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Key Points:

- Accounting for literacy in communication and outreach supports effective uptake of water harvesting technology
- Ethiopian farmers are willing to pay market interest rates to obtain financial support to invest in water harvesting technology
- Literacy affects the terms and conditions to incentivize farmers to invest in water harvesting technology

Supporting Information:

- Supporting Information S1
- Data Set S1

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Informing water harvesting technology contract design using choice experiments

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Abstract Introducing water harvesting technology is expected to be more effective and last longer if farm households are involved in their design. The main objective of this study is to inform policymakers in Ethiopia about the most important terms and conditions to incentivize farmers to enter into a contractual agreement to invest in water harvesting on their land. In order to test the influence of the way the specific contractual terms and conditions are communicated to farm households, many of whom are illiterate, a split sample approach is applied with and without visual aids for technical, institutional, and economic contract characteristics. Both samples generate significantly different results, highlighting the importance of how information is conveyed to farm households. This pattern is confirmed when examining the self-reported importance attached to the various contract characteristics. Equality Constrained Latent Class models show that contract characteristics for which visual aids were developed are considered more attentively, emphasizing the importance of adequate communication tools in a developing country context where literacy rates are limited to increase water technology innovation uptake and reduce farm household vulnerability to droughts.

Plain Language Summary Diffusion of new water harvesting technology will be more effective if farm households are involved in their design. Terms and conditions to incentivize farmers to invest in water harvesting technology are identified. Contract characteristics for which visual aids were developed are considered more attentively. Accounting for literacy in communication and outreach supports effective uptake of water harvesting technology.

1. Introduction

Water harvesting is generally considered a suitable strategy for adapting to water shortages caused by climate change [Lasage, 2015]. Typically rainwater harvesting has proven to be an affordable and sustainable solution in places which are suitable to collect rainwater, have dispersed populations and where the costs of developing surface or groundwater infrastructure are high [United Nations Environmental Program, 2005]. Rainwater harvesting is defined as a method of inducing, collecting, storing, and conserving local surface water runoff for agriculture [Lasage, 2015]. However, attempts to spread and intensify this practice have had limited success [Bouma et al., 2015]. In Ethiopia, where this study is conducted as part of the European Commission funded project Water Harvesting Technologies Revisited (WHaTeR) to explore the potential for innovation, improvement, and upscaling, there has been growing interest in agricultural water management through rainwater harvesting to enhance agricultural productivity and alleviate poverty. Here too though the technology has not been adopted to the extent anticipated [e.g., Hagos et al., 2007; Sisay, 2013], mainly because the program was top-down, technocratic and nonparticipatory [e.g., Moges et al., 2011; Searnet, 2013]. Even in cases where adoption of the technology was participatory, farmers were not so much consulted as persuaded to accept water harvesting technology on their land [Bewket, 2007], ultimately resulting in their abandonment. Rainwater harvesting is still a relatively new technology to most farm households in Ethiopia and little is known about it at institutional and community level, hence resulting in a low adoption of the technology (e.g., Feyisa, 2014). In order to realize the full benefits of adopting rainwater

harvesting technologies, enhance agricultural productivity, and reduce vulnerability to water scarcity, it is important to understand the institutional-economic factors that constrain farm households in their decision making to invest in this technology.

In this study, a choice experiment is developed with the main aim to test what triggers farm households to invest in and maintain water harvesting ponds on their land. To our knowledge, there exists no such study yet, which estimates farm households' demand for improved water harvesting technology in Ethiopia. In the choice experiment, farmers living in a drought prone area in Ethiopia are offered a menu of contracts, following the approach developed in *Tesfaye and Brouwer* [2012]. The contractual agreements include different combinations of institutional, economic, and technological terms and conditions and are introduced to a random sample of farm households in the study area to assess how to best encourage them to invest in improved water storage and hence reduce their vulnerability to water scarcity.

Analyzing farmers' choices for alternative contract designs reveals the importance they attach to the various terms and conditions [*Tesfaye and Brouwer*, 2012]. In view of the relatively high illiteracy rate in Ethiopia (according to *United Nations Children's Fund* [2014], over the period 2008–2012 on average 37% of the male and 53% of the female population could not read or write), pictograms were used in the choice experiment with as little text as possible to describe the levels of the contract characteristics. In a control group, the same choice experiment was also administered without the visual aids to test their impact on choice behavior. The first hypothesis tested here is that the way the information was conveyed to farm households in the choice experiment (with and without visual aids) significantly affects choice behavior, in particular among the illiterate population. In addition, the extent to which farmers pay attention to the different contract characteristics, with and without visualizations, was assessed using both self-reported and inferred attribute (non)attendance approaches [e.g., *Hess and Hensher*, 2010; *Hensher and Green*, 2010; *Campbell et al.*, 2011]. This leads to the second alternative hypothesis tested here that respondents do not pay equal attention to all contract terms and conditions, i.e., there exists attribute nonattendance.

The remainder of this paper is structured as follows. Section 2 first describes the methodological design of the study, including the underlying econometric model to estimate farm household demand for the presented contractual agreements to invest in improved water harvesting technology on their land. This is followed by a description of the case study area and data collection procedure in section 3. Section 4 presents the results, while conclusions are drawn in the final section 5.

2. Methodological Design

2.1. Choice Experiment Design

Choice experiments (CEs) are part of the family of stated preference methods [e.g., *Hanley et al.*, 2001]. Preferences for existing or new products, technologies, or policy programs are elicited using a social survey format, such as in-person interviews [e.g., *Bennett and Blamey*, 2001]. Although CEs were originally developed in marketing research and applied to a wide variety of consumer products in developed countries, their application in developing countries has seen an exponential growth [e.g., *Bennett and Birol*, 2010]. CEs typically ask respondents in a series of choice tasks to choose between two or more alternative policies, which are described based on their relevant characteristics [e.g., *Hanley et al.*, 2006]. This allows estimation of public demand for these policies, and preferences for their specific characteristics or attributes. Usually the benefits associated with the policies are described and the costs involved, for example, the price individual respondents would have to pay in order to secure the described policy benefits. The inclusion of a monetary price attribute in the CE allows estimation of public willingness to pay (WTP) for the policy. In this study, the alternatives between which farmers in Ethiopia are asked to choose are contracts.

