RALENTIR: Reducing land degradation and carbon loss from Ethiopia's soils to strengthen livelihoods and resilience

Measuring Changing Attitudes & Preferences: Analysis Plan

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Introduction

A core objective within RALENTIR is to understand the impact of the project interventions on the views of the community particularly in terms of management of the exclosures. This note outlines the design and use of the information in the baseline and subsequent update surveys in generating quantitative measures of the impact of the interventions. Specifically, how the discrete choice experiments information (DCE) can be used to explore whether the interventions introduced, i.e. training and access to exclosure resources to landless youth for beekeeping or oxen fattening, women undertaking sheep rearing, changed views on exclosures and their management. Measures of attitude change for the other project interventions e.g. gully management experiments and demonstrations, will also be briefly discussed.

The main idea which drives the analysis is that support for exclosures is more likely to improve where the local benefits of exclosures are increased. However, which specific types of interventions will be successful in increasing support cannot be judged beforehand as the experience of how interventions work in practice benefit is likely to change how they are viewed as studies suggest that experience of the good matters for preferences (Czajkowski et al, 2015). 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.

The primary role of the DCE surveys in the project is to measure the impact of the experience of the interventions on individual preferences in the community. As part of the baseline a DCE survey exploring preferences for different types of interventions increasing the use of the exclosure by supporting beekeeping, oxen fattening and sheep rearing by local youth and women was undertaken in February 2021. The project interventions providing training and then the associated resources and access to exclosures as necessary for beekeeping, oxen and sheep rearing for groups of youth and women started in June 2021. Following the first follow up DCE survey targeting the same individuals as in the first survey is planned for early 2022, with a final survey planned for early 2023. The sample for the DCE surveys also includes similar individuals both in the two areas where the interventions are taking place and in two areas where there are no interventions. This difference in difference type approach with “control” and “treatment areas” is designed to allow better identification of change in preference due to the interventions and that due to other factors.

Consistent with the literature on impact assessment, we would want to measure of whether interventions have changed preferences and if so how, which do not depend on parametric assumptions. The nature of the DCE data means that while we can test whether preferences have changed in a non-parametric, understanding the nature of any preference changes requires a model of behaviour and in estimation this then requires various parametric assumptions. Here we follow the standard literature and use the Random Utility Model (RUM) and specific parametrizations based around the mixed logit form which, as Train (2009) describes, can approximate any Random Utility Model.

The plan of the remainder of the note is as follows. In the next section we discuss a number of recent papers in the literature which have dealt with issues of preference stability, learning and expereibce which form the basis for the approach taken within the project. In Section 3, we describe in we can use the choice data to test whether a preference change has occurred. We also discuss how we can use the generalization of the mixed logit model, the G-MNL model (Fiebig et al. 2010), to explore the role of the experience of the interventions on individual preferences. In section 4 we describe in more detail the DCE data (and relevant information on other interventions) collected. In section 5 we provide results from an example Monte Carlo simulation to illustrate the proposed approaches.

State Preferences: Preference Stability and Experience

Individual responses to the 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. Drawing primarily on the Random Utility framework, the previous research has dealt with these issues in a number of ways.

The recent evidence on preference stability across time suggests that controlling for this is important. Liebe et al (2012) find that reasonable consistency 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 a DCE and OE CVM. 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 retest1. However, they do find that WTP is 25% lower between the test and retest1, and 15% lower between test and retest2. Czajkowski et al (2017) tests preference stability over two time points 6 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. The 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 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 state 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 use these analyses to formulate hypotheses, the models estimated are broadly similar across all the studies which consider role of learning and experience of the good on preferences, drawing on the RUM framework and being reduced form in nature. 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. Jensen et al (2013) study of provided respondent 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 2 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 survey. 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 or other changes at play.

G-MNL Model

Assume 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

$$U_{njt} = \beta_n x_{njt} + \varepsilon_{njt} \qquad (1)$$

Where ε_{njt} is unobservable error, x_{njt} the vector of attributes and β_n the utility weights, which capture heterogeneity in tastes.

