Agricultural Microcredit for Tenant Farmers: Evidence from a Field Experiment in Bangladesh [1]

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We study the impact of agricultural microcredit on the livelihood of small, marginal and landless tenant farmers in Bangladesh based on a randomized control trial (RCT). Twenty percent of eligible households acquire at least one microcredit program loan within two years of intervention. Results show that access to credit has some positive but imprecise effect on adoption of modern variety (MV) and yield rate of rice. The microcredit program increases crop farm income but has no significant effect on total income or expenditures. Although the program does not have any significant effects on household aggregate welfare, it transforms farmers' livelihood by increasing farming activities and productive asset holdings. Our study suggests that facilitating access to credit without addressing other constraints is not enough to increase investments and profits of the tenant farmers.

Keywords: Agricultural microcredit, Tenant farmer, Machine Learning (ML)

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1 Introduction

Access to credit is an enabling factor to adopt productivity-enhancing practices for credit-constrained farmers in developing countries. Credit-constrained farm households often cannot smooth consumption, resulting in sub-optimal input allocation or risk-inefficient crop choices (Kumar et al., 2013) and low productivity (Ali et al., 2014). However, access to credit is not universal; each type of financial institution typically has a targeted client group. Formal financial institutions (e.g., banks and cooperatives) are usually reluctant to lend to poor households with inadequate collateral (Littlefield and Rosenberg, 2004; Burgess and Pande, 2005). Rather, microfinance institutions (MFIs) typically lend to poor households (González, 2014), but even they prioritize non-farm businesses over farming activities (Armendáriz and Labie, 2011; Beaman et al., 2014). This phenomenon is more severe for farmers who own little land or rent land (henceforth referred to as tenant farmers) in developing countries (Hossain and Bayes, 2009).

In this study, we examine the impact of access to agricultural microcredit on the livelihood of tenant farmers in Bangladesh using a randomized control trial (RCT). The agricultural microcredit program is known as *Borgachashi Unnayan Prakalpa* (BCUP) and is administered by BRAC, one of the largest non-governmental organizations (NGO) in the world. For our study, we administer the experiment in 40 BRAC branches in rural Bangladesh, in which 20 branches are represent the treatment group and 20 branches represent the control group. The dataset consists of a single baseline and a follow-up survey conducted in 2012 and 2014, respectively. Total sample consists of 4,301 farm households: 2,155 from the treatment group and 2,146 from the control group.

Although several studies examine the role of agricultural credit on the livelihood of farm households, we examine the impact of a microcredit program designed specifically to increase the financial inclusion of tenant farmers. Previous literature on the role of agricultural credit is not conclusive. Beaman et al. (2014) find that access to loans increases investment in cultivation and agricultural output, but it has no significant effect on the net profit of farmers. A literature review by González (2014) finds inconclusive results on the impact of agricultural loans on the livelihood of farmers. There are also studies on the impact of general microcredit on business entrepreneurs. For example, Banerjee et al. (2015b) review six studies on the impact of microfinance on the livelihood of small and medium business entrepreneurs and find none of the interventions has any significant effect on household income or expenditures, albeit there are some transformative effects on the expansion of business activities. Our study provides new evidence on the role of agricultural microcredit and the comparability of agricultural microcredit to general microcredit.

After two years of BCUP intervention, 20% of eligible farm households in the treatment group acquired at least one loan from the BCUP program. The average loan amount for this group was BDT 31,100 (US$400)[2], which is approximately equal to the production cost of rice per one hectare of land.[3] To estimate the impact of the BCUP program, we apply the intent-to-treat (ITT)[4] method on various outcome variables, including the adoption of MV rice (i.e., high yielding variety (HYV) and Hybrid), rice yield rate,[5] and household income, along with other outcome variables. We apply the difference-in-difference (DID) model to estimate treatment effects. We additionally use the wild-cluster bootstrap (WCB) and randomization inference (RI) methods to estimate robust inference given that we have only 40 clusters. We additionally use the analysis of covariance (ANCOVA) method to check the precision of the treatment estimates.

Our results show that the BCUP program increases the probability of adopting HYV and Hybrid rice by 12 and 6 points, respectively, in the *Amon* (monsoon rice crop) season. Treatment households are also 7 points more likely to adopt Hybrid rice in the *Boro* (irrigation-intensive dry season rice crop) season. However, the ANCOVA method shows no significant effects on adoption rate of MV rice. We find that the BCUP intervention increases yield rates of rice by 0.66 ton per hectare and 0.47 ton per hectare in *Amon* and *Boro* season, respectively; these gain in rice yield rates are 53% and 15% compared to average yield rate in *Amon* and *Boro* seasons, respectively, in the control group during the same period. We find that the BCUP intervention increases farm income by BDT 4,700 ($59), decreases wage income by BDT 5,132 ($64), and has no significant effect on total income. Our results show some imprecise positive effect on owned-land cultivation and ownership of more livestock assets, e.g. cows and goats. Using a sub-sample data, we also find that children and working-aged male and female members increase time allocation in farming activity in the treatment group compared to control group.