The contract design here aims at investigating farmer's preferences for different contractual arrangements, which they conclude either with regional governments or nongovernmental organizations who provide them with the relevant technical and institutional-economic support to invest in private household ponds. The contract provides farmers opportunities and certainties to reduce their climate vulnerability. The contract specifies the terms and conditions of the provision of credit to finance the construction of "best practice" water ponds. So the good on offer is water security through the implementation of improved water harvesting technology, which is financed by a proposed microcredit scheme in the case study area. In exchange for the water security benefits that farmers obtain from adopting improved rainwater harvesting

Table 1. Description of the Contractual Arrangements in the Choice Experiment

Attribute	Attribute Levels
Contract provider	Regional government or nongovernmental organization
Contract duration	5, 10, or 15 years
Pond capacity	8000, 27,000, 64,000, or 125,000 L
Pond lining	Plastic or cement
Pond cover	Yes, no
Labor input	10, 20, or 30 person days
Monthly repayment loan	100, 200, 300, 400, or 500 Birr per household

technology, they periodically repay the loan they receive from the preferred credit provider plus interest. Farmers are expected to invest the credit received from the credit provider in the construction of state-of-the-art household water ponds according to the contract specifications. Contracts are offered for the duration of 5, 10, and 15 years. The descriptions of the contractual arrangements in the CE are presented in Table 1.

The contract characteristics were selected based on an extensive literature review, expert interviews, and focus group discussions. They include (i) the contract provider, (ii) contract length, (iii) water pond size, (iv) lining of the water pond, (v) water pond coverage (i.e., whether or not the pond is covered), and (vi) farmer labor input to construct the pond. The repayment rates are set based on group discussions and pretest results conducted before the main survey and are independent of the contract length, both in terms of the applied statistical design and measurement of behavioral intent. Contract length is primarily included to measure a farm household's longer-term commitment to maintaining the water pond. The group discussions showed that using land certificates as collateral, farmers can get loans ranging from 2000 to 5000 Birr (USD 105–265) (Birr is Ethiopia's national currency; one Birr equaled approximately USD 0.0494 at the time of the study) at an interest rate of 10% for 12 months from the regional government. The monthly payments for such a loan over 12 months vary between 300 and 700 Birr. Based on the focus group discussions, a repayment period of 12 months was considered a constraint given average income levels in the study area. As a result, many if not most farmers are unable to participate in the loan service provided by the local government. Contract duration was therefore extended to range between 5 and 15 years to give farmers enough time to repay the loan, and at the same time assess their longer-term commitment to their investment and maintain the water ponds. The combinations of monthly payments and contract duration in the design reflect the actual situation and imply the provision of loans in the range of 1000–5000 Birr at a market interest rate of 10%.

This is hence also the range applied in the CE, i.e., five price levels were identified in terms of a household's monthly loan repayment, varying between 100 and 500 Birr (USD 5–25). Besides the regional government, international NGOs are considered the most important alternative contract providers in the design of the CE since they have been providing financial and material support to local farmers to build community ponds in the study area. The inclusion of labor input in the contract design is based on the fact that farmers currently already contribute labor days for digging the community ponds. Labor input with levels fixed at 10, 20, and 30 person days per pond is therefore another characteristic of the contract considered in this study as an in-kind payment. Based on field visits to the study area, the community ponds constructed for the farmers in the past differ in the lining and sealant used compared to available alternative technologies, justifying their inclusion as characteristics of the contract.

Contractual arrangements are created by combining the above listed characteristics based on their levels. Because respondents cannot be shown all the possible combinations as choice options, a D-efficient design was generated in Ngene [Scarpa and Rose, 2008], consisting of 9 blocks of 10 choice tasks each. Assuming an underlying multinomial logit (MNL) model, the D-error reduced in the design generating process from an initial value of 0.041 at the start of the simulation to 0.029 for the selected design. *Bliemer and Rose* [2010] show that D-efficient MNL-based designs also perform well for mixed logit models. For this reason, the design was derived assuming a MNL specification. Each respondent was randomly shown one of these 9 blocks of 10 choice cards. Following previous experiences applying CEs in rural Ethiopia and in order to limit the cognitive burden on farmers [Tesfaye and Brouwer, 2012], each choice card shows two hypothetical contracts along with the option to choose none of the two. Inclusion of this latter "status quo" alternative is instrumental to estimate welfare measures that are consistent with demand theory [Bateman et al., 2002] and not to force respondents to accept the proposed contracts if they are not interested in either of them. During the pretest of the CE, special attention was paid to whether the design included combinations of attributes that were considered unrealistic or unfeasible by respondents.

	Contract A	Contract B
Provider		ngo
Duration (years)	10	5
Capacity (liters)	27,000	125,000
Lining	cement	plastic
Cover	no	yes
Labor days	30	10
Payment (Birr/month)	100	300
I prefer	☐	☐
		☐ None of the 2

Figure 1. Example choice card with pictograms.

In order to test choice consistency and potential preference learning [Brouwer et al., 2010], the first choice card was shown again at the end of the choice sequence as the final choice task without telling respondents. In addition, half of the respondents were presented the choice cards without pictograms and the other half with pictograms to test the effect of these visual aids in the CE. An example of a choice card with pictograms is presented in Figure 1. The choice card without the pictograms is exactly the same except for the pictograms.

The introduction of the CE was identical in both versions. Before

the start of the CE, all respondents were shown the same instruction choice card, with visualizations in the sample with visualizations and without visualizations in the sample without visualizations, to explain the objective of the CE and the choice tasks. Enumerators were trained to introduce the CE in the same way to all respondents and guide each respondent in the same way through the example choice card to ensure all respondents clearly understood the choices they were expected to make in the subsequent CE. After going through the instruction choice card, i.e., before the start of the CE, each respondent was asked if (s)he understood the choice task. Enumerators only proceeded with the CE once the respondent indicated that (s)he fully understood the choice task and (s)he was ready for the CE. They were then shown the sequence of choice tasks in the CE, where the enumerator read out loud the information on each choice card to illiterate respondents, and literate respondents were given the option to read the information on the choice cards self or have the enumerator read it out loud to them.

2.2. Econometric Choice Model

CEs are based on Lancaster's [1966] attribute-based utility theory. The related econometric basis is found in McFadden's [1974] Random Utility model (RUM), which can be approximated by an appropriately specified random parameters logit model [McFadden and Train, 2000]. The random parameters logit (RPL) model overcomes the main limitations of standard multinomial logit models by accounting for random taste variation, unrestricted substitution patterns, and unobserved correlation between alternatives [Train, 2003]. Random parameters logit models can represent heterogeneity across individuals in both observed and unobserved preferences but require computationally intensive procedures to estimate probabilities [Newman, 2003].

