Measuring changing preferences to support control of land degradation: Evidence from multiple interventions in Southern Ethiopia

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Abstract

Land and soil degradation is a major problem across sub-Saharan Africa but particularly in Ethiopia. A key part of the Ethiopian government's strategy to reduce land degradation risk is the establishment of "exclosure" areas to restore degraded common lands. It is recognized that land restoration initiatives such as exclosures need to be better designed to improve short run benefits for local communities in order to increase community support.

This paper measures the impact on local attitudes to exclosures of a project designed to enhance the local benefits of an exclosure in Southern Ethiopia. Specifically, the project trained, handed out resources, and gave access to exclosures to selected youth and women to undertake new activities in beekeeping or livestock management. The impact evaluation applied a Difference in Difference (DID) design applying a repeated DCE experiment across treatment and control areas with farmers in 2021 and 2023.

The survey data is analysed using an error components model within a mixed logit modelling framework. The results provide evidence of preference change linked to the project interventions, with increasing preference for exclosure management options associated with the interventions. There is also evidence that an individual's knowledge of the interventions played a role in the change in their preferences.

Introduction

Land and soil degradation is a major problem across sub-Saharan Africa but particularly in Ethiopia. Recent estimates put the area of degraded land at more than one-quarter of the entire country, affecting nearly a third of the population (Chirwa 2014; Gebreselassie et al. 2016). Land degradation takes many forms and has many different effects. The most adverse impacts are on the livelihoods of poor people, who depend on natural resources (Global Environmental Facility, 2019). Combatting land degradation has become a major policy objective in Ethiopia and other countries in sub-Saharan Africa, while agricultural growth is important element in overall development (OECD/FAP, 2016). The impacts of degradation and measures to restore land are inherently unequally distributed across the population in time and space, reflecting the many interdependences at the local level between community and individual decisions and the physical environment.

A key part of the Ethiopian government's strategy to reduce land degradation risk is the establishment of "exclosure" areas to restore degraded common lands. Over seven million hectares are to be set aside by 2030. "Exclosure areas" restrict traditional access rights to promote land restoration. However, groups with little access to other sources of firewood and communal grazing can be severely affected. Exclosures may aggravate the degradation of remaining communal grazing lands that are important in local livelihoods as a source of organic fertiliser, labour and 'insurance' in times of adversity. Exclosure areas have benefits, e.g. firewood & grass quotas, improved water resources, and disbenefits, e.g. of wildlife attacks on crops, that are unequally distributed amongst households depending on factors like land holding size and location (Byg et al, 2017). It is recognized that land restoration initiatives such as exclosures need to be better designed to improve short run benefits for local communities and for marginal groups in particular in order to increase community support and therefore their long-term viability (Mekuria et al. 2017).

This paper measures the impact on local attitudes to exclosures of a project designed to enhance the local benefits in Southern Ethiopia. Specifically, the project trained, gave resources including bee hives and livestock, and gave access to exclosures to selected disadvantaged groups to enable them to undertake new activities in beekeeping or livestock management. The impact evaluation applied a Difference in Difference (DID) design applying a repeated Discrete Choice Experiment (DCE) experiment across treatment and control areas with farmers in 2021 and 2023.

To allow change in preferences across attributes to be identified, the survey data is analysed using a mixed logit model allowing for a DID structure in preference parameters. The results provide evidence of preference change linked to the project interventions, with increasing preference for exclosure management options associated with the interventions.

Background

The project took place in the Southern Nations Nationalities and People Regions (SNNPR) of Ethiopia, where two learning watersheds (Aba Bora and Guder) in two agroecological zones (midland and highland) were selected. The design of the project interventions was based on successful interventions previously undertaken in North-Western Ethiopia consistent with Ethiopian Government Policy aiming to generate short term economic benefits for local communities from the exclosures (Mekuria et al. 2017; 2019). Specifically, in two case study areas (kebele) interventions were implemented by the Ethiopian Bureau of Agriculture to provide resources to selected disadvantaged groups to enable them to undertake new productive activities in beekeeping, sheep and oxen rearing drawing on the resources of the exclosures.[1]

The study areas, Aba-Bora and Guder watersheds are in the Lake Abaya Chamo sub-basin of the Ethiopian Rift Valley Lakes basin (Figure 1). The areas have many recognized challenges in terms of declining soil fertility, severe soil erosion, reduced access to surface and groundwater, and poor water quality (Sinore and Umer 2021).

[1] Each kebele is a neighbourhood of around 500-1000 households, and each typically has 3 development agents employed by the Bureau of Agriculture to employed to provide support to farmers and households covering crop production, animal production and natural resource management.