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Results from the quantile regression analysis show that increase in crop farming income is statistically significant and positive in all the quantiles of crop farming income distribution, although impacts are proportionately larger in the upper tail of the distribution. In the case of rice yield rate, the impact of the BCUP program is concentrated in the upper quantiles of the yield rate distribution. Our findings are robust to alternative specifications; we show that the positive effect of the BCUP program on MV rice adoption, rice yield rate, and farm income activity are not driven by factors other than the BCUP loan. We use the Causal Forest (CF) method following Wager and Athey (2017) to estimate the heterogeneous treatment effect on the main outcome variables and find that the treatment effects are heterogeneously distributed.

Our study complements as well as adds new evidence to the literature on agricultural and general microcredit. We find no overall positive impact of BCUP intervention on household income or expenditures, but we notice a transformation in the economic activities of farm households to adopt MV rice and allocate more time in self-employment activities to increase their income in the crop farming sector. These findings along with low take-up rate are evident in the general microcredit literature as well. Overall findings suggest that only increasing the availability of financial services may not be enough to improve welfare of farmers.

2 Background of BCUP Intervention

About 70% of the total population of Bangladesh lives in rural areas where agriculture is the primary source of employment and income (Gautam and Faruqee 2016). Tenant farmers who rent land make up a large part of the farming system. Over the last 25 years, the share of tenant farmers has increased from 44% to 58%, while their share of land operations has increased from 23% to 42% (Hossain and Bayes 2009). However, financial services for tenant farmers remained inadequate during the same period. The market share of formal financial institutions providing credit to farmers remained stagnant at around 16% to 32% (Faruqee 2010). Hossain and Bayes (2009) show that only 1.5% of farmers who own less than 0.2 hectare of land has access to bank credit. Although the number of MFIs has increased over time, their role in crop agriculture has not increased proportionally. For instance, two leading MFIs in Bangladesh, Grameen and BRAC, disburse only 15% and 13%, respectively, of their total loans for farming (Faruqee 2010). Therefore, access to credit for tenant farmers has remained a key challenge in rural areas of Bangladesh.

3 The BCUP Program

BRAC launched the BCUP program in 2009, with financial support from the central bank of Bangladesh. The main objective of the BCUP program is to increase the credit access of tenant farmers to formal financial institutions. According to BRAC Microfinance administrative data, the BCUP program has disbursed a total of US$2,500 million in loans to about 400,000 farmers as of March 2017. BRAC follows a multi-stage selection process to ensure that credit goes to targeted farmers. In the first stage, farmers must meet the following eligibility criteria: must have a national identification card, must be 18 to 60 years of age, must have resided in the area for at least three years, must have landholdings below 200 decimals (less than one hectare), and must not be a current member of another MFI. In the second stage, program organizers (POs) visit the proposed investment sites of eligible applicants to ascertain whether the loan is for farming activities. After the initial screening stages, the branch manager and POs provide detailed information about BCUP program's terms and conditions to eligible farmers. Once a farmer agrees to take a loan, (s) he is assigned to the nearest village organization (VO). A VO typically consists of four to eight teams of five farmers each from a village/community; the VO works as the primary platform for the discussion of loan utilization and collection of due installments.

The BCUP program offers several types of loans depending on farmers' needs and previous experience with loan utilization and repayment. A loan for crop production is typically the first loan for a new client from the BCUP program, which ranges from BDT 5,000 (US$63) to BDT 50,000 (US$625). BCUP also offers a maximum of BDT 60,000 (US$769) to rent land from others and a maximum of BDT 120,000 (US$1,500) for purchasing machinery. In fact, BRAC's recent record shows that 71% of BCUP loans are for crop cultivation, and the remainder is for non-crop farming activities such as livestock, fishery, land lease, and machinery purchases. As none of our samples had experience of utilizing loan from the BCUP program before, it is expected that farmers are more likely to get loans for crop production during our study period. The usual loan repayment period is one year with equal monthly installments. The farmers pay 19% interest on a reducing balance rate, which is lower than the 27% rate charged by the other microfinance programs in Bangladesh. If a farmer fails to repay installments in due time, s/he needs to pay the added interest in the remaining installments. The BCUP program had complementary extension services in the initial years, when BRAC's agricultural development officers (ADO) provided information and advice on modern cultivation systems and farm management during the monthly VO meetings. However, BRAC stopped providing extension services in 2012 due to high attrition rates and high recovery costs. Thus, our evaluation is only limited to the impact of microcredit.