The RUM can be described in the context of this specific study as follows. Suppose a farmer faces a choice among J contractual agreements related to different water harvesting technologies and contract specifications. The utility U_{ijt} associated with each contract alternative j , as evaluated by each farmer i in choice situation t can be specified as in equation (1):

$$U_{ijt} = \beta_i' X_{ijt} + \varepsilon_{ijt} \quad \forall j \in J \quad (1)$$

where X_{ijt} is the vector of explanatory variables that are observed by the analyst, including the terms and conditions (attributes) of the presented contract alternatives, the socioeconomic characteristics of the individual farmer and the descriptors of the decision context and choice task in choice situation t [Hensher et al., 2013]. β_i and ε_{ijt} are not observed and treated as stochastic influences [Train, 2003]. ε_{ijt} is the vector of error terms with an iid extreme value type I distribution. Equation (2) describes the probability of individual i selecting alternative j compared to other choice alternatives k given that cost associated with each alternative is Y_{ijt} :

$$P_{ijt} = \int \left(\frac{\exp[(\beta_i X_{ijt} + \beta_{yi} Y_{ijt})]}{\sum_{k \in J} \exp[(\beta_i X_{ikt} + \beta_{yi} Y_{ikt})]} \right) f(\beta_i) d\beta_i \quad \forall j \neq k \quad (2)$$

In order to account for unobserved preference heterogeneity across individual farmers, the coefficients associated with the contract characteristics are specified as random terms, allowing the utility coefficients β_i to vary across individuals, applying different mixing distributions with density $f(\beta_i/\theta)$. θ refers here to the density parameters such as the mean and covariance of β in the sample population. Following *Hensher et al.* [2005], a uniform distribution is used for the choice attributes' random dummy variables, the random terms of the other choice attributes, including the alternative specific constant (ASC), follow a normal distribution as this appeared to produce the best statistical fit. The price coefficient is included as a random term too because we are interested in how individual respondents attend to and weigh each individual choice attribute, and not necessarily in the estimation of theoretically correct welfare measures. For efficiency purposes and ensure model stability, the models are estimated using a Halton sequence of 500 replications in a quasi-Monte Carlo maximum likelihood simulation [*Bhat*, 2001]. Even if unobserved heterogeneity is accounted for in a RPL model, the model may fail to explain the sources of heterogeneity [*Hynes et al.*, 2008]. To this end, interactions of respondent specific household characteristics can be included with either choice specific attributes in the utility function or the alternative specific constant to improve the model fit.

Although the RPL is the standard model nowadays to model choice behavior in CEs, the model may not properly estimate attribute coefficients if there are some respondents who do not attend to all attributes. The RPL model will assign zero attribute coefficients to these respondents, which will result in lower average sample coefficients. The inferred attribute nonattendance (ANA) model picks up those attributes that are most frequently overlooked or downweighted by respondents in their analysis of the presented choice situations. Given the emphasis in this study on how attributes are communicated to respondents, attribute (non)attendance is of particular interest here.

The estimation of an ANA model is done within the Equality Constrained Latent Class (ECLC) framework [*Hensher and Greene*, 2010]. This procedure allows us to derive the implied degree of attribute processing by respondents, relying only on the information incorporated in the respondents' choices. It has been argued that the inferred ANA provides less biased estimates of ANA than respondents' self-reported estimates of the amount of attention they pay to each choice attribute [e.g., *Campbell and Lorimer*, 2009; *Scarpa et al.*, 2009; *Hensher and Greene*, 2010; *Campbell et al.*, 2011].

The ECLC approach typically requires the model to include all possible 2^K combinations of ignored attributes (where K is the total number of attributes) and, correspondingly, to define an equivalent number of classes in which the coefficients of ignored attributes are set to zero, while other coefficients are constrained to be equal across each class (for a detailed description, see for example, *Hensher and Greene* [2010] or *Campbell et al.* [2011]). This is modeled using a discrete distribution of the model's parameters over a finite set of classes. Based on their individual characteristics, respondents are implicitly placed in an unobserved or "latent" class c , each with distinct utility parameters (hence β_c). Within each class, individual decisions over consecutive choice cards are assumed to be independent, while conditional on being in a specific class, choice probabilities are generated using a multinomial logit model specification:

$$\Pr(y_{it}=j|\text{class}=c) = P_{ijt|c} = \frac{\exp(\beta'_c X_{ijt})}{\sum_{q=1}^{J_i} \exp(\beta'_c X_{iqt})} \quad (3)$$

Probabilities for unobserved class membership may be assumed constant: $\Pr(\text{class} = c) = Q_{ic}$. Correspondingly, calculating the expected value of the class-specific probabilities over classes, we obtain the unconditional probability of the sequence of choices:

$$\Pr(y_i=j) = P_{ij} = \sum_{c=1}^C Q_{ic} \prod_{t=1}^T P_{ijt|c} = \sum_{c=1}^C Q_{ic} \prod_{t=1}^T \frac{\exp(\beta'_c X_{ijt})}{\sum_{q=1}^{J_i} \exp(\beta'_c X_{iqt})} \quad (4)$$

Using Bayes theorem, it is possible to obtain the posterior estimate of individual class membership probabilities:

$$\Pr(\text{class}=c|\text{choices, data})=Q_{ic}^*=\frac{Q_{ic}\prod_{t=1}^T P_{ijt|c}}{\sum_{m=1}^C Q_{im}\prod_{t=1}^T P_{ijt|m}}, \quad (5)$$

and given the conditional estimates of the class probabilities and class-specific parameters, we can further calculate an individual-specific posterior estimate of the parameters:

$$\hat{\beta}_i=\sum_{c=1}^C \hat{Q}_{ic}^* \hat{\beta}_c. \quad (6)$$

Individual preference heterogeneity manifests itself in this case in the way how respondents analyze the attributes in each choice situation, in particular how much attention they pay to each of the attributes. To model inferred ANA, the ECLC model is estimated with several latent classes representing different heuristic rules for attribute processing. A range of classes is created where the first class is associated with respondents who consider all attributes, then several more classes are associated with respondents who ignore one of the attributes, and the last class with those who ignore all attributes. In accordance with the underlying assumption of nonattendance, the coefficients for ignored attributes in the respective class have the value zero. Conversely, the values of the nonzero coefficients are constrained to be equal across all classes, so that the coefficients capture only the attribute-processing strategies and not preference heterogeneity across respondents. The estimated individual latent class membership probabilities provide an estimate of the weights that each individual assigns to each attribute, or in other words, the probability that an individual attends to a particular attribute. Summed class probabilities across all classes where a particular coefficient is zero (including the class where all attributes are ignored) provide an estimate of the share of respondents who ignore the given attribute.

