Pre-Analysis Plan: Cognitive load, trust and rainfall insurance

American Economic Association registration: AEARCTR-0002715

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Background

Study overview

Year to year variation in yields and harvests as a result of drought can have devastating effects on smallholder farmers, which are projected to increase with climate change (Parry et al 2007). One potential mitigation is rainfall insurance which tracks precipitation using a combination of satellite and weather station data. However, literature highlights that major barriers to the uptake of such products are trust issues (Cole et al 2013) and scarcity of mental resources, particularly as planting time approaches (Mullainathan and Shafir 2013; Lichand and Mani 2016). This paper explores how cognitive load and endorsement by a trusted individual affect take-up of a novel 'commoditised' rainfall insurance product. I also test the combination of these treatments, i.e. whether the influence of a trusted individual is greater in a cognitive load context. Finally I disaggregate the effects of trust and cognitive load for risk averse and ambiguity averse individuals, as well as by wealth, gender and previous exposure to rainfall insurance.

The Project Partners

This study is carried out in collaboration with Africa Climate Resilience Enterprise (ACRE) Africa, a prominent insurance intermediary, and the Busara Centre for Behavioural Economics. Busara are a consultancy and research organisation based in Nairobi, Kenya.

The Study Site and sample selection

This study takes place in three locations in Meru county, on the Eastern slopes of Mount Kenya: Imenti North, Buuri and Tigania West. Drought and erratic rain are increasingly prevalent in the county, with a projected increase in consecutive days of moisture stress of 50% over the next 30 years for the first growing season (MoALF2016).

The sample is recruited through ACRE's network of insurance educators who operate in communities in the district, with subjects invited initially by text message and then follow up calls. A sample size of around 300 was obtained, each attending two to three hour sessions over 6 days in groups of 25 farmers from a mix of villages.

Hypotheses

H1: When provided with information about rainfall insurance, farmers under cognitive load will be less likely to purchase insurance than farmers not under cognitive load.

H2: Endorsement of information about rainfall insurance by a trusted individual will increase adoption relative to when no endorsement is provided.

H3: When farmers are under cognitive load, the effectiveness of endorsement from a trusted advisor will be greater than when they are not under cognitive load.

Experiment/ method details

All participants provided written consent and were allocated identification numbers. Participation in all cases included completing a baseline survey, receiving a presentation about rainfall insurance and completing a midline survey. The baseline survey collected basic individual and farm information (such as crops grown, hectares owned, and years of experience in farming). This included an incentivised risk aversion game and a hypothetical ambiguity aversion test.

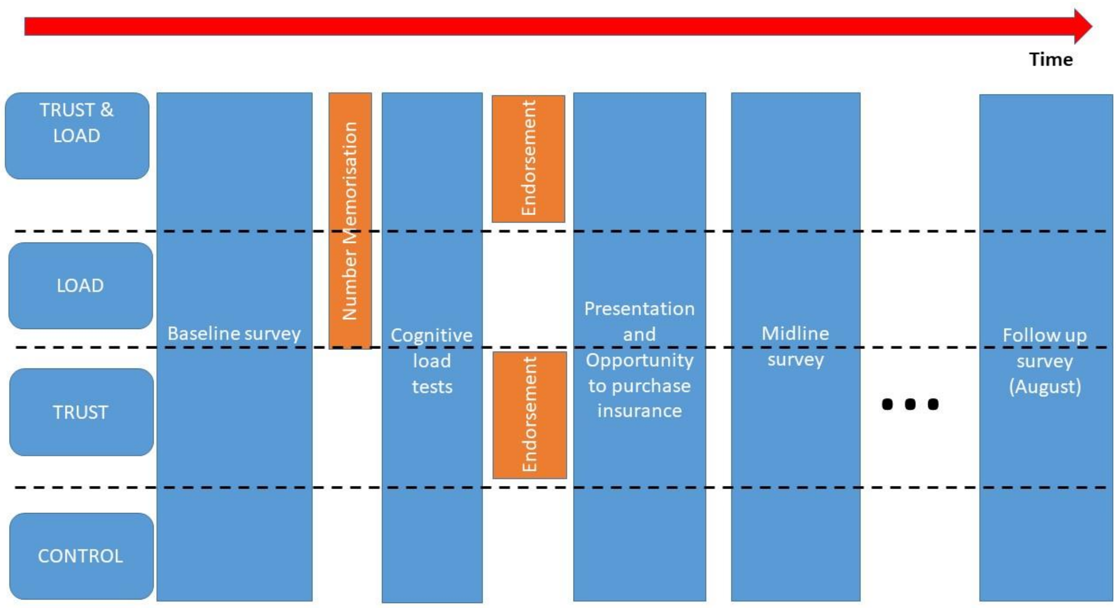
The combinations of treatments can be described by a 2x2 factorial matrix as shown in table 1, while a chronology of the sessions disaggregated by treatment group is shown in figure 1. A random sample of sessions received a short introduction by a 'trusted individual' preceding the insurance presentation. This individual was an agricultural expert, known to many of the farmers through promoting previous (mainly government) agricultural insurance products, who could personally vouch for the credibility of ACRE.