The standard deviation of the error term or the scale factor is not identifiable in choice models and requires a normalization. As observed by Fiebig et al. (2010) taste heterogeneity in equation may arise through common differences in the scale factor or via differences in individual utility weights. They introduced the G-MNL model as a simple way to nest both possibilities within a single specification.

$$\beta_n = \sigma_n \beta + \gamma \eta_n + (1-\gamma)\sigma_n \eta_n \qquad (2)$$

Where σ_i is the scale factor, υ_n an idiosyncratic individual taste heterogeneity, and $\gamma$the weighting factor which captures the importance of overall scaling relative to individual differences in utility weights. As discussed by Fiebig et al. (2010), this model can be seen as the weighted average of the two extreme cases of how scale and taste heterogeneity enter the model. When $\gamma = 0$ or $\gamma = 1$, the model can be represented as $\beta_n = \sigma_n \beta + \eta_n^*$, with σ_n the scale factor as before and η_n^* remaining taste heterogeneity. When $\gamma = 0$ this latter is proportional to scale whereas when $\gamma = 1$ this is independent of the scale factor. In this both scale and taste heterogeneity are modelled explicitly with $\sigma_n \sim LN(1,\omega),\ \eta_n \sim MVN(0,\Sigma)$

Following the formulation of the G-MNL in Henscher et al (2015, P674), this can be extended to allow taste heterogeneity and scale to be functions of individual characteristics $z_n$or h_n e.g. the information set or whether respondents are in areas where interventions occur

$$\beta_n = \sigma_n \beta + \delta z_n + \gamma \eta_n + (1-\gamma)\sigma_n \eta_n,\ \sigma_n \sim exp(1 + \varphi h_n + \omega w_n) \text{ where } w_n \sim N(0,1) \ (3)$$

Czajkowski et al (2016) applied a version of this model to explore the impact of different information sets recognizing that different information sets could have different scale parameters as well as impact on taste heterogeneity. In their model they also allow the information sets to influence the variance of taste heterogeneity and the scale parameter,[1] $\sigma_n \sim exp(1 + \varphi h_n + exp(\lambda h_n)\,\omega w_n)$. Hence although a value of $\gamma$is not possible to estimate in their model (this is set to zero), they present

[1] It is not clear quite clear whether these are included separately as the the preference heterogenity is represented as $\beta_i \sim f(\mathbf{b} + \boldsymbol{\phi}'\mathbf{z}_\mathrm{i}, \boldsymbol{\Sigma} + \boldsymbol{\psi}'\mathbf{z}_\mathrm{i})$

estimates which distinguish between impacts of information on the mean of the scale parameter which determines the relative importance of $\beta_n x_{njt}$ part of utility relative to the random error ε_{njt}, and how variable this is across the population.

Modelling Changing Preferences and Attitudes

Consider now the different sources of changes in preferences within the project and how they might be captured. Define $\tau = 0{,}1$ (initially) as two periods where the survey and in particular the DCE experiments are to be applied. Within the DCE experiments at time $\tau$the individual *n's* utility for alternative *j* in choice set *t* can be written as U^{τ}_{njt}. Hence, it is assumed that within choice *t,* alternative *i* will be chosen if $U^{\tau}_{nit} > U^{\tau}_{njt}, \forall j \neq i$. Within this framework, any individual *n* will face the same set of choice tasks $\tau = 0{,}1$, a preference change will be generated when as $U^{0}_{njt} > U^{0}_{nit}, \forall j \neq i$, $U^{1}_{njt} > U^{1}_{nit}$, some $j \neq i$

Overall Impact

By adapting the standard Difference in Difference (DiD), it is possible to provide a semi-parametric method of testing whether there has been a change in preferences associated with the interventions

$$\varDelta Y_{nt} = \alpha_{0t} + \alpha_{1t} X^{0}_{nt} + \alpha_{2_t} D_{nt} + \varepsilon_{nt} \qquad (4)$$

Where $\varDelta Y_{nt}$ is a measure of whether choices differ between $\tau = 0{,}1$, X^{0}_{nt} are a set of prior characteristics measured in the baseline, $D_{nt} = 0{,}1$ is a dummy variable if the individual is in one of the areas where interventions take place, i.e. the treatment areas. As in the standard DiD approach, α_{1t} accounts for prior information thought to affect the common trend between control and treatment areas within choice *t*, α_{2t} the impact of the treatment on choice *t.* Within this framework testing for whether the interventions have had an impact on choices overall is simply the joint hypothesis $H_0{:}\, \alpha_{2t} = 0$, all t. A non-parametric version of the framework will also be used by applying matching methods to control for difference in trends across control and treatment areas (Heckman et al, 1999).