Due to the limited data size and the large number of attributes in our CE design (yielding 121 possible combinations of nonattended attributes), we aimed to estimate the most parsimonious and logical model, and therefore limit the model to the latent classes where none, all, or only one attribute is ignored. A similar approach is applied by *Scarpa et al.* [2012]. Including all 121 possible combinations is technically not feasible to estimate. This avoids the risk of mining for the best model specification over a limited sample size or finding a model that is intractable for interpretation. This approach gives us nine classes in total: class 1 is defined for all attributes attended, classes 2–8 where every time one of the choice attributes is ignored, and class 9 assumes that none of the attributes received any attention. Due to the constraint on the sum of latent class probabilities, the probability for class 9 is calculated after the model estimation. How individual attribute class probabilities would change as a result of including additional combinations of attribute classes is not tested further here. Using this approach, the main goal is to see how class membership, and hence the role individual attributes play in the choice process, differs across the two samples with and without the visual aids.

3. Case Study Area and Data Collection

The study is carried out in the administrative district Halaba, located in the Southern Nations and Peoples Regional state, 310 km south of Addis Ababa, the capital city of Ethiopia. The area of 640 km² is located in a relatively flat, semiarid region, crossed by the river Bilate. The average elevation is 1800 meters above sea level (m asl), ranging from 1550 to 2150 m asl. In combination with the rainfall intensity, the gentle slopes generate sufficient overland flow to be stored in ponds, lending itself as a suitable technique to reduce water scarcity that limits agricultural production in the area.

The total population in the district was estimated in 2007 at just over 232 thousand people, with almost all inhabitants residing in rural areas. The rural villages are accessible in the dry season by means of a dry weather road [Deneke and Abebe, 2008]. There are two rainy seasons: one from March to May with an average rainfall of 240 mm (standard deviation of 120 mm) and one from July to September with an average rainfall of 320 mm (standard deviation of 135 mm) [Amha, 2006]. The latter period is considered the main rainy season. The average annual temperature ranges from 17.6 to 22.5°C, and the average evaporation rate is about 1750 mm/yr [Shewangizaw and Michael, 2010]. The soils in the study area are fertile. Besides teff,

the main food grain in Ethiopia, other food crops grown in the study area are maize, wheat, barley, beans, and chili pepper (Amha, unpublished MSc thesis, 2006). In the absence of rivers in large parts of the area, communities largely depend for their drinking water supply either on community ponds or increasingly on groundwater from public boreholes. However, the groundwater table is deep (97–360 m), the soil is sandy, hence accelerating seepage, and dependency on deep water boreholes entails a high risk of dental fluorosis [Kocanda *et al.*, 2013]. Farmers use private ponds for supplementary irrigation of higher value crops and livestock drinking. In addition, water harvesting is used occasionally for domestic consumption, such as washing clothes, but not as drinking water.

In this study, 150 farm households without private water ponds living in 12 different villages in the case study area were surveyed and interviewed in person following a stratified random sampling procedure. The households were proportionally divided over the 12 villages and one half answered the textual/numerical choice cards, while the other half answered the choice cards with visualizations (pictograms). Blocks of choice sets were assigned randomly to respondents in the 12 villages. Between 12 and 13 interviews were carried out per village, and each block was answered by 16 or 17 respondents. The head of each of these farm households was interviewed by a trained enumerator based on a thoroughly pretested questionnaire. Each interview lasted between 30 and 45 min.

4. Results

4.1. Sample Characteristics

The split samples' household and farm characteristics are presented in Table 2. No official statistics are available to assess the representativeness of the samples. Despite the random sampling procedure, a few significant differences exist between the two subsamples, most importantly related to monthly household income. Differences were tested using the nonparametric Mann-Whitney test statistic. Test results reported here are available from the authors. The sample who received the version of the CE with the visualizations has, on average, an income level that is 33% lower than that of the sample who received the version without the visualizations. This is partly related to respondents' education level. However, the standard deviation of the mean income statistic for the sample that received the visual aids is very high with a variation coefficient of 84% compared to 49% for the sample without the visual aids, indicating that the mean value is not very accurate and there exists a substantial spread in the self-reported income levels in this subsample. Moreover, closer inspection of the self-reported income values reveals that almost a quarter of the respondents in the sample with visualizations refused to dis-

close their income level, whereas all respondents except one in the other sample stated their income. Also the share of respondents who cannot read or write is substantially (22%) higher in the sample with the visualizations. These differences will therefore have to be controlled for when comparing the choice modeling results in the two split samples.

The other differences between the two subsamples are limited. The sample with attribute visualizations includes, on average, slightly older respondents from smaller households with slightly less primary education, but more completed

Table 2. Sample Household and Farm Characteristics Across the Two Subsamples

Household and Farm Characteristics	Without Attribute Visualizations	With Attribute Visualizations
<i>General Sociodemographic Household Characteristics</i>		
Average age (years)	32	35
Share of male respondents (%)	85	79
Average number of household members (persons)	6.7	5.9
Share of respondents who cannot read or write (%)	37	45
Share of respondents with primary school education (%)	57	41
Share of respondents with secondary or higher education (%)	7	9
Average monthly household income (Birr) (st. dev.)	898 (441)	599 (506)
Share of households with off-farm income activities (%)	10	12
Share of respondents receiving remittance (%)	4	1
Share of households having (access to) credit (%)	54	53
<i>Farm Characteristics</i>		
Share of households with a land use certificate (%)	95	97
Average size of land owned by a household (ha)	1.1	1.1
Average number of crops grown per household	1.7	1.4
Average number of livestock (TLU)	2.9	3.4
Share facing water shortages (%)		
Once every 2 years	68	55
Once every 5 years	31	37
Share with dead livestock due to droughts (%)	48	43
Average annual drought damage (Birr/household) (st. error)	2893 (190)	3812 (426)
Share expecting droughts to increase in the next 10 years (%)	69	49
Number of observations	75	75

secondary school education. The share of respondents having access to credit or receiving remittances from family members abroad is more or less the same across the two samples.