Table 1: 2x2 factorial design for trust and cognitive load treatments

	No endorsement	Endorsement by trusted individual
Priming	T1, n= 75	T2, n= 75
No priming	T4, n= 75	T3, n= 75

Following the baseline survey, a random sample of farmers within each session received a number memorisation task to induce cognitive load. This was immediately followed by Ravens and Stroop tests of cognitive performance. The state of cognitive load was maintained until the start of the midline survey when members of this treatment group were asked to recall the number.

Figure 1: Sequencing of the experiment



The midline questionnaire included questions to understand the farmers' experience of the treatments, and asked about changes in behaviour as a result of the presentation such as adoption of fertiliser, improved seed and soil and water conservation practices.

At harvest time an end-line survey will be carried out by telephone including questions on any final payments received, harvest outcomes and any resilience strategies employed.

Data Collected

Baseline

- Education, age, farm size, gender, mother tongue, years' experience in farming
- Village
- Wealth:
    - Land and livestock
    - Liquid wealth: we asked "how much money do you have in your pocket/ MPESA[1] account right now"
- Risk aversion as tested through incentivised game.
- Ambiguity aversion
- Previous experience with rainfall insurance
- Alternative/ complimentary adaptation strategies. These included:
    - Uptake of drought tolerant or improved maize
    - Use of fertiliser or other agrichemicals
    - Soil and water conservation measures
    - Non-farm income (Kenyan Shillings)
- Sources of support – we asked "to what extent would you rely on support from the community and/or relatives?" Membership of community organisations such credit associations and farmers organisations.
- Rainfall- subjective experience of last two growing seasons was obtained by asking "how have the rains been recently?"

Midline

- Quantity of crop insurance purchased (Kenyan Shillings)
- Weather expectations for next growing season.
- Intentions to use fertiliser, hybrid seed and/or soil and water conservation techniques.
- Reasons for purchasing or not purchasing rainfall insurance

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[1] MPESA is the mobile payment system prevalent in Kenya

Power calculation

Accounting for clustering, I calculate that for each 150 individuals in a two cell comparison in table 1, an effect size of less than 0.5 standard deviations can be detected. This could reduce to around 0.3 standard deviations with the use of control variables to reduce residual variance.

Data cleaning, checks for balance and treatment implementation

On receiving data I will check treatment allocation has occurred as planned, and check for balance. I propose to drop the observations which involve non-response or replace a missing observation by the sample average. Note that this method is only valid if no selection is suspected – which is something I intend to investigate if item non-response is substantial.

Testing the Hypotheses

The main dependent variable of interest is insurance purchase. I expect the data to principally contain individuals purchasing a single unit of insurance or no insurance but there will also be cases of multiple purchase. If there is insufficient variation in the latter case for useful analysis, I will analyse purchase (y_i) as a binary decision.

I can estimate the following specification for the determinants of insurance purchase via OLS:

$$y_i = \alpha + \beta_1 trusted_i + \beta_2 load_i + \beta_3 trusted_i \times load_i + u_i \quad (1)$$

Here y_i is a dummy variable (1 or 0) indicating whether insurance was purchased. Robust standard errors will be used, and in addition a specification including village fixed effects will be tested.

The intent-to-treat impact of the cognitive load treatment individually is given by β_2 (hypothesis 1) and the trust treatment by β_1 (hypothesis 2). The coefficient β_3 is the measure of whether trust has a greater or smaller effect in the context of cognitive load. A t-test of $\beta_3 = 0$ therefore tests hypothesis 3. A positive (negative) coefficient for β_3 indicates trust is more (less) important and/or the effect of cognitive load is reduced (increased) when the two treatments are combined.

In order to increase the precision of estimates, I can estimate (2), which includes X, a set of covariates collected at baseline such as gender, education, age, risk aversion and ambiguity aversion.

