1. Introduction

The authors conduct a drought insurance experiment in Ethiopia. They examine whether uptake of index-based insurance is enhanced if farmers are allowed to pay after harvest (addressing a liquidity constraint). They also test to what extent uptake can be enhanced by promoting insurance via informal risk-sharing institutions (*Iddirs*). The main results of the paper are that the delayed payment insurance product increases uptake substantially when compared to standard insurance, from 8% to 24%, and leveraging informal institutions results in even greater uptake (43%). They also find suggestive evidence that the delayed premium product is indeed better at targeting the liquidity constrained.

They report on the outcomes of an RCT in rural Ethiopia that focused on two major reasons for low adoption of insurance: (i) lack of liquidity to pay for the insurance premium, and (ii) lack of information about, or trust in, the insurance product. To study the role of liquidity constraints during the planting season we allow (randomly selected) farmers to pay the premium after harvest—they allow smallholders to postpone premium payment until after the harvest, and henceforth call this insurance product IOU. Second, they randomly vary the marketing channel, and leverage support of leaders of *Iddirs*, which are informal social institutions in Ethiopia, for the product in some experimental arms—the leaders are informed of how the insurance works and are responsible for promoting it.

This paper extends the important findings of Casaburi and Willis (2018) outside the contract farming setting by analyse the uptake increase under other contracting arrangements, taking into consideration that most smallholders are not engaged in contract farming. Their design also further extends the findings of Dercon et al. (2014) because it combines marketing through informal groups with delayed premium—with possible synergies both in terms of uptake and defaults. Their result is in line with the findings of Casaburi and Willis (2018) in the context of contract farming, but they find some evidence that the demand-increasing effect of the IOU may be larger for people with low savings or income, supporting the idea that liquidity constraints impede uptake of insurance.

In our replication, we use R to reproduce the main results of the original paper using the data provided by the author. In addition, to further study the heterogeneous effects of the (different types of) insurance, we extend the paper by applying the causal forest method developed by Wager and Athey (2017). Finally, we compare our results with those obtained by the authors and explain the differences. (More details of results and conclusions needed.)

1. Methodology
   1. Original study

They worked together with Oromia Insurance Company (OIC) in Ethiopia and used multi-level randomization at the *Iddir* level to assign the 144 *Iddirs* to six experimental arms: 1) Standard Index Insurance (control group); 2) Standard Index Insurance via *Iddir* promotions; 3) IOU insurance; 4) IOU insurance with Contract; 5) IOU insurance via *Iddir* promotions; and 6) IOU insurance via *Iddir* promotions with Contract. And they collected data on household demographic characteristics including age, sex, marital status, education and family size; household income, households’ level of exposure to drought, experience in buying crop insurance before the experiment, household production and saving variables.

To verify whether randomization resulted in balanced groups we regress household observables and farming variables on treatment group dummies and a constant. The constant reflects the comparison group. The coefficients indicate whether other groups are significantly different from the comparison group, and we test for differences between other groups by Wald tests. The results suggest the randomization worked well.

Then, they present insurance uptake across treatment arms and do regression analysis, both showing that uptake change induced by *Iddir* promotions in isolation is statistically insignificant, as is IOU with binding contract.

They perform a heterogeneity analysis, to figure out if they can attribute the increase in uptake under IOU insurance to the relaxation of the liquidity constraint. To proxy for liquidity, they distinguish between households with above and below-median income, and between households with and without savings (self-reported). And for both proxies, the coefficients of the simple IOU product are higher for the liquidity-constrained. However, while the IOU coefficient of the (more) constrained subsample is consistently different from zero, and the coefficient for the complementary sample is not, the relevant coefficients are not statistically different from each other (according to a Wald test). This can also be seen by the insignificance of the coefficients using the interaction term instead of subsamples.

* 1. Replication

We generate five dummies indicating whether each individual is in one of the five treatment groups and a dummy indicating the status of uptake. Then we generate the controls used in the article, including demographic variables: Age (in years), Sex (male=1; female=0), Marital status (married=1; not-married=0), Education (years of schooling), Family size, Total income in the last month (in Birr), Drought (a dummy taking value of 1 if the household experienced a drought in the last three years), and Insurance (a dummy taking the value of 1 if the household had purchased index insurance during the past three years); and farming variables: capturing quantities of crops produced in the last cropping season (maize, haricot, teff, sorghum, wheat, and barely), a measure of total land under cultivation, and a dummy taking the value 1 if the household had any formal savings.