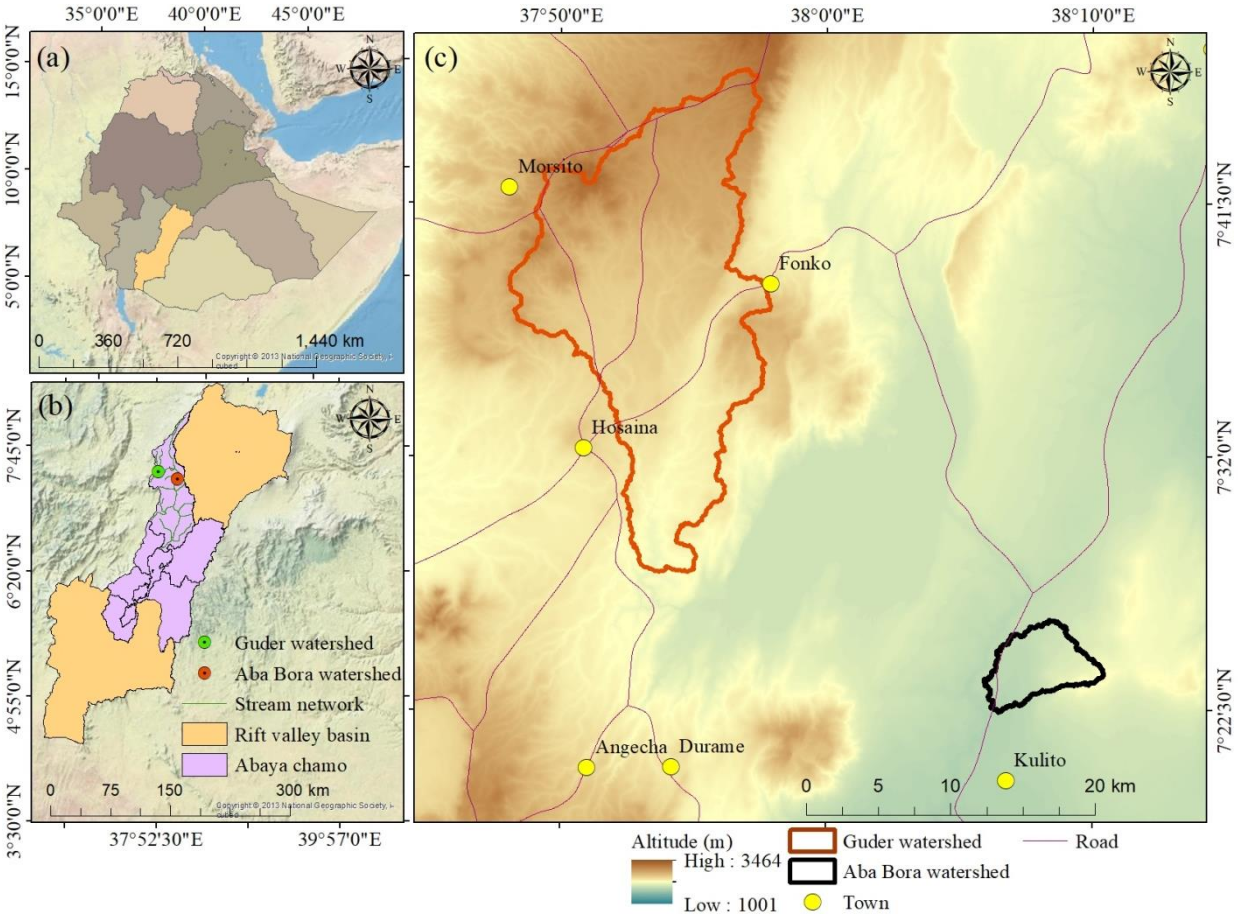


Figure 1. Location of the study area: (a) Rift Valley Lakes basin, (b) Abaya Chamo sub-basin, and (c) Aba-Bora and Guder watersheds (Source: Mekuria et al. 2023).

For beekeeping, cooperative groups of youths were established, with an agreement made between the groups and the community, to provide the groups permission to use exclosures resources. The groups were given training in bee management techniques (honey and planting bee forage e.g. herbaceous plants within Exclosures) by practitioners from the Bureau of Agriculture, and then provided with beehives. The expectation was that beehives would be placed within exclosures, and the groups would manage the bees, harvest honey and undertake marketing of the honey.

Within each watershed, female headed households were to be selected, given training in sheep production systems by the Bureau of Agriculture, and then provided with ewes, with a tup/ram shared across groups of women. Everyone in the community is already given a grass quota to use from the exclosure. The sheep were to be grazed around the homestead but also drawing on the grass quota from the exclosure areas, allowing the women to use their existing grass quota from the exclosure more effectively.

Finally, groups of youths were formed within each watershed with the selected individuals given training in intensive livestock management by the Bureau of Agriculture. Each group was then provided with four oxen, with an agreement made between the groups and the community to provide permission to access the exclosures to collect grass in a cut and carry system for the oxen.