$y_i = \alpha + \beta_1 trusted_i + \beta_2 load_i + \beta_3 trusted_i \times load_i + \beta_4 X + u_i$ (2)

If there is substantial variation in the outcome variable (i.e. purchases of 1,2,or 3 or more insurance cards, then it could be possible to analyse as an additional outcome variable insurance purchase as a ratio of the value of expected harvest (or the ratio with inputs purchased). It will be desirable to carry out this analysis because using long-run rainfall data in that location, we can compare purchase decisions to a level of full insurance. Expected utility theory predicts that individuals will fully insure under conditions of actuarial fairness (where the price is equal to the probability of loss). I expect that given basis risk, actuarial unfairness, and ambiguity aversion, purchase will be substantially below full insurance.

Individual Heterogeneity

Tests for heterogeneous effects will be carried out as follows and for the following reasons:

Variable	Trust treatment	Cognitive Load treatment
Risk aversion	No predicted effect.	**Zero effect:** Literature, e.g. Lichand and Mani (2016) indicates that cognitive load does not operate through the channel of risk aversion, which leads us to expect an interaction to have a value of zero.

Ambiguity aversion	**Positive:** As per Bryan (2010), I expect that in the presence of ambiguity aversion, the trust treatment effect may be stronger, since ambiguity averse individuals place more value on the reduction in ambiguity provided by the treatment	**Negative:** limiting processing capacity may have the effect or raising ambiguity for subjects, therefore an ambiguity averse subject may be more likely to reject the product under these circumstances.
Wealth	Indeterminate	**Positive:** following Mullainathan and Shafir (2013), wealthier individuals should be less susceptible to 'scarcity' thinking which will cause them to undervalue rainfall insurance.
Previous experience of rainfall insurance	**Negative:** personal experience with similar products is expected to provide a more important source of ambiguity reduction than that provided by the trusted individual	**Positive:** those who have experienced similar products may require less cognitive capacity to process information about a new product.
Gender	Indeterminate	Indeterminate

These heterogeneous effects can be tested using sub-sample analysis, and/or a specification similar to (2) above, but with the covariate measure (risk, wealth etc.) replacing one of the treatments in the interaction variable.

Additional analysis

Clarke (2011) predicts an inverted U shaped relationship between index insurance demand and risk aversion due to the presence of basis risk (the possibility for crop failure for reasons other than rainfall and therefore no insurance pay-out) This can be tested by including a quadratic term for risk aversion in one or more specifications.

Bryan (2010) finds that increasing risk aversion predicts lower insurance purchase for ambiguity averse individuals, but higher insurance purchase for the ambiguity neutral. I intend to test this through a triple difference specification or sub-group analysis, but acknowledge that power may be limited to draw firm conclusions.

I will also analyse the free text answers to the question 'Why did you buy/ not buy the insurance'. This could either support or undermine the theories of this paper, but will certainly provide a great opportunity for learning for this and future studies.

Analysis of Mid line outcome variables

We expect that those who buy rainfall insurance will be more likely to use higher risk (technological) inputs and less likely to use soil and water conservation techniques (as per Karlan et al 2014). However, an OLS regression of improved seed uptake on insurance purchase will suffer from a selection problem since those who buy insurance might be systematically different to those who do not buy and we cannot isolate the effect of insurance purchase. However if treatment effects are sufficiently strong, I will use the treatments to instrument for the endogenous insurance purchase decision in predicting uptake of these practices.

Further end line analysis will need to be planned at a later stage.

References

Bryan, Gharad (2010) ‘Ambiguity and Insurance’, Working paper.

Clarke (2011) A Theory of Rational Demand for index insurance, PhD thesis, University of Oxford.

Cole, S; Giné, X; Tobacman, J; Topalova, P; Townsend, R; Vickery, J (2013) Barriers to Household Risk Management: Evidence from India *American Economic Journal: Applied Economics 2013, 5(1): 104–135* http://dx.doi.org/10.1257/app.5.1.104

Lichand and Mani (2016) *Cognitive droughts* working paper.

Karlan, D; Osei, R; Osei-Okoto, Isaac; Udry, C; (2014) ‘Agricultural Decisions After Relaxing Credit and Risk Constraints’, *QJE,* 597–652.

Mani, A; Mullainathan, S; Shafir, E; Zhao, J (2013) ‘Poverty Impedes Cognitive Function’ *Science* 341 (6149), 976-980

MoALF. (2016) ‘Climate Risk Profile for Meru.’ Kenya County Climate Risk Profile Series. The International Center for Tropical Agriculture (CIAT) and the Kenya Ministry of Agriculture, Livestock and Fisheries (MoALF), Nairobi, Kenya.

Mullainathan, S; Shafir, E (2013) *Scarcity: The True Cost of Not Having Enough,* Penguin books.

Parry, M.L., O.F. Canziani, J.P. Palutikof and Co-authors (2007): Technical Summary. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge, UK, 23-78.