Turning to the farm characteristics, differences between the two samples are very small and in most cases negligible. Similar sample shares have a land use certificate, necessary to get access to credit, and have on average the same amount of land per household, growing on average the same number of crops. Livestock ownership is included as another measure of household wealth and is measured in Tropical Livestock Units (TLU). The subsample with attribute visualizations has slightly more livestock (3.4 TLU) than the subsample without (2.9 TLU).

Finally, self-reported water shortage in the dry season over the past 2 years is somewhat higher in the sample without visualizations than in the sample with visualizations. The same applies to the share of farm households who faced dead livestock as a result of droughts. However, the average annual damage costs are higher in the sample with visualizations. The difference is not significant though at the 5% level. A majority of 69% of the respondents in the sample without visualizations and 49% in the sample with visualizations expect rainfall shortages to increase in the next 10 years.

4.2. Choice Modeling Results

A majority of the farmers are interested and willing to enter into a contractual agreement to invest in improved household water ponds to reduce their vulnerability to water scarcity and thereby improve their livelihoods. Sixteen of the 150 respondents (11%) were not interested in the contract and consistently chose the opt-out, either because they could not afford to pay or their land was considered too small to build a new water pond. As expected, an equal distribution of choices is found between the two hypothetical contract alternatives. The first contract alternative is chosen in 45% of the choice occasions and the second in 44% of the cases, confirming there is no selection bias present in the hypothetical contract alternatives due to design errors. As expected, the higher the payment level, the lower the share of farmers choosing these more expensive alternatives. Note that average monthly income in the sample with visualizations is close to the highest bid level in the CE (Table 2). As a result, alternatives with the highest bid level were chosen in only 4.9% of the choice occasions in the sample with visualizations and in 3.8% of the choice occasions in the sample without the visualizations.

As an aside, comparing the alternative chosen in the first choice task with the one in the 11th identical last choice task, the consistency of the choices is remarkably high. Eighty-eight percent of the respondents chose the same contract alternative in the identical first and last choice task. This is higher than the consistency rates found in previous studies [e.g., *Brouwer et al.*, 2010]. No significant influencing factors could be detected when regressing consistent and nonconsistent choices on a number of sociodemographic and socioeconomic respondent characteristics (e.g., age, gender, education, and farm characteristics) and design characteristics (levels of the choice attributes), possibly due to the limited number of nonconsistent choices.

Two models are estimated, splitting the sample households as before into two (those who received visual aids and those who did not) as we wanted to see what effect the visual aids have on choice behavior (our first hypothesis). The contract provider, pond lining and pond cover are included in the models as dummies, whereas contract length, labor input, capacity of the pond and payment are included in the model as continuous variables. In addition to the characteristics of the proposed contract, also the most relevant covariates are included in Table 3, namely respondents' household income and literacy rate, based on the differences observed in Table 2. The former is interacted with the price attribute and the latter with the ASC to assess the overall impact of literacy on choice behavior. Household income and hence ability to pay is expected to influence a respondent's WTP a specific contract price, while there is no expectation beforehand to assume that a respondent's literacy rate would affect one or more specific contract attributes. No significant effects could be detected for other influencing factors, in particular farmers' current risk exposure and damage costs and perception of future droughts.

The RPL choice models are estimated in NLOGIT version 5.0, accounting for the panel data structure of the model and unobserved preference heterogeneity. Both models are highly significant as can be seen from the chi-square test statistic. The pseudo R^2 is high for this type of cross-section analysis and slightly higher for the sample with the attribute visualizations than for the model without the attribute visualizations. All 11 choices are included in the model estimation procedure, yielding 825 observations per subsample, i.e.,

Table 3. Estimated Random Parameters Logit Choice Models for the Two Subsamples Including Covariates

Variables	Without Attribute Visualizations				With Attribute Visualizations			
	Coefficient Estimate	St. Error	St. Dev. Rnd. Pars	St. Error	Coefficient Estimate	St. Error	St. Dev. Rnd. Pars	St. Error
ASC	3.548***	0.751	3.211***	0.562	5.521***	0.928	2.834***	0.548
<i>Choice Attributes</i>								
Contract provider = regional government	0.417***	0.146	0.689	0.489	0.059	0.194	1.837***	0.337
Contract duration (years)	−0.035**	0.017	0.040	0.029	0.034*	0.017	0.046	0.034
Pond capacity (m ³)	0.013***	0.003	0.019***	0.004	0.003**	0.002	0.007**	0.003
Pond lining = cement	0.139	0.163	1.419***	0.368	−0.406**	0.169	1.502***	0.333
Top of pond = covered	0.788***	0.187	1.720***	0.311	1.182***	0.211	1.949***	0.360
Nonmonetary payment (labor days)	0.008	0.008	0.023	0.015	−0.006	0.009	0.038***	0.014
Monthly payment (Birr)	−0.003***	0.001	0.004***	0.001	−0.004***	0.001	0.005***	0.001
<i>Covariates</i>								
ASC × 1 if respondent is illiterate	−1.419**	0.688			−0.514	0.868		
Payment × 1 if income is higher than average	0.002	0.001			−0.002	0.001		
<i>Model Summary Statistics</i>								
Log-likelihood	−616.168				−562.596			
Pseudo R ²	0.320				0.379			
Chi square statistic (18 d.o.f.)	580.375***				687.518***			
Number of observations	825				825			

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

75 respondents making 11 choices in each subsample. The reason for including the 11 instead of 10 choices is that a comparison of the RPL models based on 10 and 11 choices shows that the latter explain slightly more of the choice variation than the latter. The Aiken Information Criterion (AIC) adjusted for the number of observations is reduced from 1.571 to 1.537 for the RPL models with 10 and 11 choice tasks, respectively, in the sample without attribute visualizations, and from 1.442 to 1.408 in the sample with attribute visualizations. Similarly, McFadden's pseudo R^2 increases by 4% from 0.307 to 0.320 in the sample without attribute visualizations, and from 0.366 to 0.379 in the sample with attribute visualizations. This suggests that for some of the respondents who answered differently in the 11th choice task (12% of the sample population) their choice in the repeated choice task seems to better reflect their preferences, further reducing the variance in choice behavior.