During early 2021, following the selection of the two case study watersheds, the project team worked with kebele and district level administrative personnel to develop criteria for selecting beneficiaries for each intervention at each site. The final agreed criteria aim to prioritize the following:

- Beehives. Age, Dropped Out of High School, Physical Ability, Experience in Apiculture; Land Less Than 0.125 Ha, Individual Motivation
- Sheep: Female, Age, Head of households, Main income from casual work, Housewife, Government safety net supported women, School dropouts, physical ability, Motivation, Experience in Goat/sheep production, Women with disabled/sick husbands, ability to get or grow supplementary livestock feed.
- Oxen: Age, Poverty level, land less <0.125 ha, Motivation and interest, physical ability, ability to get or grow supplementary feed, Experience in livestock management.

At each of the two sites, the number of beneficiaries were selected into the following groups:

- Beehives: Youth focussed groups organised into 4 groups with 8 members per group (32 beneficiaries, 15 modern beehives per group)
- Oxen: Youth focussed groups organised in 3 groups with 5 members per group (15 beneficiaries, 4 oxen provided per group)
- Sheep: Women working as 30 individuals (2 sheep provided per individual)

The beneficiary selection took place between May and July 2021. The Kebele administrative bodies in collaboration with the Kebele level agricultural office or extension workers identified potential beneficiaries based on the criteria, with further involvement of the Kebele Food Security Committee, with the final selected beneficiaries endorsed by the district agricultural office.

Preference Stability

The main idea which drives the analysis is that support within the community for exclosures is more likely to improve where the local benefits of exclosures are increased. However, whether

the interventions would be successful in increasing support cannot be judged beforehand. Whether the experience of the project interventions, on supporting beekeeping, oxen fattening and sheep rearing by local youth and women, will increase support for such interventions is likely to depend on a wide range of factors such as whether they are seen as successful for the individuals involved, how fair the allocation of the associated resources is perceived etc. As discussed in detail below, the impact of the interventions on support is measured using repeated discrete choice experiments.

Individual responses in DCE surveys may vary over time for a range of reasons. Preference instability, learning and fatigue around the survey instrument, general changes affecting respondents' environment and situation, as well as the individual's learning about the good or service involved and changing their preferences in response to this experience. The recent evidence on preference stability across time suggests that controlling for these factors is important. Liebe et al (2012) find reasonable consistency of choices in a test–retest study of landscape externalities of onshore wind power where respondents answered the same choice sets at two different points in time. Brouwer et al, (2016) "tests the temporal stability of preferences, choices and WTP values" for reducing contamination in freshwater systems eliciting preferences at three time points over two years using both DCE and open ended contingent valuation tasks. They find a fairly high choice consistency between the test and two retests (63% and 59%), with 20% of respondents completely consistent between test and retest 1. However, they do find that willingness to pay (WTP) is 25% lower between the test and retest1, and 15% lower between test and retest 2. Czajkowski et al (2017) tests preference stability over two time points six months apart using a DCE study of forest management in Poland. The authors compare stability of choices and WTP estimates (mean and distribution) and find that only respondents who always chose the status quo were perfectly consistent. They formally reject the hypothesis that the marginal WTP distributions are identical over time but observe that the mean WTP is relatively stable.

The stability of preferences within a DCE and the possible learning and fatigue effects has been extensively studied (e.g. see the literature review in Czajkowski et al (2015)). Czajkowski et al (2015) consider learning and fatigue effects within a sequence of 26 DCE choice tasks, where both the order of alternatives within choice tasks and the order which respondents are presented choice tasks are randomized. By using models which allow scale, the importance of the non-random part of individual choices, to vary by position of the choice task, they estimate WTP for each choice task position and find variation, although no significant difference in WTP across tasks. They do find evidence of learning effects with the importance

of the explainable non-random part of choices increasing after a number of choice tasks have been completed, but no fatigue effects.

The hypothetical nature of stated preference choices means that research into how the information given to respondents affects their choices has had a long history (Bergstrom and Dillman, 1985), with evidence that there are often information effects on mean WTP values (Munro and Hanley, 2001). A number of studies have also considered the implications of preference change for different models of learning e.g. Bayesian, in response to different levels of experience and information about the good. Czajkowski et al (2015) find evidence that additional experience of a good makes consumer preferences more predictable but not such strong evidence that the variability of the parameter driving this reduces which would be consistent with their model of Bayesian learning. Czajkowski et al (2016) test for the effect of information sets on preferences for biodiversity conservation, motivating the analysis with a theoretical model of how information can affect variance of WTP based in individuals who update the information on their preferences using Bayesian learning.

