Replication_Group_1

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I. Introduction

- Briefly explain the original study and its contribution to the literature
- Discuss the importance of replication in economics research and the goals of the replication paper

The study found that low uptake of insurance among smallholder farmers impairs their ability to manage risks associated with crop failure and reduce incentives for modernization. Conducted through a randomized control trial, the study observed a significant increase in insurance uptake among the sample population by deferring premium payments and leveraging community leaders to promote the product. The study's findings have implications for policymakers and stakeholders working to improve the financial resilience of smallholder farmers in developing countries.

The study 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. The 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. The 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.

However, the heterogeneity analysis in this paper only focuses on two household characteristics and is simply based on subsample regressions, leaving a gap of heterogeneous effects of the insurance to be filled up. Based on this, we try to use the causal forests developed by Wager and Athey (2017) to look deeper into how different types of insurance designs affect people with diverse socio-economics and production characteristics in our study, improving the understanding of how to design contracts for different households in order to achieve better promotion.

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Our replication and extension study aims to build on the original study's findings by replicating the results using the same data and methods. Additionally, we will estimate heterogeneous treatment effects using a multi-arm causal forest approach to investigate whether the effects of insurance on smallholder farmers vary across different subgroups of the population. Through this analysis, we hope to contribute to a better understanding of how insurance can be used to support agricultural development in low-income countries.

In our study, we aim to estimate heterogeneous treatment effects using a multi-arm causal forest approach. This differs from the original study, which also estimated heterogeneous treatment effects but used a different method. Specifically, our approach allows us to estimate treatment effects for different subgroups of the population and account for potential interactions between different variables. Our results will contribute to a better understanding of the impact of insurance on smallholder farmers and inform policies aimed at improving their financial resilience.

(More details of results and conclusions needed.)

The paper is structured into six sections. The first section is the introduction, which provides an overview of the study and its objectives. The second section is the literature review, which discusses the existing research on the topic and identifies the research gaps that the study aims to address. The third section is the methodology, which describes the data sources, study design, and statistical techniques used to analyze the data. The fourth section is the results, which presents the findings of the study. The fifth section is the extension, which discusses the multi-arm causal forest approach used to estimate heterogeneous treatment effects. The sixth and final section is the conclusion, which summarizes the study's key findings and their implications for policy and future research.

II. Literature Review

- Summarize the literature relevant to the original study and the replication
- Discuss any issues with the original study that have been raised in the literature

III. Methodology

- Describe the data and methods used in the original study
- Explain the steps taken to replicate the original study, including any changes made to the methods or data
- Discuss any challenges faced in replicating the original study

C1. Replication Methodology: In this subsection, we describe the methodology used to replicate the original study. We provide a detailed explanation of the data and methods used in the original study, including any necessary assumptions or model specifications. We also explain the steps taken to ensure that our replication accurately reproduces the original study's results.

The authors 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 randomisation resulted in balanced groups they regress household observables and farming observables on treatment group dummies and a constant. The constant reflects the comparison group and the coefficients indicate whether other groups are significantly different from the comparison group. They 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 conduct regression analysis with and without additional controls including *Kebele* fixed effects and all baseline socio-economic characteristics, all showing that uptake change induced by *Iddir* promotions in isolation is statistically insignificant, as is IOU with binding contract. They 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, and the result shows robustness.

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.

To accurately replicate the results reproduced in the original study, we follow the steps shown in the paper and try to explain the dicrepancies if there are any of them. The steps of our replication are described as follows.

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. The randomisation works well if we see the coefficients of the treatment dummies are not significant, which shows that covariates do not affect the treatment assignment and therefore there is no severe selection bias.

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 exclude the subsample from a the *Kebele* Dalota Mati and run the same regression. We also conduct Wald tests to test if the coefficients of each two treatment dummies are statistically the same, verifying whether the treatment effects of different types of insurance designs differ.

C2. Extension Methodology: In this subsection, we describe the methodology used for our extension analysis, which seeks to estimate heterogeneous treatment effects using a multi-arm causal forest approach. We provide an overview of the statistical methods employed, including any necessary assumptions or model specifications.

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 $\hat{\mu}(x)$ using

$$\hat{\mu}(x) = \frac{1}{|i : X_i \in L(x)|} \sum_{|i:X_i \in L(x)|} Y_i. \tag{1}$$

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 $\hat{\tau}(x)$ using

$$\hat{\tau}(x) = \frac{1}{|i : W_i = 1, X_i \in L|} \sum_{|i:W_i=1,X_i \in L|} Y_i - \frac{1}{|i : W_i = 0, X_i \in L|} \sum_{|i:W_i=0,X_i \in L|} Y_i. \tag{2}$$

on the I sample. Following Athey and Imbens (2016), the splits of the tree are chosen by maximizing the variance of $\hat{\tau}(x)$ for $i \in J$.

Step 2: Propensity trees use only the treatment assignment indicator W_i to place splits, and save the responses W_i 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.

C3. Estimating Heterogeneous Treatment Effects: In this subsection, we provide a detailed explanation of our approach to estimating heterogeneous treatment effects using the multi-arm causal forest method. This includes information on the choice of tuning parameters, model diagnostics, and methods used for inference.

Our approach to estimating heterogeneous treatment effects using the multi-arm causal forest method consists of several steps:

Data preparation: We first prepare the data by selecting relevant covariates and outcome variables, and by converting categorical variables to numeric ones. We also specify the reference level for the treatment variable.

Propensity score estimation: We estimate the propensity score, which is the probability of receiving treatment conditional on the covariates. This is done using logistic regression, where the treatment variable is the dependent variable and the covariates are the independent variables.