The discrete and categorical nature of the data capturing preferences and other attitudinal values means that $\varDelta Y_{nt}$ cannot be defined as a simple linear difference but is defined by some non-linear function. For example, for each τ within each choice set *t,* define the choice made as $Y^{\tau}_{njt} = j,\ j = 1{,}2{,}3$. From this, we can define a number of $\varDelta Y_{nt}$ as outcome variables of interest. To examine choice stability simply define $\varDelta Y_{nt} = 1 \ \ if \ \ Y^{0}_{njt} = j, Y^{1}_{njt} = j$, 0 otherwise (Brouwer et al, 2016). There is prior evidence of status quo effects in choice stability which we will also examine.[2] Let the status quo choice in the DCE experiments be represented by choice 3. Hence, we can define status choice consistency as $\varDelta Y_{nt} = 1 \ \ if \ \ Y^{0}_{njt} = 3, Y^{1}_{njt} = 3$. The status quo effects will also be examined by considering movements to and away from the status quo choice, i.e. $\varDelta Y_{nt} = 1 \ \ if \ \ Y^{0}_{njt} \neq 3, Y^{1}_{njt} = 3$ and $\varDelta Y_{nt} = 1 \ \ if \ \ Y^{0}_{njt} = 3, Y^{1}_{njt} \neq 3$ respectively.

The framework provided by equation (4)[3] will also be used to measuring whether there have been impacts of the intervention on a range of other variables capturing attitudes to the governance of the exclosure and watershed management and basic household welfare measures. Table 1 below summarizes these outcome variables

Table 1 Outcomes Variables: Preferences and Attitudes

[2] For example Czajkowski et al (2017) found those choosing the status quo made more consistent choices.
[3] Including the matching approach

	Variable/Question
Choice Experiment	
	Overall Choice Stability
	Status Quo Stability
	Move to Status Quo
	Move away from Status Quo
Other	
Governance of Exclosure	How do you feel that access to the exclosure is being managed?
	How do you think grass from the exclosure should be distributed?
	In your view, to which degree do the kebele officials do what is good for the community?
	In your view, to which degree does the kebele committee for the area closure do what is good for the community?
	Is there anyone in the kebele whose needs should be more strongly considered in the distribution of the benefits from the exclosures?
	In your view, how important is the exclosure for your kebele overall, for example, in terms of its role in water and soil conservation?
	In your view, how important is the exclosure for your own household?
Watershed management	Do you think there is a land degradation problem in your community?
	Do you think the watershed activities used help control land degradation?
	Do you think the watershed activities used help control gully formation?
Health, Happiness & Control	Taking all things together, would you say you are (happy)
	All in all, how would you describe your state of health these days?
	Some people feel they have completely free choice and control over their lives, while other people feel that what they do has no real effect on what happens to them.
Welfare	Household Dietary Diversity (last 7 days)
	Household Food Expenditure (last 7 days)
	Household Non-Food Expenditure (last month)

The baseline survey includes a wide range of information which might be expected to affect the overall trends in equation (4) and therefore should be included inX_{nt}^{0}, including demographic information, uncertainty over choice *n*, measures of values, wealth measures ,etc. Table XX specifies the set of base variables which will to be included in this set. The robustness of the results will be considered with respect to specifications of different sets of variables e.g. without covariates. Without demographic covariates etc. This type of exploration may provide useful information on the source of difference in trends will potentially information on the

Table 2 Baseline Information used as Controls

Variable	Definition
Household Demographics	Number of Adults, Age, Gender, Marital Status
Farm Characteristics	Area of land, land quality,
Income Status	Income sources, access to credit, part of the Safety net programme
Access to Resources	Water and fuel source
Household network	Membership of EQUIB etc, close friends
Wealth and Assets	Wealth index based on yes/no answers, ownership of land, TLU
Uncertainty over choice *n*	Likert question in how certain respondent is about choice
Choice complexity	To define distance metric of distance between choices (between 1,2 or between, 1,2,3) e.g. standardized mean squared error of difference between choices
Values	Schwartz values Questions

Understanding Preference Change

The framework set out in equation (4) allows for a semi-parametric test as to whether preferences have changed as a result of the interventions. However as discussed, to examine the nature of the preference change and its implications, requires a parametric approach. The basic approach to be undertaken will apply the G-MNL approach used by Czajkowski et al (2016). Define individual utility, utility weights and scale parameter an explicit function of $\tau = 0{,}1$. That is

$$\beta_n^\tau = \sigma_n\beta + \delta_1\tau + \delta_2 D_n^\tau + \gamma\eta_n + (1-\gamma)\sigma_n\eta_n \qquad (6)$$

$$\sigma_n^\tau \sim exp(1 + \varphi_1\tau + \varphi_2 D_n^\tau + \rho Z_n + exp(\lambda_1\tau + \lambda_2 D_n^\tau)\,\omega w_n) \qquad (7)$$

where , $\eta_n \sim MVN(0, \Sigma)$, $w_n \sim N(0{,}1)$ and $D_n^1 = 1$ for individuals in the areas with interventions in the follow-up survey and zero otherwise. In this framework, the coefficients on τcapture the effective common "trends" type or general preference stability effects across the treatment and control groups, while the coefficients on D_n^τ should capture the impacts of the interventions themselves on preferences. Three effects are distinguished; the impact on mean of the β_n^τparameters, i.e. $\delta_k, k = 1{,}2$; the impact on the mean value of scale σ_n^τ, i.e φ_k, and finally the variance of the scale parameter λ_k.