While these studies formulate different hypotheses, the models estimated are broadly similar, applying reduced form to capture the role of learning and experience of the good on preferences in the Random Utility Model framework. This contrasts with the marketing literature in this area where drawing on the Erdem and Keane (1996) model, structural models of learning within choice models have been estimated for a wide range of contexts (Ching et al, 2013).

There have also been stated preference studies which have measured the impact of the real world experience of a good on preferences and WTP. The Jensen et al (2013) study provided respondents with an electric car for three months to use as though it were their own car, with individuals' preferences on electric vehicles were elicited using a DCE at two time points. The DCE results show significant changes in the valuation on individual characteristics before and after the experience with almost half of the estimated coefficients significantly different between the two surveys. However, all changes in this study were attributed to the experience of EV vehicles, which therefore assumes that there are no issues around preference stability, learning about the survey tasks accounted for.

Experimental Design

Discrete Choice Experiments

A DCE survey was designed to measure the impact of the experience of the interventions on individual preferences in the community. A baseline DCE survey of households was undertaken prior to the interventions being implemented in February/March 2021, in four kebeles, the two kebeles where the interventions were going to take place (treatment areas) and in two control areas, similar in geography and demographic composition to the treatment areas. A follow up DCE survey targeting the same individuals took place in February/March 2023. As discussed below this design allowed a difference in difference type approach to be used, to control for preference instability, learning around the survey instrument, general changes affecting respondents' environment and situation, as well as identifying the impact of the interventions, i.e. the individual's learning about the good or service involved and changing their preferences in response to this experience.

The choice of DCE attributes and attribute levels drew on the qualitative focus groups and key stakeholder interviews undertaken by Lemma (2020) in a closely related context. These identified a number of aspects of the exclosures that were most important to people in the community. First, the amount of grass quota each household received every year from the exclosure. Second, the extra community work which all households living in the kebele are required to provide to the community e.g. in terms of helping build water and soil conservation structures. A third important aspect was the damage caused by the wild animals e.g. wild warthogs and monkeys, to crops close to the perimeter of the exclosure. This was captured by asking whether individuals were willing to contribute to a fund set up to compensate other members of the community who experience crop damage caused by animals from the exclosure. Finally, adjustments and extra access to exclosures that might be made to help disadvantaged groups within the exclosure. These were designed to capture the key aspects of the interventions implemented, i.e. promoting beekeeping in exclosures by groups of youths, sheep production by female headed households, and oxen management by groups of youths.

The attributes and levels are presented in Table 1. The DCE choices include two intervention alternatives and a status quo option. Figure 2 provides an example choice card. The DCE choices were obtained from a D-efficient design for a main effects only model. The design was specified to include 20 choices split into two blocks of 10 choices. The status quo option was defined based on the respondents' current situation. For each choice, respondents were also asked to select one option from the three alternatives and then asked rate how sure they were of their choice. The whole baseline survey was piloted in December 2021.