As expected based on the relatively low number of opt-out choices, the ASC's relating to the hypothetical contract alternatives are positive and highly significant in both subsamples. However, they are also surrounded by substantial preference heterogeneity as can be seen from the significant standard deviation of the random parameters. The contractually requested in-kind contribution (household labor) is not statistically significant in either model and hence plays no role in contract selection, also not when interacted, for example, with covariates such as household size as a proxy for the availability of household labor. The finding that this contract condition is neglected by the farmers in their decision-making process suggests that it is not considered important or that the opportunity costs of labor may be low in the study area. This latter explanation could not be verified as this was not further investigated during the survey. The pretest results showed that this variable might not be significant at the 10% level, but it was kept in as a contract condition in view of the fact that it is common practice to provide own labor in building community and private ponds. Moreover, the coefficient estimate was negative based on the pretest results, even if farmers in both subsamples do not seem to care much about this contract condition. The monetary payment (credit payback with interest) is highly significant and as expected negative: the higher the payback sum, the less likely a farmer will choose a contract alternative. Although the size of the coefficient's standard deviation is considerable, suggesting that some respondents attach a positive utility to the payment, the normal distribution is highly significant and produced a better statistical fit than assuming that the coefficient is constant across respondents as a fixed effect or assuming a bounded triangular distribution as in Kragt [2013]. Contrary to expectations, no significant income or wealth effect on WTP could be detected in the estimated choice models.

In the subsample without the attribute visualizations, the specific lining of the water pond does not play a significant role, while the contract provider is not considered important in the subsample with the attribute visualizations. Remarkably, the standard deviations of the corresponding random parameters in both samples are statistically significant suggesting that there exists variation in the valuation of these attributes

across farmers. In the subsample without the visual aids, farmers prefer that the contracts are provided by the regional government instead of international NGO's (the baseline category), possibly due to the fact that the regional government also provides other inputs already such as fertilizer and seeds [e.g., *Raman and Dessie*, 2013], and in the subsample with the visual aids plastic lining (the baseline category) is preferred to cement. This latter finding can be explained by the fact that the plastic lining retains water longer than cement, which often cracks and results in water leakage during the dry season. Note that this specific contract characteristic is surrounded by significant preference heterogeneity though.

Farmers in both samples prefer, all else being the same, bigger water ponds that are covered to avoid evaporation, health risks associated with attracting malaria mosquitos and children from drowning. Whereas the positive impact of the specified size of the pond on choice behavior is bigger in the sample without visualizations, pond cover is valued higher in the sample with visual aids. Both contract characteristics are surrounded by significant preference heterogeneity. Contract duration is also significant in both samples, but short-term contracts are preferred in the sample without visual aids and long-term contracts in the sample with visual aids.

Finally, literacy rate has a significant effect on choice behavior in the sample without visualizations and not in the sample with visualizations. Illiterate farmers who have not been shown the pictograms are significantly less likely to choose one of the contract alternatives and more likely to stay with the status quo. The fact that the same effect is not statistically significant in the sample with the visual aids might suggest that the role of illiteracy has been offset when using visual aids. However, this result has to be interpreted with the necessary care in view of the fact that the literacy rate in the subsample without the visualizations is somewhat lower.

We also estimated the choice models for the two subsamples of literate and illiterate farmers and included a dummy for the version of the CE (with or without visualizations). These choice model results, presented Annex 1 to this paper, confirm that the application of visual aids only significantly affects the subsample of illiterate farmers and not the subsample of literate farmers. Illiterate survey respondents are more likely to choose one of the hypothetical contract alternatives if they were shown the version with visual aids.

4.3. The Influence of Visual Aids on Choices for the Contractual Agreements

Comparing choice consistency across the two split samples, those who received the version of the CE including the attribute visualizations were slight more consistent in their choices (89.5%) than those who received the version without visualizations (86.5%). The *Swait and Louviere* [1993] test procedure was carried out to compare the results from the split samples with and without the visualizations to formally test the first hypothesis. In the two step approach, the first hypothesis of equal preference parameters is convincingly rejected at the 1% significance level (likelihood ratio test statistic is 46.952 with 16 degrees of freedom), implying that the two estimated choice models are not the same, and the use of visual devices significantly affects choice behavior. Based on the outcome of this first hypothesis test, we know that the two models are not the same, but we are unable to identify whether this is due to differences in preference or scale parameters [*Louviere et al.*, 2000]. Hence, although somewhat redundant, we also report the outcome of the second hypothesis of equal scale parameters (likelihood ratio test statistic is 2.222 with only 1 degree of freedom). This second hypothesis cannot be rejected at the 10% level, and suggests that there exist no statistically significant differences in the error variance of the estimated choice models.

4.4. Stated and Inferred Attribute (Non)attendance

The upper part of Table 4 shows the number of attributes that guided farmers' choices in the CE (answers are missing for five respondents). Although respondents were allowed to select multiple attributes, 57% of the sample without visualizations stated one attribute only. This was less than a quarter in the sample with visualizations. Hence, more attributes were attended to in the sample receiving the visual aids. The bottom part of Table 4 shows how many respondents indicated that a specific choice attribute played a role and thus was attended to during the choice-making process. Because respondents were allowed to select as many attributes as they wanted, the numbers in the bottom part do not add up to the total number of respondents in each subsample. It is important to point out that not mentioning an attribute does not necessarily mean that the attribute was ignored. *Alemu et al.* [2013] find, for example, that respondents may not ignore attributes completely even if they claim so in the survey. The relatively low shares of attribute

Table 4. Stated Attribute Attendance Across the Two Subsamples

	Without Attribute Visualizations		With Attribute Visualizations		Equality of Proportions <i>p</i> -Value
	Number of Respondents	Share (%)	Number of Respondents	Share (%)	
<i>Number of Attributes Attended</i>					
None	1	1.4	0	0.0	1.000
1 attribute	42	57.5	17	23.6	0.001
2 attributes	17	23.3	19	26.4	0.810
3 attributes	4	5.5	26	36.1	0.001
4 attributes or more	9	12.3	10	13.9	0.970
Total	73	100.0	72	100.0	
<i>Attended Choice Attribute^a</i>					
Contract provider	11	15	19	25	0.153
Contract duration	12	16	24	32	0.036
Pond capacity	15	20	34	45	0.002
Pond lining	21	28	44	59	0.001
Pond cover	41	55	36	48	0.414
Labor input	4	5	1	1	0.612
Monthly payment	23	31	19	25	0.585

^aMultiple attribute selection was possible, hence the reason that the shares do not add up to 100%.

attendance presented here therefore have to be interpreted with the necessary care. Only one respondent indicated that none of the attributes guided his choices, suggesting he ignored all attributes.

