of the good (Whittington, 2002; Whittington and Pagiola, 2012).

Similarly, the perception question used for the latent variable indicator model has two sets of questions as follows (with response options in parentheses):

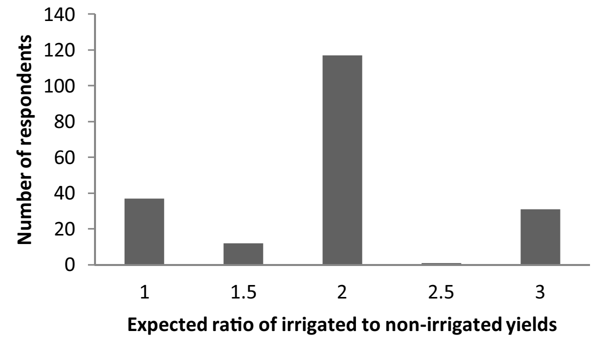


**Fig. 2.** Distribution of perceived expected ratio of irrigated yield (output per ha) compared to rain-fed yield.

1. Do you think year-round irrigation farming increases crop yields per unit of land? (Yes, No).
2. If yes, how many times do you think crop yield would be increased in irrigation farming, if you compared it with rain-fed agriculture for a given amount of land? (1 (the same), 1.5, 2, 2.5, . . . 5).

The intention of the 1st question was to prepare respondents for answering the main question about perceived output. To use the distribution of expected output as an indicator of the latent variable output from irrigation farming, we generate a dummy variable called EXPECTATION, which is equal to 0 if the respondent believes that expected yields (production per unit land) would be increased by less than 100% with irrigation, and otherwise has the value 1. This variable is used as the dependent variable for the latent variable indicator model in Eq. (2). The justifications for this threshold value are: (1) experts in the focus group discussion believed that irrigation could increase yields per unit land by 100–200% compared to rain-fed agriculture and; (2) no respondents expected crop yields would be more than 3 times higher with irrigation, and therefore 2 times serves as a reasonable threshold value (Fig. 2).

Although this series of questions may appear overly complex for survey respondents, this is a standard format economic valuation literature for the questionnaire format as recommended in a developing-country setting (Whittington, 2002). Other studies suggest that respondents in developing countries understand more complex valuation questions than those presented in our study. For example, Kassahun and Jacobsen (2015) showed that farmers in similar context understand more complex questions, such as choice experiments.

Finally, we asked questions regarding the social, demographic and economic status of the respondents. This information was used to control for other factors in the choice response model and the latent variable model. Total household gross cash income was calculated as the value (revenue) of all marketed agricultural output plus income from off-farm activities (mostly small trading businesses) by all members of the household. The value of marketed agricultural output was based on annual average prices for 2007/8 (2000 in the Ethiopian calendar). The total household income was divided by the total number of household members and per capita income was used as a regressor in the choice model. Per capita income was hypothesized to have a positive effect on WTP due to the diminishing marginal utility of money. Similarly, the amount of cultivated land per capita is an indirect measure of wealth and the potential for income generation, so we also hypothesized this to have a positive effect on WTP as in Asrat et al. (2004). Furthermore, livestock holding, which is measured in per capita Tropical Live-

[4] The questionnaire can be obtained from the corresponding author upon request.

[5] We ask this because during the survey period irrigation farming had not yet begun. Farmers were aware that they were going to get irrigation access and establish irrigation users' cooperatives. During that time, the reservoir was completed, although the irrigation channel system was still under construction.

[6] During the focus group discussion and the pretest, farmers preferred the money to be collected under the control of their own newly established irrigation users' cooperative rather than the government.

[7] ETB (Ethiopian National Currency). 1 ETB = 0.103 USD during the study period.

[8] Out of 210 interviewed respondents, data from 12 households were removed from the analysis due to inconsistent responses between the dichotomous choice and the follow-up open-ended valuation responses.