Figure 2: Example Choice Card

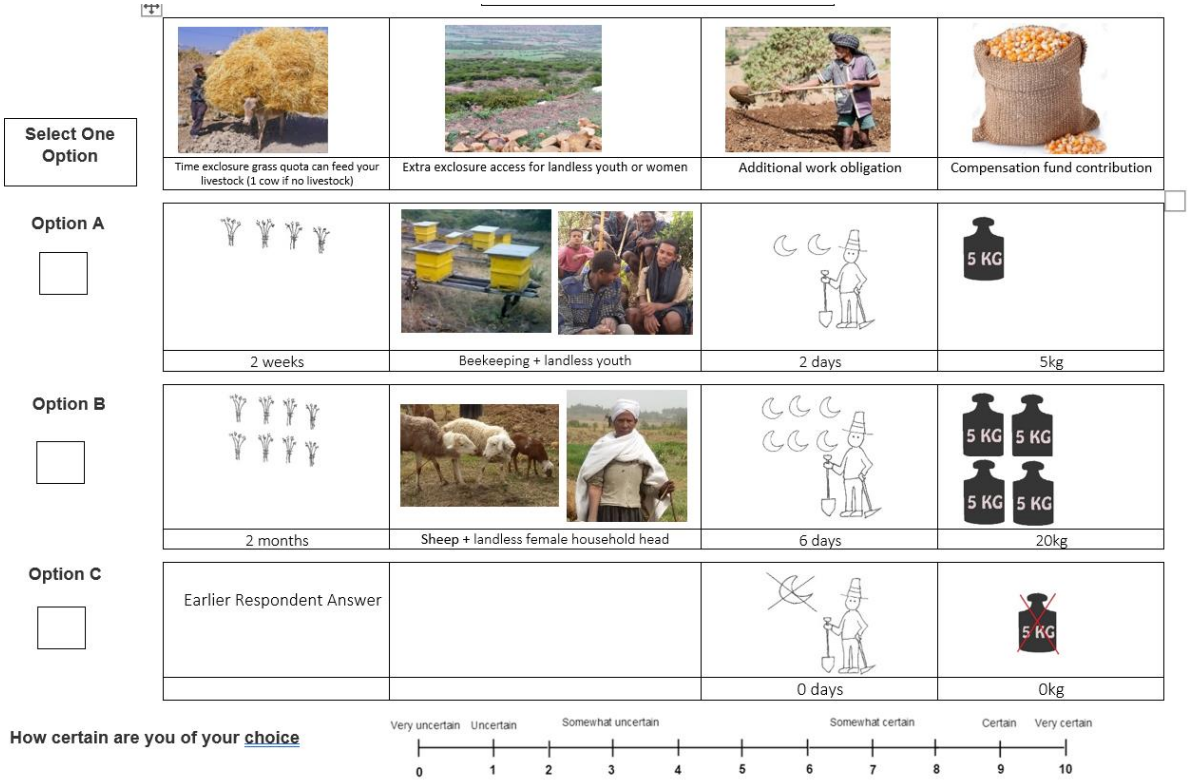


Table 1 Attributes and Attribute Levels*

Attribute	Level	Status Quo
Grass Quota	2 weeks, 1 month, 2 months, 5 months (based on their current livestock)	Individual level
Intervention providing access to exclosure for disadvantaged groups	Bees + youth, Bees + women, Sheep + women, Oxen + youth	No Intervention
Extra Household Work commitment	2 days, 6 days, 10 days, 15 days	No extra work commitment
Maize Fund contribution	5kg, 10kg, 20kg, 30kg	No Fund Commitment

*Each respondent faced 10 choices.

Econometric Modelling

We assume a standard choice model framework, where in each survey *k =0,1,* an individual *n* faces choices *t,* where in any choice the individual will choose alternative *j* out of *J* alternatives based on the utility associated with that alternative

$$U_{knjt} = \beta_k x_{njt} + \varepsilon_{knjt} \quad (1)$$

Where ε_{knjt} is unobservable error, x_{njt} the vector of attributes and β_k the vector of utility weights. This approach is applied to each different sample (treatment and control) in each survey (baseline and endline).

To test the possible sources of any apparent change in preferences across the surveys, we also consider pooled version of the models allowing the utility weights to vary using a difference in difference structure, i.e.

$$\beta_k = \beta_o + \beta_1 D(1) + \beta_2 k + \beta_3 D(1)k \quad (2)$$

where $D(1) = 0,1$ captures the treatment area effect, β_1 the average difference in the utility weight between the control and treatment area in the baseline survey, β_2 any trend effect affecting both control and treatment samples across the two surveys e.g. due to learning about the survey instrument, and β_3 the treatment effect associated with learning about the interventions.

The attribute capturing the different interventions is included as a set of three dummy variables capturing the combination of different groups and activities, namely bees and youth, sheep and women, oxen and youth. The excluded category, bee activity with women, represents the combination which was not implemented in the interventions. Although one might expect that any treatment effects might be concentrated around these three dummy variables, treatment effects on the other attribute variables are also included, namely, individual grass quota, extra work contribution and willingness to contribute to a maize insurance fund. The base model (1) and (2) also allows for attribute specific constants and include error components within a mixed logit estimation framework (Hess and Palma, 2019).

There is no explicit financial cost variable in the list of attributes, but if the extra work contribution has a negative welfare weight, the willingness to contribute extra labour can be used to value each attribute *r* and how it may change across surveys, i.e.

$$WTC_{kr} = -\beta_{k,r}/\beta_{k,extralabour}\ .^{2} \quad (3)$$

We might expect any treatment effects associated with the learning about the different types of interventions to differ systematically depending on how aware the survey respondent was of the interventions. In the endline DCE surveys, follow up questions were also asked (in both treatment and control areas), on whether the individuals were aware of the interventions, and if so whether they had talked to someone involved.[3] These variables were converted to two dummy variables for knowledge of the intervention (*knowledge*), and talked to beneficiary (*talked*) for each of the interventions. These are incorporated by adjusting equation (1) for the three dummy variables capturing the different interventions, namely bees + youth, sheep + women, oxen + youth

$$\beta_n = \beta_o + \beta_1\ D(1) + \beta_2 k + \beta_3\ D(1)k + \ \beta_4\ D(1) * k * knowledge + \beta_5\ D(1) * k * talked \quad (4)$$

with the extra parameters β_4 and β_5 representing the impact of knowledge of the interventions and having interacted with the beneficiaries.