Causal forest estimation: We then estimate the causal forest using the multi-arm version of the method, where we include all treatment arms in the model. The causal forest is a collection of decision trees, where each tree predicts the outcome variable for a particular treatment arm, given the covariates and the propensity score.

Treatment effect estimation: Once the causal forest is estimated, we use it to estimate the heterogeneous treatment effects. This is done by calculating the difference in predicted outcomes between each treatment arm and the reference arm, for each individual. These differences are the estimated treatment effects.

C4. Sensitivity Analyses: In this subsection, we describe the sensitivity analyses conducted to assess the robustness of our results to potential model misspecification and data limitations. We also discuss any limitations or caveats to our approach and provide suggestions for future research.

We also perform a sensitivity analysis to assess the robustness of our results to different specifications of the causal forest model. This involves varying the parameters of the model, such as the number of trees and the minimum leaf size, and comparing the estimated treatment effects across different models.

C5. Challenges and Limitations: In this subsection, we discuss any challenges faced in replicating the original study, including any discrepancies or issues with the data or code. We also discuss the limitations of our replication and extension analysis and provide suggestions for improving future research.

When checking the dataset we obtained from the official resource, we found that the numbers of *Iddirs* of three groups—IBI, IOU and IOU_C, are much larger than the results in the original paper, while the total number of *Iddirs* and the numbers of observations of all groups are consistent. This issue indicates the fact that households in each *Iddir* received different kinds of treatment, which is inconsistent with what the authors state in the paper. And the original paper does not explain whether/how they recategorise the households into new *Iddirs*. We tried to contact the corresponding author, but he could not provide us a clear explanation in time because of some private reasons. So, due to this ambiguity, our randomisation does not work as well as that of the original study, and it leads to regression results that are different from those obtained by the authors.

IV. Results

- Present the results of the replication study and compare them to the original results
- Discuss any discrepancies between the two studies and their potential causes

The results of randomisation are shown in Table 1 and 2, from which we can see that the significance levels of much more coefficients increase compared to the original paper. It means that different treatment groups produce on average very different products and thus the treatment status may affect almost all important observables. Therefore, we cannot ignore the selection bias. We believe this is resulted from the data issue we show in the last section. However, we cannot correct it and the reliability of our study will be declined.

Table 1 Balance tests on socio-economic variables.

Table 2 Balance tests for production variables and savings.

Figure 2 presents insurance uptake across treatment arms. The delayed payment of insurance offered by the IOU product increases uptake substantially when compared to standard insurance, from 8% to 24%. By far, the combination of IOU and promotion through Iddir outperforms all other treatments: uptake rates increase to around 43%. Our results are the same as those in the original paper, except Group 6 that were offered the most elaborate package including IOU, *Iddir* leader promotion, as well as the binding contract. The uptake rate of this group is a bit lower than that of the original experiment (27% vs. 32%). We checked the data and found out the reason for this discrepancy: there were 80 households (around 5%) in this group finally took up an IOU via *Iddir* but WITHOUT a contract, which fills exactly the gap between our result and the authors'. From this we know the authors take these households into account when calculating the uptake rate of this certain group. In our subsequent research, we follow the authors' way of calculation.

Fig. 2. Uptake rates across IOU treatments, 95% CI clustered at Iddir level.

The results of regression analysis (Table 3) are also quite similar to what the authors obtained. Uptake of individual IOU contracts is not significantly greater than standard insurance in the presence of a binding contract. IOU insurance with and without Iddir promotion both have significant positive effects on the uptake rate. However, introducing a binding contract to the IOU has a chastening effect on uptake rates with and without Iddir promotions, suggesting that much of the additional adoption induced by delayed payment is either motivated by the prospect of strategic default, or the result of farmers who are unsure about their ability to pay the future premium – and thus scared away once a binding contract is introduced – also in the absence of opportunistic intentions. People need a high degree of trust to sign a binding contract—especially when the consequences of signing are possibly not fully understood. The Iddir could assuage such concerns by acting as a trusted third party, resulting in increased uptake rates also in the presence of a contract. However, in our results, Index Insurance via Iddir has a significant impact on the uptake in the parsimonious model, which may also be caused by the data issue.

Table 3 Insurance uptake rates increase under IOU.

V. Extension

- Describe any additional analyses or tests performed using the replicated data
- Discuss the implications of the extended analysis for the original findings and the literature

VI. Conclusion

- Summarize the findings of the replication and extension studies

- Discuss the implications of the replication for the original study and the literature
- Recommend any changes to the original methods or data for future research

In this study, we replicate the main results obtained by Belissa et al. (2019) and use the causal forests developed by Waiger and Athey (2017) to conduct heterogeneity analysis, trying to have a closer look at the heterogeneous effects of the multi-arm treatments of the insurance design on households with different socio-economic and production characteristics.

The replication task does not fully reproduce the results obtained by the authors. We download the dataset from the official website and find an obvious data issue that leads to discrepancies in the results—the numbers of *Iddirs* of three treatment groups are much higher than those shown in the original paper. This indicates that some *Iddirs* received different types of policy impacts, which is different from what the authors state in the paper. With inability to solve this issue, we show that our randomisation does not work as well as the original study. However, we still obtain very similar results in the subsequent analysis, including the uptake rates of different types of insurance designs and the effects of the insurance designs gained from the regressions. We can still conclude that delaying weather insurance payment (IOU) increases uptake and promoting weather insurance via *Iddir* leaders increases uptake of IOU. And we also find a negative role of binding contracts.

We then use the multi-arm causal forest to extend the heterogeneity analysis.

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MATHEMATICAL APPENDIX