Hence, if the interventions increase the average weighting for an individual characteristic, e.g. a preference for providing beehives for youth, we would expect a positive estimated value of δ_2 for that attribute. The overall experience of the interventions could make the utility more predictable from the researchers perspective increasing the mean of the overall scale factor φ_2. As in Czajkowski et al (2016), it is also possible that there may be impacts on the spread of the scale factor which implying a negative λ_2 if uncertainty reduces as a result of the interventions.

"WTP" space

Monte Carlo Simulation

To explore how well the methods are likely to be able to identify the impact of the treatments on preferences relative to other effects in this section we now present the results of a series of Monte Carlo experiments broadly following the design by Fiebig et al (2010). We use the DCE baseline survey design with the following attributes to generate 50 simulated datasets.

Table 3

Attribute	**Levels**	**Status Quo**
Grass Quota	2 weeks 1 month 2 months 5 months	Individual from via log normal
Intervention	Bees + youth; Bees + women; Sheep + women; Oxen + youth	No Intervention
Extra Work commitment	2 days 6 days 10 days 15 days	No extra work commitment
Fund contribution	5kg 10kg 20kg 30kg	No fund commitment

In each simulated dataset, the deterministic part of utility associated with each choice is generated assuming that grass quota, work commitment and fund contribution are continuous variables with the interventions being captured via separate dummy variables. The choice sets uses the baseline design with two alternatives plus the status quo choice. The true model is assumed to have an attribute specific constant for alternatives 1 and 2 which are not the status quo. There are 500 observations in each dataset, randomly split between assumed treatment and control groups.

The model structure used to generate the simulated data is nested withing the following equations

$$\beta_n^\tau = \sigma_n\beta + \delta_1\tau + \delta_2 D_n^\tau + \gamma\eta_n + (1-\gamma)\sigma_n\eta_n \qquad (6)$$

$$\sigma_n^\tau \sim exp(1 + \varphi_1\tau + \varphi_2 D_n^\tau + exp(\lambda_1\tau + \lambda_2 D_n^\tau)\,\omega w_n) \qquad (7)$$

Within this framework, a range of different simulations are undertaken. The structure of these is described in Table 4 below. To provide an initial evaluation of the potential performance of the econometric estimation to identify treatment and trend effects, three different Monte Carlo experiments are reported on.[4] The first has no trend or treatment effects nor allows for any heterogeneity and tests the performance of the clogit in a base case scenario. The second considers the change in the preference on the dummy associated with the youth-based interventions, increasing by 0.1 this coefficient for both treatment and control groups to capture a trend in this variable and by an additional 0.15 for the control group alone to capture a treatment effect.[5] The third treatment allows for the same change in preference on the dummy variable associated with the youth based interventions, plus unobserved heterogeneity in the attribute specific constant, with an additional non-random trend and treatment effect on the attribute specific constant.

[4] A variety of other simulations were also undertaken to explore the sensitivity of the results to trend and treatment effects in each individual attribute and also combined attributes (these are available on request)

[5] The models are estimated with the treatment women plus sheep treatment as the omitted category with effects coding used for the dummy variables representing the different treatments.

Table 4: Monte Carlo Experiments

Experiment	Trend	Treatment	Heterogeneity	Estimation Method
A	No	No	No	Conditional logit
B	Yes – Youth Preference	Yes –Youth Preference	No	Conditional logit
C	Yes –Youth Preference +ASC	Yes –Youth Preference +ASC	Yes - ASC	Mixed-logit