**Table 1**
Descriptive statistics for households surveyed in the Koga watershed, and the expected impact of the variable on choice, the latent variable and on the indicator function.

| Variable | Description | Mean | Std. dev. | Expected sign |
|---|---|---|---|---|
| CHOICE | 1 if household is willing to pay the proposed bid price for reliable irrigation services, otherwise 0 | 0.63 | 0.49 | |
| BPRICE | Bid Price per Kada of irrigable land per year | 44.36 | 14.56 | – |
| PCINCOME | Per capita income in thousands of ETB | 1.11 | 1.45 | + |
| PCTLU | Per capita livestock holding in Tropical Livestock Unit | 0.68 | 0.36 | ± |
| LANDPERHH | Cultivated land per household size (Kada/household size) | 1.05 | 0.55 | + |
| EXPERIENCE | 1 if household head has practical irrigation farming experience, otherwise 0 | 0.17 | | + |
| DEPRATIO | Dependent ratio (economically dependent household per economically active) | 0.87 | 0.64 | – |
| LVC | Impact of the latent variable on choice | | | + |
| ASC | Alternative specific constant | | | |
| – | | | | |
| Variables associated with the latent variable model | | | | |
| ILLITERATE | 1 if the household head is illiterate, otherwise 0 | | | – |
| YOUNG | 1 if age is less than 43, otherwise 0 | 0.55 | | + |
| FAMEDU | Highest formal schooling completed by any household member in years | 5.59 | 4.16 | + |
| CONSTANT | | | | |
| SIGMA | The variance of $\eta$ | 1 | | |
| – | | | | |
| Variables associated with the latent variable indicator model | | | | |
| EXPECTATION | 1 if the respondent believes that perceived expected output increment greater than 2 times in irrigation agriculture compared to rain-fed agriculture, otherwise 0 | 0.75 | | |
| LVI | Impact of the latent variable on EXPECTATION | | | + |
| Tau | Constant for the latent variable indicator | | | |

Note: the sample includes 198 households in the Koga watershed of Ethiopia.

stock Units,[9] was included in the choice response model. In many developing countries, livestock holding is considered a wealth indicator and insurance against crop failure (Tegebu et al., 2012) and should therefore affect WTP positively. However, there is no clear evidence of the relationship between livestock holding and WTP in previous studies (Asrat et al., 2004).

The bid price should have a negative effect on the probability of positive response. The dependency ratio, defined as the ratio of economically dependent household members[10] to economically active household members, is expected to affect WTP negatively. Two possible factors might lead to a negative dependency ratio. The first is that irrigation farming requires a considerable amount of labor. A higher dependency ratio might be related to lower input for irrigation farming and consequently lower expected output and lower WTP. Second, a higher dependency ratio means more people need to share the total household income which may potentially lead to a lower WTP as the share of income declines. Previous empirical evidence supports a negative sign for the dependency ratio. Asenso-Okyere et al. (1997) reported that WTP for health insurance declines as the dependency ratio increases in Ghana.

To understand the disparity in WTP between those who have irrigation experience and those who do not, we use irrigation farming experience as an explanatory variable. We hypothesized that those households who have irrigation farming experience can more readily realize the benefits of reliable irrigation services and are therefore likely to value irrigation facilities more. However, it is also possible that those without experience will overestimate the actual benefits compared to those who have more realistic expectations. Thus, expanding the choice modeling to accommodate perception and attitudes can help to differentiate between these kinds of issues.

Finally, when selecting explanatory variables for the latent variable model, we used the standard ICLV model approach in the literature, in which the latent variable model (Eq. (1)) is specified as a function of personal characteristics (Ben-Akiva et al., 1999; Daly et al., 2012b). In our case, we selected household head education, the highest educational achievements within the household and age category for the household head to explain the latent variable. The highest educational achievements within the household capture intra-household influence on latent behavior because education has a spillover effect. The age category is divided into two: below the average age of the sampled household heads (YOUNG category) and above the average age of the sampled household heads (OLD category). Therefore, this is a binary variable with 1 for YOUNG and 0 for the other half.