4 Experimental Design

We administered a cluster-randomized control trial experiment to evaluate the impact of the BCUP 511035065program511035065HMHossain,Md Marup511035065660884170Let's give the reference here after the acceptance. Ok?. Forty BRAC branches were randomly chosen, with 20 assigned to the treatment group and 20 assigned to the control group. For each branch, we randomly selected six villages within an eight-kilometer radius of the BCUP branch office, for a total 240 villages.

We conducted a household-level census to identify eligible households in all 240 villages. The census covered 61,322 households, among which 7,563 households fulfilled the eligibility criteria and were will to take an agricultural loan. We randomly selected 4,301 households from the eligible household list as our study sample. We present the similarity between the selected and non-selected eligible households in Annex table 1. Results show that both groups are statistically similar in all the eligibility criteria used to select the sample for this study. The mean difference between the two groups is significant for only one (cultivated land) out of ten variables at the 10% significance level.

Once the baseline survey was completed, we randomly selected 20 BCUP branches for the treatment group and 20 BCUP branches for the control group. The final sample includes 2,155 households in the treatment group and 2,146 households in the control group. We also collected time allocation information from a subsample of 1,607 households. Contamination between the treatment and control BCUP branches is unlikely because each branch is located in a different sub-district and each sub-district is a separate government administrative unit with a well-known geographical boundary. We present the locations of the treatment and control branches in Annex figure 1, which shows that only a few treatment and control branches are located next to each other. Because the BCUP program administration was aware of the status of each branch in the study, it was unlikely that the POs would disburse loans in a control branch.

One important aspect of the sample of this study is that none of the participants could be a member of any other microfinance institution during the selection period. Therefore, sample of this study is different from microfinance members. From our census data, we find that 43% of the households have at least one member having microfinance involvement. We present households characteristics by their microfinance membership in Annex table 2. Results show that households with microfinance membership have higher household size and are better educated on average. Microfinance households have less cultivated land and rent more land from other households compared to non-microfinance households.

After the baseline survey, we gave the list of treatment branches to BRAC-BCUP administration, whereby BRAC launched the BCUP program in all the treatment branches. The POs visited all the villages to locate borrowers following the same criteria mentioned in the previous section. We did not provide information on our study sample to the BCUP program, but we expected the BCUP program would select our sample households eligible for loans.

5 Baseline Survey and Balance

We conducted the baseline survey in July-August 2012 to collect detailed information on household demographics, asset holdings, expenditures, farming systems, engagement in economic activities, and income. We expect no systematic differences between the treatment and control groups at the baseline because treatment status was randomly assigned. Table 1 shows a statistical comparison between the treatment and control groups. We present the baseline mean for the control and treatment groups in columns 1 and 2, respectively, and the mean differences in column 3. In addition to absolute mean differences, we also present the normalized difference[6] between the two groups for each variable in column 4. The normalized difference is used to assess the similarity in the covariates' distributions (Imbens and Wooldridge, 2009). The significance level of the mean differences (p-value) is presented in column 5. ay of assessing similarity in covariates' distributions . The significance level of the mean differences (p-value) is presented in column 5.

[Table 1 here]

Results show the treatment and control groups are well balanced for most of the covariates. The mean differences between the treatment and control groups are different for 2 out of 37 variables listed at the 10% significance level. Results also show that all normalized differences are less than 0.15. An important point to note is that for some of the outcome variables, although the mean differences are not statistically significant even at the 10% significance level, we notice the magnitudes of the differences are large (e.g., farm and non-farm business incomes, number of goats, etc.). In the regression framework section, we discuss in detail our impact-identifying strategy in the presence of such differences in the baseline characteristics. From the baseline data, we find that 7% of the control group and 5% of the treatment group have an NGO membership before the survey, which occurred because sample households misreported their microfinance membership during the census. We expect this is not a large percentage to generate a biased impact estimates. Nevertheless, we estimate program impacts excluding these households as a robustness check.

We can also examine the overall characteristics of our sample from table 1. Average households size is five persons, with a male member (94%) heading most of the sample households. Household heads are typically less educated, with only three years of formal education on average. Sample households also belong to the lower tail of the distribution of land. Households have limited ownership of cultivable land (0.15 hectare). The smaller amount of landholdings also implies that some households may resort to the rental market to increase the size of their operational land. Our baseline data show that around 64% of the households are either purely tenant farmers or mixed tenant farmers who cultivate both owned and rented land.

6 End-line Survey and Attrition

We conducted the follow-up survey in July-August 2014, two years after the baseline survey. We successfully re-interviewed about 96% of the respondents. The attrition rate was similar between the treatment and control groups: 3.9% in the treatment group and 3.6% in the control group. A small percentage of attrition is expected because one of the eligibility conditions of this study that a household needed to be a permanent resident of the village. We check whether the attrition rate is different between the treatment and control groups, which could potentially create biases in impact estimates. We also test whether the attrition rate is related to any observed characteristics.