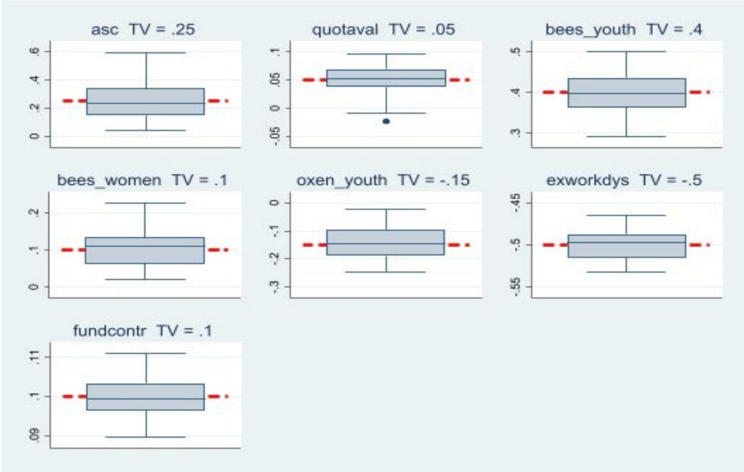
Coefficient Estimates

To consider how well the DCE estimations captures the underlying coefficients, Relative to equation (6), figures 3-5 show the box plots of the estimated β coefficients, the δ_2 estimates of the changes in preferences in the treatment areas, and the δ_1 of the trends which affect both treatment and control areas. In each case the underlying true parameter value is indicated by the red line.

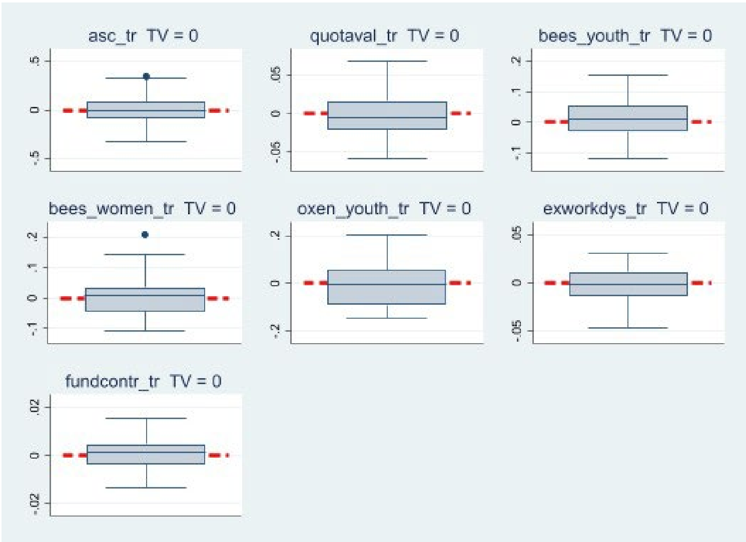
The Figure 3 results for Experiment A, show that without any treatment and trend effects (or underlying heterogeneity), the conditional logit provides average estimates close to the actual values. In Figure 4while on average the estimates (estimated via the conditional logit) do identify both positive treatment and trend effects. However, the former seem slightly negatively biased, while the trend estimates are somewhat positively biased.

The true model in Experiment C has both unobserved heterogeneity in the attribute specific constant (ASC), and a deterministic trend in the ASC in addition to the preferences changes within Experiment B. The figure 5 results show a similar pattern to the Experiment B results with the preference trend effect positively biased while the treatment effect is negatively biased. In contrast the trend effect in the ASC appears to be captured accurately on average.

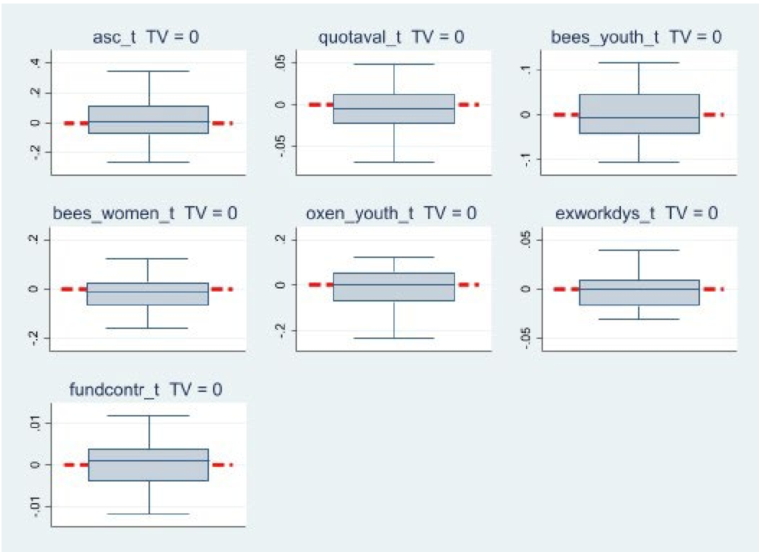
Figure 3: Estimated Coefficients: Experiment A