## 3. Results

### 3.1. Descriptive results

The descriptive results provide basic information about the sample for which the WTP models are estimated (Table 1). About 55% of the respondents are below the average age (43 years). They belong to the YOUNG category in our subsequent analysis (Table 1). The average per capita income of the household is 1100 ETB per year. Only 17% of the sampled households have previous irrigation farming experience because of the proximity of their land to a natural river (Koga River).

About 63% of the respondents are willing to pay for reliable irrigation services, and 75% believe that crop yields will increase 2–3 times with irrigation compared to rain-fed agriculture (Table 1). About 80% of those who stated that crop yields will be increased by less than 2 times with irrigation, indicated a zero WTP for reliable irrigation services (Table 2). On the other hand, about 91% of

[9] The Tropical Livestock Unit (TLU) values used for different species of animals are: 1 for camel; 0.7 for cattle; 0.8 for horse/mule; 0.5 for donkey; and 0.1 for goat/sheep (Asrat et al., 2004). Note that this is different than the TLU system used elsewhere, which distinguishes between animal ages as well as species.

[10] Children below 15 years and household members above 65 years old.

**Table 2**
Distribution of choice and perceived expectation regarding crop yield, for households surveyed in the Koga watershed.

| Willing to pay bid price (CHOICE) | Expected increase in yield per ha with irrigation (EXPECTATION) | |
|---|---|---|
| | ≤2 times current output (EXPECTATION = 0) | > 2 times current output (EXPECTATION = 1) |
| No (CHOICE = 0) | 41 | 33 |
| Yes (CHOICE = 1) | 8 | 116 |
| Total | 49 | 149 |

Note: the sample includes 198 households in the Koga watershed of Ethiopia.

**Table 3**
Distribution of choice and perceived expectation regarding crop yields for households surveyed in the Koga watershed.

| Willing to pay bid price (CHOICE) | Household head has experience with irrigated farming (EXPERIENCE) | |
|---|---|---|
| | No (EXPERIENCE = 0) | Yes (EXPERIENCE = 1) |
| No (CHOICE = 0) | 71 | 3 |
| Yes (CHOICE = 1) | 93 | 31 |
| Total | 164 | 34 |

Note: the sample includes 198 households in the Koga watershed of Ethiopia.

respondents who have irrigated farming experience are willing to pay for reliable irrigation services (Table 3).

### 3.2. Model results

#### 3.2.1. Base model (model with omitted variable)

The base model has a binary logit specification. The variables bid price (BPRICE), per capita income (PCINCOME), dependency ratio (DEPRATIO) and irrigation farming experience (EXPERIENCE)[11] are significant with the expected signs (Table 4). Per capita livestock holdings (PCTLU) and the cultivated area per household (LANDPERHH) are not significant.

#### 3.2.2. ICLV model

Similar to the base model, all explanatory variables (except per capital livestock holding and per capita cultivated land) are significant in explaining respondents' choices (Table 4). What differs is the addition of the latent variable, which has a positive and significant effect on respondents' WTP for reliable irrigation services. An important question here is how the addition of the latent variable improves performance over the base model. Model selection criteria indicate improved performance for the choice response model with the latent variable. For example, the Akaike Information Criterion (AIC) is 165.6 for the base model and 148.5 for the choice response model with the latent variable (Table 4).

In addition, the latent variable affects the choice positively and significantly in both the choice model (LVC) and the latent variable indicator model (LVI). If the household head is illiterate, he or she has a lower latent variable. The highest formal schooling completed by any household member (EDUFAM) and being in the younger age category has a positive effect on the latent variable.