Looking at the numbers, we can conclude that there is not a single attribute that was considered by all respondents. In other words, our second alternative hypothesis that respondents did not pay attention to all attributes is confirmed. Moreover, there is considerable variation in the degree of attention paid to different attributes: while about half of the respondents primarily considered pond cover and pond lining during their choices, only five respondents paid attention to the requested household labor. In line with earlier findings in the literature [e.g., *Campbell et al.*, 2008; *Scarpa et al.*, 2009; *Carlsson et al.*, 2010; *Kragt*, 2013], the monetary payment attribute was not attended by all respondents either. Only between 25 and 31% of the respondents stated that they accounted for this attribute in their choices. Still, pond cover, pond capacity, and pond lining are among the more attended attributes compared to the somewhat lower levels of attendance to the institutional contract characteristics such as the contract provider and contract duration. Comparing stated ANA across subsamples, we furthermore observe that the degree of nonattendance is significantly lower for pond capacity, lining and contract duration, that is, for three out of the seven attributes that received visual support in the split sample experiment.

We also estimated the RPL choice models presented in section 4.2 for the two subsamples accounting for self-reported ANA, by restricting the attributes respondents did not list to attend to zero in the estimation procedure. However, the latter estimated choice models were less robust and explained less of the observed choice behavior than the conventional RPL models without stated ANA. Similar results were found, for example, by *Carlsson et al.* [2010], *Scarpa et al.* [2012], and *Alemu et al.* [2013]. Due to space restrictions, these models are presented in Annex 2 to this paper.

The ECLC model to assess inferred ANA is estimated using the software Biogeme [*Bierlaire*, 2003]. The usual search across the range of starting values was performed and the resultant models were compared on the grounds of their convergence and final likelihood. The statistically best fit model estimation results are presented in Table 5. As before, the estimation results are reported separately for the two subsamples. Note that for some class probabilities the estimation procedure reports very small numbers with very high standard errors, which is due to the optimization of the multiparameter likelihood function with several close-to-zero coefficients.

The first important observation from Table 5 is that in both subsamples the share of respondents who attended to all attributes (class 1 probability) is very low and not statistically significant, which means that all respondents ignored certain attributes during their decision making. At the same time, the probability of not attending to all attributes is quite high in both subsamples, suggesting that our second alternative hypothesis cannot be rejected. This is somewhat contrary to the finding reported before in Table 4 that only one respondent stated not to attend to any of the attributes. A possible explanation may be that since the ECLC model is specifically

Table 5. Estimated Inferred Attribute Nonattendance ECLC Models Across the Two Subsamples

Variable	Without Attribute Visualizations				With Attribute Visualizations			
	Coefficient Estimate	St. Error	t Test	p-Value	Coefficient Estimate	St. Error	t Test	p-Value
ASC	−2.340***	0.269	−8.69	0.001	−1.830***	0.182	−10.04	0.001
Contract provider = regional government	4.240**	1.620	2.62	0.010	1.060***	0.310	3.41	0.001
Contract duration (years)	0.002	0.015	0.14	0.880	−0.302***	0.047	−6.48	0.001
Pond capacity (m ³)	0.003**	0.001	2.26	0.020	0.043***	0.008	5.64	0.001
Pond lining = cement	−0.198	0.124	−1.59	0.110	−1.330***	0.420	−3.17	0.001
Pond cover = covered	0.972***	0.132	7.39	0.001	1.570***	0.366	4.29	0.001
Labor input (labor days)	0.001	0.007	0.07	0.950	−0.017	0.014	−1.22	0.220
Monthly payment (Birr)	−0.004***	0.001	−8.02	0.001	−0.010***	0.002	−4.93	0.001
PrClass1: all attributes attended	0.035	0.026	1.33	0.180	0.000	1.000	0.00	1.000
PrClass2: contract provider ignored	0.000	1.000	0.00	1.000	0.000	1.000	0.00	1.000
PrClass3: contract duration ignored	0.450***	0.081	5.57	0.001	0.367***	0.078	4.70	0.001
PrClass4: pond capacity ignored	0.057*	0.030	1.92	0.060	0.000	0.000	0.00	1.000
PrClass5: pond lining ignored	0.000	0.000	0.00	1.000	0.000	0.000	0.00	1.000
PrClass6: pond cover ignored	0.000	0.000	0.00	1.000	0.127**	0.051	2.51	0.010
PrClass7: labor input ignored	0.000	1.000	0.00	1.000	0.000	1.000	0.00	1.000
PrClass8: monthly payment ignored	0.019	0.027	0.69	0.490	0.223**	0.082	2.73	0.010
PrClass9: all attributes ignored	0.440***	0.094	4.67	0.001	0.283***	0.124	2.28	0.011
Initial Log-likelihood	−829.309				−852.410			
Final Log-likelihood	−626.397				−679.742			
Likelihood ratio test	405.8	$p < 0.001$			345.3	$p < 0.001$		
Number of observations	825				825			

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

used to address ANA, the coefficients are estimated only for those respondents who attended to at least some of the attributes. The high probability may also be related to the fact that class membership is based on an ex-post calculation procedure as described in section 2.2. This would imply that other class probabilities, which are currently zero or nonsignificant, have been underestimated. This might to some extent be the case judging by the results presented in Table 4. Alternatively, it may be that some respondents truly ignored some attributes and had low weights for others, and the optimization routine used to estimate the ECLC model picked this up as an indication that they ignored all attributes. This would be in line with some of the small probability values and the nonsignificant class probabilities in other cases where respondents suggested that they ignored an attribute.

The second important observation is that almost all nonattendance shares, including the share of respondents ignoring all attributes, are considerably lower for the subsample of respondents who were shown the choice cards with pictograms. That is, the attributes for which visual aids were developed are considered more attentively by the respondents, as can also be observed for the stated attribute attendance in Table 4. This confirms our findings in the previous section 4.3 and our first alternative hypothesis that the way the information in the CE is conveyed to respondents significantly affects their choice behavior. Third, in the absence of visualizations, farmers pay more attention to pond cover and the monthly payment. Fourth, in both subsamples, contract duration is the most ignored contract characteristic. Finally, given the differences in the inferred degrees of ANA across the subsamples, it is not surprising to observe that the estimated attribute coefficients are also different.