Data Collection

Data were initially gathered from 248 households in Aba-Bora and 274 in Guder (522 in total) selected from fours kebeles (a control and treatment area for each watershed) in February and March 2021. Random samples of households were drawn from lists provided by each kebele administration. After pre-testing elsewhere, the baseline data was collected during February and March 2021 using a team of enumerators employing tablets, with the questionnaires available in both English and Amharic. In the second survey in 2023, the aim was to ask the same individual the same set of choice task questions in the same order. Individuals were matched using a master list of personal id numbers. This enabled 451 individuals to be matched across the two samples.

[2] Willingness to contribute values are calculated from separate regressions for each group and survey, to avoid assuming identical scaling across treatment and control samples and the two surveys.

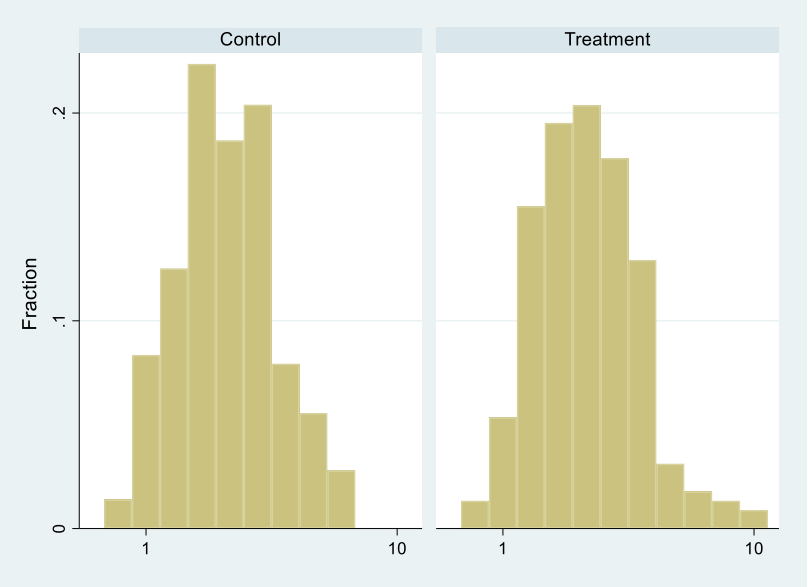
[3] For example, for the sheep intervention, respondents were asked. "Do you know whether in the last 12 months or so, training in sheep husbandry and sheep have been provided to any women in the kebele allowing them to start a sheep production enterprise?" with answers on a Likert scale 1 - I am sure this has not happened to 5 1- I am sure this has happened. In terms, of those shop had talked to someone involved the question was asked "In the last 12 months, I have talked to someone who has received training in sheep husbandry and been provided sheep in the kebele? (1 – not at all, to 5 - at least once a week)". The two dummy variables knowledge of the intervention, and talked to beneficiary take the value of one for responses of 4 or 5 on the two underlying questions respectively.

Results

Descriptive Analysis

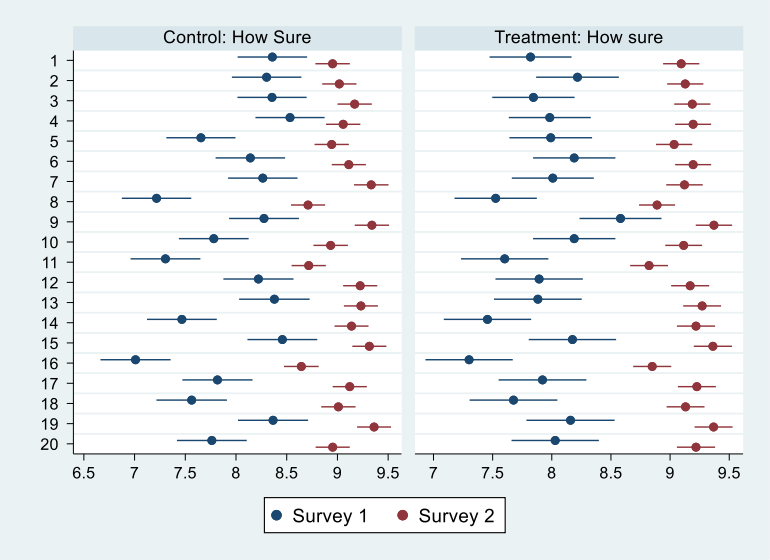
Analysis of the number of consistent choices made across the baseline and endline surveys shows that 70% of intervention A choices were consistently chosen in the treatment areas (68% in the control areas), with 51% of intervention B choices consistently chosen across both surveys (48% in the control areas). Figure 3 shows the total number of consistent choices by individual across the two surveys for the treatment and control groups. The Kolmogorov–Smirnov test for equality of distribution functions rejects the hypothesis that the control and treatment group distributions are identical at 10% (p-value=0.089). The figure and test results also suggest that there are smaller numbers of consistent choices in the control group.