The two model formulations also differ in their confidence interval estimates of key marginal WTP value. The marginal WTP for reliable irrigation services is −27.6, 20.6 and 32.8 ETB for the dependency ratio, per capita income and irrigation farming experience, respectively, for the choice response model in the ICLV estimates. For each one of these estimates, the standard error estimates are higher compared to the base model estimates (Table 5). Consequently, this leads to larger confidence interval estimates for the mean and the aggregate WTP for the choice model in the ICLV estimates (Table 6). However, the mean WTP estimates of both models are essentially equal, about 55 ETB per Kada of irrigable land, and are estimated using Eq. (15) from the parameter estimates of preference space models holding all variables at their mean and irrigation farming experience at 0.

Another noticeable difference between the two models is the marginal values of the alternative specific constant (ASC) and the latent variable marginal WTP. Incorporation of the latent variable makes ASC insignificant in the ICLV model estimates. The marginal WTP value of the latent variable is 28 ETB for respondents who have positive underlying expectations for various aspects of future irrigation productivity. However, it is intuitively meaningless to only change the marginal WTP value of the latent variable. Instead, further analyses should be conducted to determine the cross marginal impact of the latent variable explanatory variables using the estimated coefficients of the latent variable model (Eq. (1)) and the choice model (Eq. (9)) without using indicators (attitudinal or perception data). This makes the ICLV model approach of incorporating attitudinal and perception data even more interesting. Once the ICLV model has been estimated, perception or attitudinal data is not required for prediction (Ben-Akiva et al., 1999). Thus, through the latent variable we can infer that being literate, having an education and being young result in higher expectations regarding yield increases due to irrigation and also in a higher WTP for reliable irrigation services.

#### 3.2.3. Model with perception (model with endogenous explanatory variable)

In this simple binary logit model, the dummy variable perceived expectation of crop yield (EXPECTATION) is directly estimated in the choice model (Eq. (14)). It is positive and highly significant. The relative magnitude of the coefficient (Table 4) as well as its marginal effect (Table 5) is the highest among all the estimated coefficients in the model. This also drives all model selection criteria in favor of it. As we have stated earlier in the methodology section, this feature often leads researchers to incorporate perception without adjusting its face value. However, the overall standard errors of the model is the largest and hence confidence interval of mean WTP (Table 6).

The signs of all the other significant variables are consistent with the base and the ICVL models. However, the standard error associated with marginal WTP estimates of irrigation farming experience is 2.19 and 1.71 times the base and the ICVL models respectively (Table 5). Similarly, the standard error associated with the marginal WTP of EXPECTATION is significantly higher than the latent variable estimates in the ICLV model. Here, the important point is to determine what causes the high variance associated with the mean WTP compared with the estimate in the ICLV model (Table 6). First, direct incorporation of EXPECTATION as the explanatory variable leads to a downward bias in the price coefficient more than the effect of the omitted variable bias. Second, in contrast to the ICVL models, the covariance of price and EXPECTATION is positive (Appendix A), which means that given the fact that the coefficient of EXPECTATION is larger than the coefficient of the latent variable (LVC), and with positive value of $K$ (Eq. (18)), the overall increment in the

[11] The scale of the data for farmers with irrigation experience may differ from the inexperienced farmers. Thus, combining two data sets may create inconsistent parameter estimates (Swait and Louviere, 1993; Ben-Akiva and Morikawa, 1990). However, in our case we did not find evidence of scale difference in the estimated models (scale estimated explicitly within the model in Biogeme, see Bierlaire and Fetiarison (2009)).