5. Conclusions

Introducing and implementing improved water harvesting technology on farm land in drought prone areas, as in this case study, is expected to be more effective and last longer if farm households are involved in the design of the water pond and better use is made of the available technical knowledge and expertise. The main objective of this study was to inform policy makers in Ethiopia about the most important terms and conditions to incentivize farmers to enter into a contractual agreement to invest in and maintain water ponds on their land and reduce their vulnerability to droughts. The novelty of the study is that we use a CE to identify the importance farmers attach to both the technical and institutional-economic contract characteristics to improve water management in dryland agriculture and reduce farm household vulnerability to increasing periods of droughts. Water harvesting has been identified by the FAO [2014] as a critical element in strengthening land users' capacity to adapt to climate change, requiring substantial more action in Sub-Saharan Africa than currently is the case to improve water management in both rainfed and irrigated agricultural systems

Annex 1. Estimated Random Parameters Logit Choice Models for the Samples With Literate and Illiterate Survey Participants

Variables	Illiterate Survey Participants				Literate Survey Participants			
	Parameter Estimate	St. Error	St. Dev. Rnd. Pars	St. Error	Parameter Estimate	St. Error	St. Dev. Rnd. Pars	St. Error
ASC	3.687	2.484	4.574**	2.258	3.004***	0.694	2.260***	0.433
<i>Choice Attributes</i>								
Contract provider = regional government	0.436**	0.184	1.535***	0.330	0.117	0.160	1.457***	0.351
Contract duration (years)	−0.006	0.016	0.027	0.028	0.009	0.016	0.048*	0.029
Pond capacity (m ³)	0.007***	0.002	0.008***	0.003	0.008***	0.002	0.017***	0.003
Pond lining = cement	−0.167	0.163	1.272***	0.326	−0.141	0.167	1.695***	0.357
Top of pond = covered	0.592***	0.163	1.129***	0.335	1.176***	0.218	2.297***	0.384
Nonmonetary payment (labor days)	0.004	0.008	0.020	0.014	0.004	0.009	0.036**	0.014
Monthly payment (Birr)	−0.002***	0.001	0.002***	0.001	−0.005***	0.001	0.005***	0.001
<i>Covariates</i>								
ASC × 1 if version includes pictograms	1.756**	0.776			1.199	0.791		
<i>Model Summary Statistics</i>								
Log-likelihood	−517.306				−677.148			
Pseudo R ²	0.310				0.363			
Chi square statistic (17 d.o.f.)	463.895***				772.618***			
Number of observations	682				968			

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

and reduce exposure to dry spells. The practical relevance of the results presented here is that they help regional policymakers identify how water harvesting can be rolled out as a farm household climate risk adaptation and mitigation strategy, accounting for the literacy rate of local farmers in this developing country context, and support effective uptake of contractual agreements through adequate communication.

Sixty percent of the sampled farmers in this study indicated to face severe droughts and water shortages. Previous attempts to build heavily subsidized community water ponds in the area largely failed. Hence this attempt to assess if framing water security management in the study area as a private investment decision, facilitated through a contractual agreement, is of interest to the farmers involved. The results in this study clearly show that demand for the offered contractual agreements is high and farmers are willing to pay market interest levels to obtain the financial support (microcredit) for such an investment decision.

Making sure farmers understand the specific contractual terms and conditions they commit to was a challenge, hence the reason for the use of visual aids in a split sample approach. This was expected to also accommodate the fact that a considerable share is illiterate. Both samples indeed generated significantly

Annex 2. Estimated Random Parameters Logit Choice Models Accounting for Stated Attribute Nonattendance

Variables	Without Attribute Visualizations				With Attribute Visualizations			
	Coefficient Estimate	St. Error	St. Dev. Rnd. Pars	St. Error	Coefficient Estimate	St. Error	St. Dev. Rnd. Pars	St. Error
ASC	3.433***	0.859	3.431***	0.637	4.789***	0.775	2.753***	0.439
<i>Choice Attributes</i>								
Contract provider = regional government	0.192	0.192	0.260	0.807	0.384	0.417	2.457***	0.608
Contract duration (years)	−0.018	0.017	0.018	0.034	0.084***	0.030	0.012	0.048
Pond capacity (m ³)	0.013***	0.003	0.014***	0.004	0.005	0.004	0.012***	0.004
Pond lining = cement	0.057	0.207	1.353***	0.413	0.182	0.184	1.313***	0.322
Top of pond = covered	0.670***	0.172	1.344***	0.323	0.857***	0.213	0.968**	0.455
Nonmonetary payment (labor days)	−0.017	0.012	0.003	0.019	0.003	0.023	0.001	0.039
Monthly payment (Birr)	−0.003***	0.001	0.003***	0.001	−0.003*	0.001	0.005***	0.001
<i>Covariates</i>								
ASC × 1 if respondent is illiterate	−1.221	0.981			−0.256	0.866		
Payment × 1 if income is higher than average	−0.001	0.001			−0.003***	0.001		
<i>Model Summary Statistics</i>								
Log-likelihood	−637.935				−609.274			
Pseudo R ²	0.296				0.328			
Chi square statistic (18 d.o.f.)	536.840***				594.162***			
Number of observations	825				825			

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

different results, highlighting the importance of how information is conveyed to survey participants in a developing country context. Although choice consistency was very high in both subsamples, there are indications that whilst controlling for differences in income and education levels the sample who received the version of the CE with the visualizations made more stable and less random choices.

The observed variation in the significance levels across the different contract characteristics indicates that some are considered more important than others. This pattern is confirmed when examining the self-reported importance attached to the various contract characteristics, with the water harvesting technology such as pond lining, cover and capacity being valued highest. Here too we detect important differences between the two subsamples and observe that the contract characteristics for which visual aids were developed are considered more attentively. In conclusion, the use of visual aids in CEs has a significant effect on choice behavior and ultimately on the economic values derived from the estimated choice models in this study carried out in a remote developing country context. The empirical evidence of such effects in the existing literature is very limited and deserves more attention in future stated preferences research.

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