To conduct balancing tests, we regress observable controls, including demographic variables and farming variables, on treatment group dummies and a constant, to see if the coefficients of the group dummies are statistically significant.

For regression analysis, we regress the uptake status on five group dummies, and then add controls and *Kebele* fixed effects to the parsimonious model. Finally, we also exclude the subsample from a certain *Kebele*, Dalota Mati, which all the defaults in the dataset come from, to increase the statistical power of the analysis.

* 1. challenges

1. Results
   1. Balance test

The results show that the randomisation does not work as well as the original paper, since the significance levels of some coefficients increase, showing that the treatments affect some observables and thus we cannot ignore the selection bias.

* 1. Regression analysis

The results of regression analysis are quite similar to what the authors obtained. Except the parsimonious model, where Index Insurance via *Iddir* has a significant impact on the uptake, Index Insurance via *Iddir* and IOU Insurance with Contract do not increase the uptake rate, with or without adding controls and dropping the sample from the *Kebele* where defaults took place.

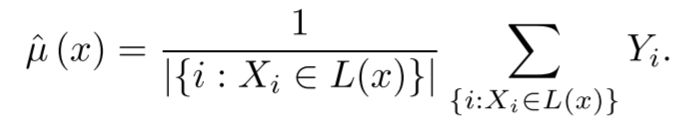
* 1. Heterogeneity

1. Extension
   1. Introduction of Causal Forest

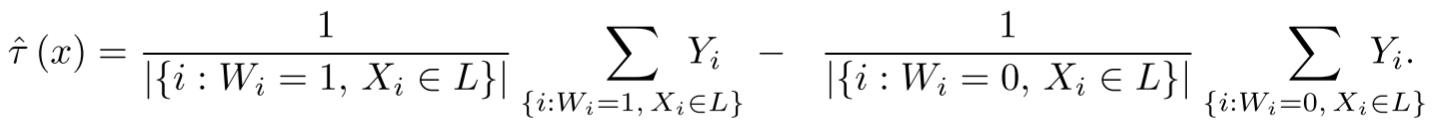
For extension of the replication, we apply a non-parametric causal forest, which is developed by Wager and Athey (2017) and can achieve better matching with many covariates, for estimating heterogeneous treatment effects that extends Breiman’s widely used random forest algorithm. In the potential outcomes framework with unconfoundedness, causal forests are pointwise consistent for the true treatment effect, and have an asymptotically Gaussian and centred sampling distribution. The causal forests give us a better understanding of treatment effect heterogeneity, so we apply this method to the original paper, which reveals the treatment effects of a drought insurance, to analyse the heterogeneity of the effects on individuals with different characteristics.

The steps of the method can be briefly summarised as follows:

Step 1: The causal forest uses double-sample trees to split the available training data into two parts: one half (I) for estimating the desired response inside each leaf, the other half (J) for placing splits. Double-sample regression trees make predictions ˆµ(x) using



on the leaf containing x, only using the I-sample observations. The splitting criteria is the standard for CART regression trees (minimizing mean-squared error of predictions). Splits are restricted so that each leaf of the tree must contain k or more I-sample observations. And double-sample causal trees are defined similarly, except that for prediction we estimate τˆ(x) using



on the I sample. Following Athey and Imbens [2016], the splits of the tree are chosen by maximizing the variance of ˆτ(Xi) for i ∈ J.

Step 2: Propensity trees use only the treatment assignment indicator Wi to place splits, and save the responses Yi for estimating τ. The splits are chosen by optimizing, e.g., the Gini criterion used by CART for classification.

Step 3: Compute a random forest by Monte Carlo averaging.

Under regularity assumptions, causal forests can realise unconfoundedness and therefore achieve consistency without needing to explicitly estimate the propensity. And given all the preliminaries needed, we can state reliable results on the asymptotic normality of random forests.

* 1. Application and Results

1. Conclusion