**Table 4**
Coefficient estimates and model evaluation statistics for the three models.

| | Base | | | ICLV | | | Model with perception | | |
|---|---|---|---|---|---|---|---|---|---|
| Name | Value | Std. err. | *t* | Value | Std. err. | *t* | Value | Std. err. | *t* |
| The choice response model | | | | | | | | | |
| ASC[a] | −3.150 | 0.90 | −3.50 | −1.860 | 1.44 | −1.29 | −0.885 | 1.13 | 0.43 |
| LVC | | | | 1.920 | 0.75 | 2.55 | | | |
| EXPECTATION | | | | | | | 2.350 | 0.52 | 4.53 |
| BPRICE | −0.065 | 0.01 | −4.65 | −0.068 | 0.02 | −2.9 | −0.052 | 0.01 | −3.46 |
| PCTLU | −0.002 | 0.59 | −0.00 | −0.433 | 0.89 | −0.49 | 0.018 | 0.64 | 0.03 |
| LANDPERHH | −0.035 | 0.39 | −0.09 | 0.507 | 0.65 | 0.78 | −0.001 | 0.43 | −0.00 |
| DEPRATIO | −1.230 | 0.37 | −3.30 | −1.890 | 0.74 | −2.55 | −1.280 | 0.45 | −2.83 |
| PCINCOME | 1.320 | 0.35 | 3.80 | 1.410 | 0.54 | 2.60 | 1.140 | 0.38 | 2.98 |
| EXPERIENCE | 1.700 | 0.66 | 2.56 | 2.250 | 1.07 | 2.11 | 1.770 | 0.75 | 2.37 |
| – | | | | | | | | | |
| Latent variable indicator model | | | | | | | | | |
| LVI | | | | 2.26 | 0.95 | 2.37 | | | |
| Tau | | | | 0 | | | | | |
| – | | | | | | | | | |
| Latent variable model | | | | | | | | | |
| Constant | | | | 0.504 | 0.361 | 1.40 | | | |
| YOUNG | | | | 0.749 | 0.277 | 2.70 | | | |
| ILLITERATE | | | | −0.934 | 0.279 | −3.35 | | | |
| FAMEDU | | | | 0.082 | 0.034 | 2.46 | | | |
| Sigma | | | | 1 | | | | | |
| – | | | | | | | | | |
| Model statistics | OLM | | | ICLV | | Adjusted[b] | Model with perception | | |
| N.Parameter | 7.00 | | | 13.00 | | 8.00 | 8.00 | | |
| int.LL | −137.24 | | | −274.49 | | −137.24 | −137.24 | | |
| Final.LL | −89.81 | | | −166.91 | | −82.26 | −77.43 | | |
| Adj.P.R2 | 0.35 | | | 0.39 | | 0.40 | 0.44 | | |
| LR.chi2 | 94.86 | | | 215.15 | | 109.95 | 119.62 | | |
| AIC | 165.62 | | | 307.82 | | 148.53 | 138.87 | | |
| BIC | 163.54 | | | 303.96 | | 146.15 | 136.50 | | |

Note: the sample includes 198 households in the Koga watershed of Ethiopia.
ICLV denotes the latent variable indicator model.
[a] ASC is defined as 1 for not choosing to accept the bid, and 0 for choosing to accept it.
[b] “Adjusted” refert to model statistics for the choice response model, excluding the impact of the latent variable indicator model.

**Table 5**
Estimates for marginal willingness to pay for reliable access to irrigation water for the three models.

| Name | Estimates for Marginal Willingness to Pay (standard errors) | | |
|---|---|---|---|
| | Base | ICLV | Model with perception |
| ASC | −48.69<br>(6.67) | −27.19<br>(13.36) | −17.151<br>(17.61) |
| – | | | |
| LVC | | 28.07<br>(8.26) | |
| – | | | |
| EXPECTATION | | | 45.543<br>(13.22) |
| – | | | |
| PCTLU | 0.03<br>(9.11) | 6.33<br>(12.41) | 0.355<br>(12.37) |
| – | | | |
| LANDPERHH | 0.53<br>(5.95) | −7.41<br>(9.85) | −0.012<br>(8.35) |
| – | | | |
| DEPRATIO | −19.01<br>(3.24) | −27.63<br>(4.08) | −24.81<br>(6.84) |
| – | | | |
| PCINCOME | 20.4<br>(6.11) | 20.61<br>(8.21) | 22.09<br>(8.15) |
| – | | | |
| EXPERIENCE | 26.28<br>(10.69) | 32.89<br>(13.64) | 34.30<br>(23.45) |

Notes: the standard errors (in parentheses) are calculated using the delta method.
ICLV denotes the latent variable indicator model.
The sample includes 198 households in the Koga watershed of Ethiopia.

variance of WTP is the highest in the model with perception. Nevertheless, the estimate of the mean WTP is not significantly different from both the base and ICLV models.