a) **Beta**

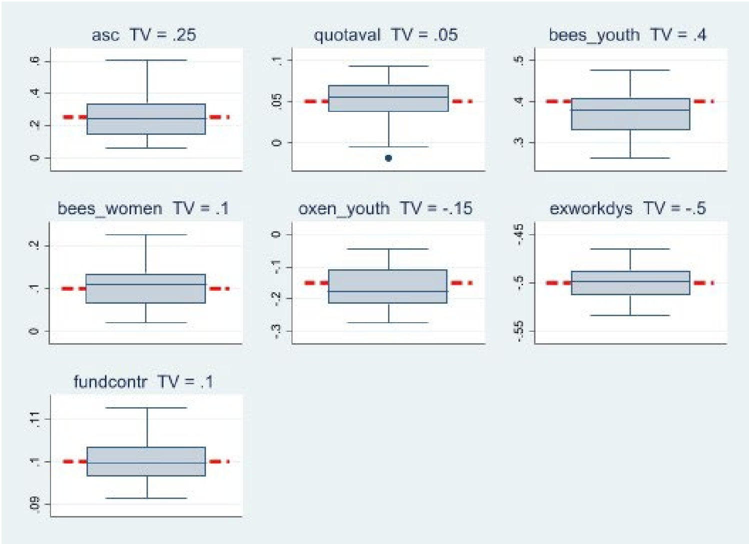


b) Treatment

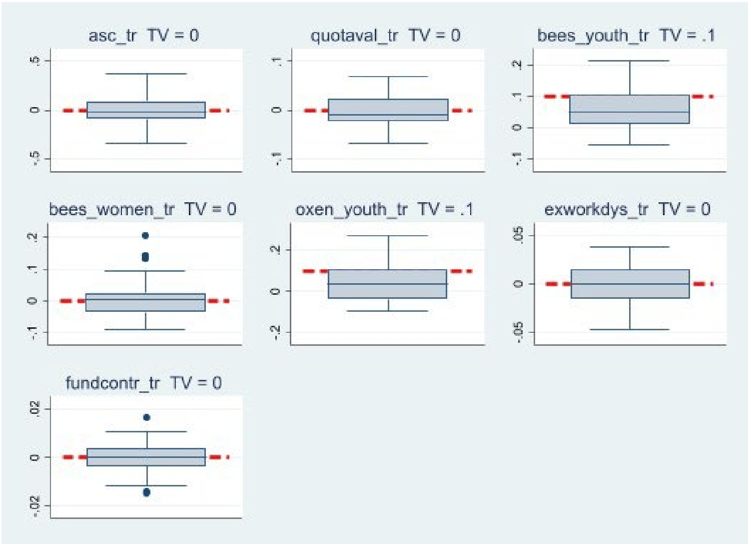


c) Trend

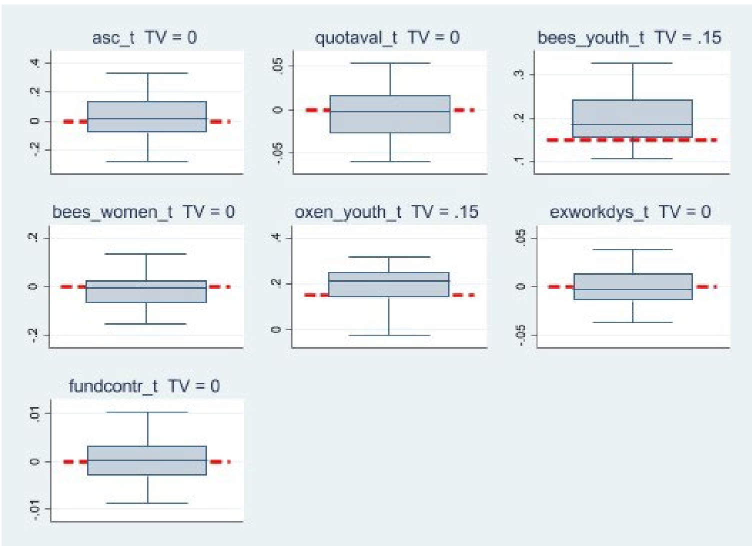
Figure 4: Estimated Coefficients: Experiment B