Figure 3: Number of consistent choices across DCE surveys by group



As described above, for each choice set respondents were asked about the certainty of their choice. One might expect that after respondents learn and then reflect about their answers from the baseline DCE survey, their levels of certainty increase in the endline survey. Figure 4 captures the average certainty across the choices and confirms that, on average, choice certainty was highest in the second survey.

Figure 4: Certainty of choices across DCE surveys by control and treatment group



Econometric Results

To provide an overview of the validity of the choice model across the samples, Table 2 reports the results when the model is estimated separately for each sample, i.e. for the treatment and control samples and baseline and endline surveys. Over all samples, the estimated coefficients are well specified with positive and significant utility weights for intervention dummies, negative coefficient for the maize fund and the extra work contribution. Perhaps surprisingly the individual quotas derived from the exclosure are not positively valued by respondents. However, this is consistent with some of the qualitative interviews where farmers had somewhat mixed views about the grass quota (Lemma, 2020). Although they kept collecting their share every year, they complained about the quality and quantity of the grass. Poorer farmers with no livestock also indicated that often sold their quota to better off farmers at a low price.

Table 2 Estimation: By Group and Survey

Variable	Control Baseline	Control Endline	Treatment Baseline	Treatment Endline
ASC Option A	6.946	7.824	5.878	27.841
	(7.63)	(5.67)	(7.85)	(1.71)
ASC Option B	6.734	7.615	5.723	27.568

	(7.41)	(5.53)	(7.64)	(1.69)
Bees & youth =1	0.440	0.521	0.247	0.592
	(5.49)	(4.83)	(2.88)	(5.09)
Sheep & women=1	0.791	1.537	0.526	1.756
	(7.36)	(11.9)	(5.22)	(12.7)
Oxen & youth=1	1.036	1.739	0.755	1.838
	(10.1)	(12.5)	(7.5)	(12.8)
Extra grass quota	-0.009	-0.003	0.001	-0.003
	(0.56)	(0.16)	(0.06)	(0.15)
Maize fund	-0.005	-0.008	-0.013	-0.016
	(1.43)	(2.28)	(3.74)	(4.21)
Extra workdays	-0.023	-0.015	-0.019	-0.014
	(3.92)	(2.06)	(3.37)	(2.07)
Sigma (error component)	2.336	2.391	3.095	12.619
	(6.24)	(5.84)	(5.31)	(1.76)
Log Likelihood	-1681.4	-1414.0	-1961.1	-1400.2
Rho squared 0	0.396	0.477	0.331	0.495
Adj Rho 0	0.393	0.474	0.328	0.491
rho2_C	0.063	0.163	0.085	0.198
adjrho_C	0.059	0.159	0.081	0.194
AIC	3380.8	2846.0	3940.3	2818.4
Halton Draws	500	500	500	500
Individuals N				

Robust t ratio in brackets. Separate estimation for treatment and control areas for baseline and endline surveys. Error components model estimated within mixed logit framework.

To explore this more formally, Table 3 reports the pooled estimation across all samples consistent with equations (1) and (2). The second and third columns provides the estimates for the control area respondents, the remaining columns are the differences across the treatment area samples, the trend effects and finally the change in the estimated attribute coefficients for the treatment areas in the endline survey after accounting for the common trend effects. At the individual coefficient level these show that there are significant trend effects, i.e. across both control and treatment groups, for the dummies representing sheep and women, and oxen and youth interventions. There is also evidence of significant treatment effect in terms of the relative valuation of sheep and women intervention. Overall, the joint test of the hypothesis that there are no treatment effects is also rejected at 5% significance.

Table 3: Trend and Treatment Effects

	Control		**Treatment Area**		**Trend**		**Treatment Effect**	
	$\hat{\beta}_0$	**T-ratio**	$\hat{\beta}_1$	**T-ratio**	$\hat{\beta}_3$	**T-ratio**	$\hat{\beta}_4$	**T-ratio**
ASC Option A	7.312	(10.511)	-2.034	(3.651)	0.433	(0.550)	1.456	(1.064)
ASC Option B	7.100	(10.207)	-1.978	(3.550)	0.436	(0.553)	1.334	(0.975)
Bees & youth =1	0.440	(5.491)	-0.191	(1.632)	0.081	(0.618)	0.254	(1.360)

Sheep & women=1	0.791	(7.371)	-0.265	(1.806)	0.745	(4.679)	0.471	(2.078)
Oxen & youth=1	1.036	(10.146)	-0.280	(1.953)	0.703	(4.197)	0.364	(1.544)
Extra grass quota	-0.009	(0.554)	0.011	(0.437)	0.006	(0.246)	-0.011	(0.330)
Maize fund	-0.005	(1.427)	-0.008	(1.668)	-0.003	(0.647)	0.001	(0.152)
Extra workdays	-0.023	(3.924)	0.004	(0.497)	0.008	(0.790)	-0.002	(0.167)
Sigma (error component)	2.651	(8.817)						
Log Likelihood		-6499.97						
AIC	13065.94							
BIC	13304.49							
Halton Draws	500							

Robust t ratio in brackets. Pooled estimation for treatment and control areas for baseline and endline surveys. Error components model estimated within mixed logit framework.