## 4. Discussion

Our ICLV model estimates the value of reliable irrigation services, providing an upper limit for the value of off-site soil conservation, and suggests factors affecting the WTP for irrigation services in the Koga Watershed. The choice response model with the latent variable improves upon a base model without the latent variable, and corrects model statistics and model sensitivity biases in a model with perception, i.e., a model with direct use of perceived expectation.

Regardless of the potential limitations related to using and omitting perception and attitudinal data in choice models, the mean WTP estimate from the three models is essentially the same (Table 6). This means that if one is only interested in the expected value, the three estimation procedures provide equivalent estimates. However, a number of important questions are more appropriately addressed using the ICLV model. These include the extent to which the expected value is affected by the expectations of the respondents if these differ significantly from expert opinion, the magnitude of the variance around the expected value and the empirical estimates of factors that affect WTP. These factors are typically outcomes of interest for valuation studies.

The inclusion of the latent variable in the choice response model increases the standard error associated with the mean and the aggregate WTP compared to the base model (Table 5). For example, the difference in the lower bound of the aggregate WTP confidence interval between the base and the choice response model with the ICLV is about 161,000 ETB. A plausible explanation for

**Table 6**
Mean and aggregate willingness to pay for reliable access to irrigation water and the confidence interval for willingness to pay, in the three models.

| Outcome | Base | ICLV | Model with perception |
|---|---|---|---|
| Mean WTP (ETB) per 0.25 ha of irrigable land | 54.68 | 54.82 | 55.61 |
| Standard error | 6.97 | 9.98 | 12.86 |
| *t*-value | 7.85 | 5.5 | 4.33 |
| – | | | |
| Mean confidence interval | | | |
| Lower | 41.03 | 35.27 | 30.41 |
| Upper | 68.33 | 74.37 | 80.81 |
| – | | | |
| Aggregate WTP(ETB) | 1,531,000 | 1,534,000 | 1,557,000 |
| – | | | |
| Aggregate confidence interval | | | |
| Lower | 1,148,000 | 987,000 | 851,000 |
| Uppers | 1,913,000 | 2,082,000 | 2,262,000 |

Notes: ETB denotes Ethiopian National Currency. 1 ETB = 0.103 USD during the study period.
ICLV denotes the latent variable indicator model.
The sample includes 198 households in the Koga watershed of Ethiopia.
The aggregate WTP is obtained by multiplying the mean WTP by the total irrigation command area, which is equal to 28,000 Kada (7000 ha).

greater variance with the ICLV model is that including the latent variable accommodates respondents' uncertainty when valuing reliable irrigation services and corrects potential biases in other parameter estimates. On the other hand, direct inclusion of EXPECTATION in a choice model exaggerates the variance (uncertainty) of the mean and the aggregate WTP. Whether the lower bound for the aggregate WTP of the ICLV model is below the threshold that would be required for successful reduction of sedimentation related unreliability of irrigation service is unknown at present. However, the estimation of accurate confidence intervals for the mean or the aggregate WTP could be of considerable importance for the decision to finance transfer programs.