a) **Beta**

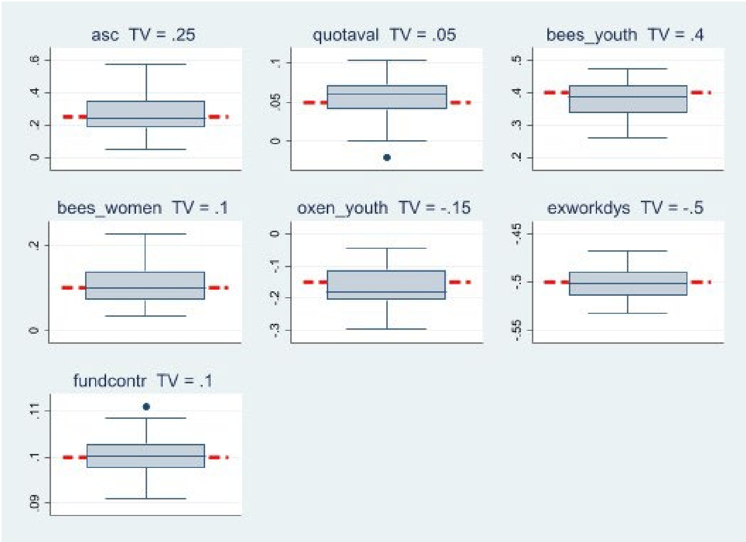


b) Treatment

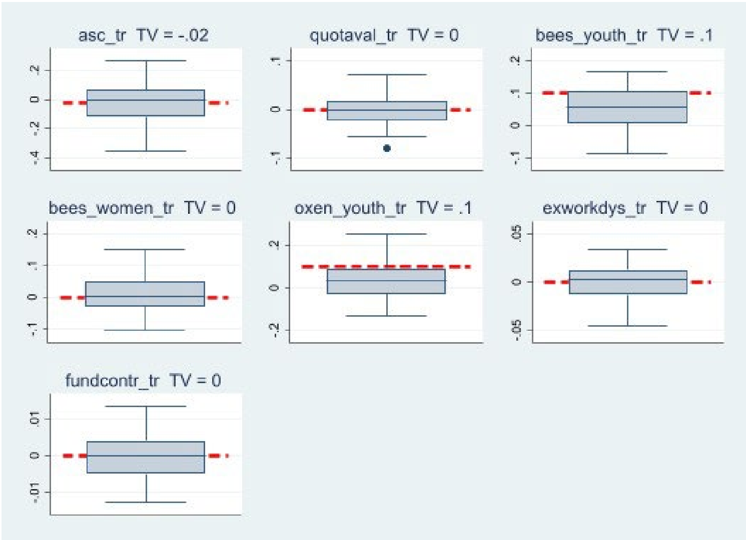


c) Trend

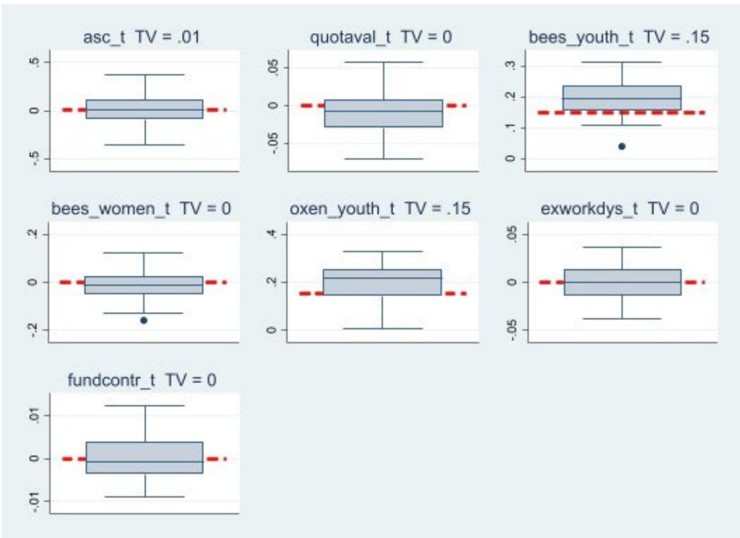
Figure 5: Estimated Coefficients: Experiment C



a) **Beta**



b) Treatment



c) Trend

Joint Hypotheses Tests

Figure 1 shows the implied changes in choices from the simulated datasets for the control and treatment groups associated.