To draw out the implications, we use equation 3 to calculate the willingness to contribute extra household labour for each attribute, using the separate estimations by treatment and control and survey reported in Table 2. These values are reported in Table 4.

Table 4 Willingness to Contribute Extra Work for Attributes

	Control			Treatment			
Variable	Baseline	Endline	Change (1)	Baseline	Endline	Change (2)	Net Change (2)-(1)
Bees & youth =1	18.9	33.8	14.9	12.9	43.0	30.1	15.1
	(3.19)	(1.96)		(2.28)	(1.87)		
Sheep & women=1	34.0	99.8	65.9	27.5	127.5	100.0	34.1
	(3.63)	(2.09)		(2.93)	(2.05)		
Oxen & youth=1	44.5	113.0	68.5	39.5	133.5	94.0	25.5
	(3.72)	(2.04)		(3.12)	(2.02)		
Extra grass quota	-0.397	-0.196	0.201	0.057	0.200	0.144	-0.057
	(0.55)	(0.16)		(0.06)	(0.15)		
Maize fund	-0.216	-0.538	-0.322	0.705	1.133	0.428	0.750
	(1.23)	(1.41)		(2.50)	(1.69)		

Robust t ratio in brackets. Separate estimation for treatment and control areas for baseline and endline surveys using Table 2 estimates. WTC calculated using equation (3).

The WTC values indicate that all respondents have significant positive valuations for the different type of interventions across all samples. For example, in the baseline survey in treatment area, respondents are willing to contribute an extra 12.9 days of labour from their household in order to allow groups of bees and youths to use the resources of the exclosure, and this increases to 43 days in the endline survey. As in the Table 2 the estimated values for

the quota indicate that respondents do not appear to value this aspect of the output of the exclosures. There is evidence from the treatment area that the contribution to the maize fund is seen as a significant cost but not in the control sample.

Turning to the changes in the valuations across the surveys, there are some fairly large changes in the valuation of the attributes representing the different types of interventions implemented. These indicate a trend in increasing willingness to contribute extra labour to provide greater access to the exclosure resources for disadvantaged groups, with particularly large changes for the sheep and women and oxen and youth types of intervention. Turning to treatment areas, after allowing for the trend effects there are additional increases in WTC values for all three interventions but particularly for the sheep and women case.

The Table 3 results show that there are significant treatment effects. In order to explore the sources of these Table 5 reports the estimation results focussing on the coefficients capturing the baseline treatment effect β_3, the knowledge effect β_4, and talked with beneficiary effect β_4, as outlined in equation (4).

Table 5 Effects of Knowledge of Interventions and Interaction with beneficiaries

	Treatment Effect		**Knowledge**		**Talked to beneficiary**	
	β_3	**T-ratio**	β_4	**T-ratio**	β_5	**T-ratio**
Bees & youth =1	-0.662	(1.893)	0.201	(2.498)	0.046	(0.552)
Sheep & women=1	-0.573	(1.317)	0.271	(2.744)	-0.061	-(0.623)
Oxen & youth=1	-0.209	(0.451)	0.172	(1.653)	-0.090	-(1.022)
Sigma (error component)	2.606	(7.671)		Log Likelihood		-6486.23

Robust t ratio in brackets. Pooled estimation for treatment and control areas for baseline and endline surveys consistent with equation (1) and (4) . Error components model estimated within mixed logit framework.

These results appear to indicate there are significant effects relative to the base when respondents are aware of the interventions, with all the estimated values of the dummy variables β_4, positive and significant (at least at 10%). The impact of actually knowing the beneficiaries however is statistically insignificant.

Summary and Conclusions

This paper measures the impact on local attitudes to exclosures of a project designed to enhance the local benefits of an exclosure in Southern Ethiopia. Specifically, the project trained, handed out resources, and gave access to exclosures to selected youth and women to undertake new activities in beekeeping or livestock management. The impact evaluation applied a Difference in Difference (DID) design applying a repeated DCE experiment across treatment and control areas with farmers in 2021 and 2023.

The survey data is analysed using an error components model within a mixed logit modelling framework. The results provide evidence of preference change linked to the project interventions, with increasing preference and willingness to contribute labour for exclosure management options associated with the interventions. There is also some evidence that an individual's knowledge of the interventions plays a role in the change in their preferences.

The research adds to the evidence on preference stability in DCE experiments and specifically the impact of experience of a public good on individual preferences within local communities for exclosure management. This suggest that such interventions are likely to increase the level of community support for further exclosures.

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