Another relevant consideration is the distribution of perceived expectation of crop yield (EXPECTATION) and the choice response data (Table 2). The distribution indicates that the mean WTP is underestimated compared to expert assessment because a large proportion of those stating a zero WTP expect much lower yield gains than predicted by experts. This may be associated with a lack of irrigation farming experience because our valuation study was conducted before the commencement of irrigation services. Furthermore, the effect of expectations of reliable irrigation services can be seen from the impact of the latent variable on choice via the ICLV model. We noted that the latent variable represents various aspects of perception about future irrigation farming and by construct handles extreme opinions, from very negative to very positive expectations about irrigated farming. The model shows that farmers with low expectations are also those who want to pay less. Consequently, WTP will also be underestimated compared to expert assessments as the threshold for the binary variable is the expert assessment of increased yield. One could question whether our alignment of farmers' expectations with experts' assessment is correct. For example, experts may estimate the potential yield increase under ideal conditions, whereas farmers also include the situations where collaboration, lack of maintenance, risk and other factors cause the yield to increase less than potentially possible. Alternatively, the underestimation of WTP may be due to a lack of irrigation farming experience. The distribution of irrigated farming experience (EXPERIENCE), the choice response data (Table 3) and our models indicate the importance of irrigated farming experience directly in the valuation of reliable irrigation services. Consequently, conducting valuation studies before experience has been obtained will likely lead to a lower WTP.

Consistent with our hypothesis, income is positive and significant. With the introduction of irrigated agriculture, the expected income of a household was estimated to increase (Ayele, 2011). As incomes increase, households should be willing to pay more for reliable access to irrigation water. On the other hand, the dependency ratio has a negative effect on WTP, which is consistent with our hypothesis. From a policy point of view, the average dependency ratio might not be affected during the lifetime of a financial transfer program. However, considering the sensitivity of the dependency ratio, the variable could be an important factor in financing sediment reduction projects, at least temporarily.

### 4.1. Potential limitations

The current study is based on a relatively small sample, which calls into question its representativeness. However, given that the number of registered households who benefit from irrigation in the 7 administrative districts is 5757, we only extend the conclusions to a small population. In fact, we include 12% of the households in the two selected districts for the survey out of a population of 1727. Second, the households are relatively homogeneous in the area (see also Kassahun and Jacobsen (2015) for a discussion hereof), which also means that we are able to estimate the quite complex ICLV model regardless of the small sample size and get significant parameter estimates despite the small sample size. Consequently, we do not consider the small sample size to be a major problem.

## 5. Conclusion

We implemented three alternative econometric models based on survey data and contingent valuation methods to estimate the value farm households assign to reliable access to irrigation water when the households did not have previous irrigated farming experience. In contrast to many previous studies, we accounted for the expectations of future yield increases due to irrigation to reduce bias in valuation estimates and its uncertainty. All three models produce similar conclusions regarding mean willingness to pay (WTP) for reliable access. A key result of our study is that ignoring future expectations in modeling will likely underestimate the uncertainty of the mean or aggregate WTP. On the other hand, directly including survey responses of perceptions or expectations in the modeling likely will overestimate the uncertainty of the mean or aggregate WTP. Thus, the estimation of accurate confidence intervals for the mean or aggregate WTP is of considerable importance for the decision to finance projects that will improve the reliability of irrigation services. Our results indicate also the importance of income and irrigation farming experience in determining a farmer's willingness to pay for reliable irrigation services. We find that willingness to pay increases by about 60% with irrigation farming experience.

## Acknowledgments

We thank the Cornell University Integrated Watershed Management and Hydrology Program for funding this research through a gift of Cornell donor providing funds for research in Africa. We appreciate also the helpful comments of two reviewers who have assisted us in improving the clarity of our discussion.

## Appendix A. : Covariance between bid price and other coefficients from three estimated models.

| Name | Base | ICLV | Model with perception |
|---|---|---|---|
| ASC | 0.0088 | 0.0187 | 0.0110 |
| LVC | | −0.0085 | |
| EXPECTATION | | | 0.0003 |
| PCTLU | −0.0009 | 0.0016 | −0.0003 |
| LANDPERHH | 0.0003 | −0.0020 | 0.0006 |
| DEPRATIO | 0.0010 | 0.0073 | 0.0012 |
| PCINCOME | −0.0006 | −0.0035 | −0.0006 |
| EXPERIENCE | −0.0007 | −0.0082 | −0.0015 |

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