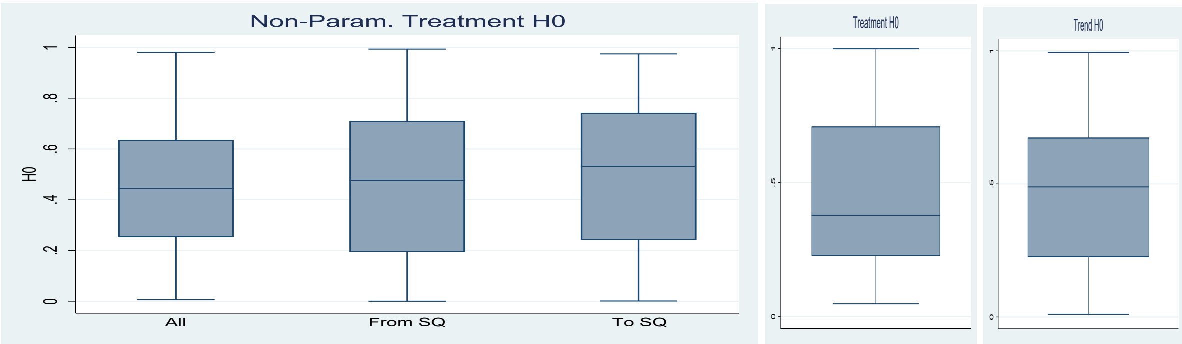
Figure 1: Changes in Choices

a) Experiment A **b) Experiment B** **c) Experiment C**

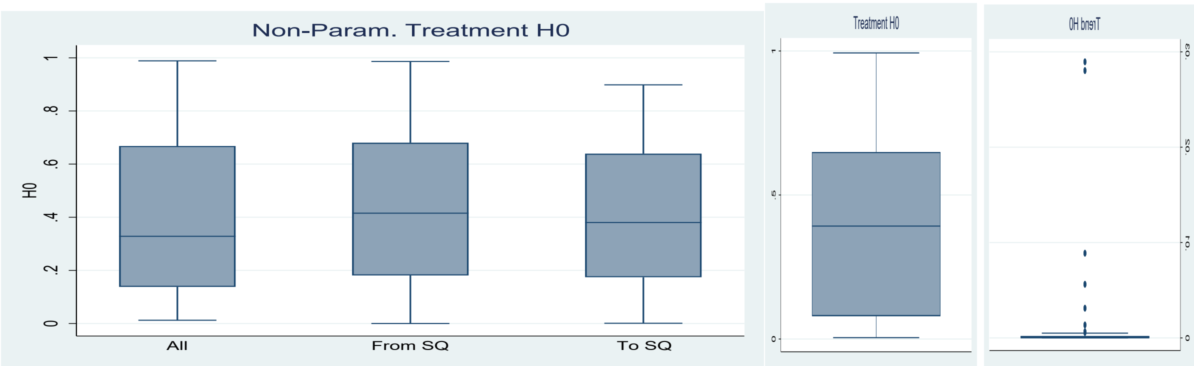
For each dataset we use semi-parametric method outlined above to test for overall preference changes. Figure 2 provides the box plots for the p-value results of these joint hypothesis tests for both experiments.

In Experiment A with no treatment or trend changes, both the parametric and non-parametric tests capture the failure to reject the Null hypothesis of no-change. These appear to suggest that the parametric tests typically reject the null of no preference changes when the underlying changes in choices in the treatment and control groups are of the order given in Figure 1. The results for experiment B and C are more mixed. In experiment B, the null of no trend is rejected in most cases, but in the non-parametric tests, and for the overall treatment change test, it does not properly pick up the change. In experiment C the tests do not appear to be particularly powerful in any case. This suggests further exploration is required to both consider alternative tests and also to understand the circumstances when we might expect these tests to have some power.

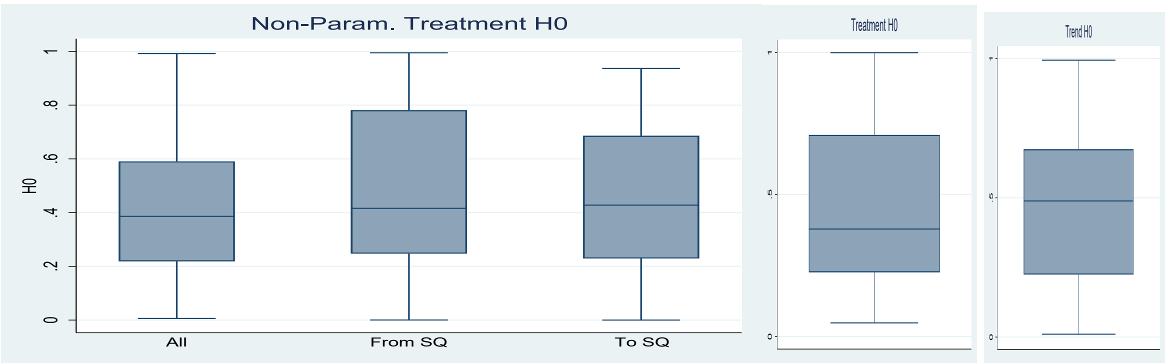
Figure 2: Joint Hypothesis Test for No Change in Preferences: P-values



a) Experiment A (Non-parametric , Parametric Treatment Effect, Parametric Trend Effect)



b) Experiment B (Non-parametric, Parametric Treatment Effect, Parametric Trend Effect)



c) Experiment C (Non-parametric, Parametric Treatment Effect, Parametric Trend Effect)

Appendix

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