Annex table 3 shows the regression results. We find that household treatment status is not significantly related to attrition rate in any regression specifications. We include observable characteristics in column two and find only the household head's education level has a significant relationship with the attrition rate at the 10% significance level. In column 3, we additionally control the interaction of treatment status and observable characteristics, and find that only the interactions of household size and landholdings with the treatment status are statistically significant. As we do not find any consistent pattern in the relationship between attrition rate and observable characteristics, we conclude that the attrition rate is unlikely to generate any biases in our impact estimates. The rest of our analysis is based on the 4,141 balanced panel households, where 2,072 are from the treatment group and 2,069 are from the control group. For the time allocation analysis, we use a balanced panel data of 1,236 households.

7 Regression Framework

We use the intention-to-treat (ITT) method that compares the average outcomes of the treatment and control groups to estimate the impact of BCUP intervention on the outcome variables. ITT estimates are based on initial treatment assignment irrespective of households' actual participation in the program. Because we find that some of our outcome variables are not perfectly balanced, we estimate the program impacts, adjusting for baselines covariates. We use the difference-in-difference (DID) model in the estimation. Consider the following regression model,

$$Y_{it} = \alpha + \beta_1 T_i + \beta_2 W_t + \beta_3 (T_i \times W_t) + \mu X' + \eta_d + \varepsilon_{it}, \tag{1}$$

where Y_{it} is an outcome for household i at time t, T_i is a dummy variable indicating the treatment status, W_t is a dummy variable taking the value of 1 if the observation is from 2014 and 0 otherwise, X is a vector of the bassline covariates, and ε_{it} is an idiosyncratic error. We control the district-level fixed effects (η_d) to improve the efficiency of the estimates (Bruhn and McKenzie, 2009). β_3 is the ITT estimate showing the average impact of the BCUP program on outcome variable Y.

We cluster all standard errors at the branch level to account for intra-cluster correlation. Although the clustered standard error is widely used, it has limitations as its biasness depends on the number of branches instead of the number of households. Cameron and Miller (2015) propose a wild bootstrap procedure when the number of clusters is not too small. Following Cameron and Miller (2015), we re-estimate the standard errors based on the wild cluster bootstrap (WCB) procedure, which is expected to minimize biases in estimation. WCB estimates the error term from equation (1) and creates bootstrap datasets to estimate the distribution of $\hat{\beta}$. MacKinnon et al. (2016) show that different versions of WCB can also over-reject or under-reject a hypothesis and find that the randomization inference (RI) does a better job in case of a small number of clusters. RI is a permutation-based method to examine whether the treatment effect estimated in equation (1) is observed by chance. RI estimates the distribution of $\hat{\beta}$ using all the alternative combinations treatment assignment. It is important to note that RI tests a sharp null hypothesis of the zero-treatment effect on individual households, whereas the DID model tests a null hypothesis of the zero-average treatment effect. In the Appendix, we detail the steps of the WCB and RI methods. These two methods of inference complement one another. WCB checks whether our conclusions are robust allowing individual treatment effects to vary. RI checks whether our conclusions are robust not relying on asymptotic normal approximations. The advantage of RI is that it is strictly based on the randomization.

ANCOVA (or lagged dependent variable model) is another alternative model to estimate the causal effect of BCUP intervention adjusted for baseline difference. McKenzie (2012) suggests that with a single baseline and follow-up survey, the ratio of variances of DID and ANCOVA estimators is $2/(1+\rho)$, where ρ is the autocorrelation between the baseline and follow-up information. The author mentions that although estimating DID is a common practice in many experimental studies, the ANCOVA estimator is preferable in terms of gaining more power in estimation. We estimate the ANCOVA estimator using the following equation:

$$Y_{iPOST} = \alpha + \beta_2 T_i + \beta_1 Y_{iPRE} + \mu X' + \eta_d + \varepsilon_{it}, \tag{2}$$

where all the notations are the same as equation (1). Y_{ipost} and $Y_{iPRE}$are end-line and baseline values of an outcome variable, respectively. β_2 is the ANCOVA estimator. Like with the DID model, we cluster standard errors at the branch level and control the same set of baseline covariates and district-level fixed effects in the ANCOVA model.

8 Results

8.1 *Access to Credit*

Table 2 presents the impact of BCUP intervention on household access to credit from different sources. We consider other sources (e.g., banks, other MFIs, and informal lenders) to examine whether the BCUP loan substitutes for or complements other credit sources. We show impact estimates on whether a household acquires a loan in panel A, and the respective amount in Panel B. In panel A, we find that treatment households are 20 points more likely to acquire a loan from the BCUP program. We do not find any significant impact of BUCP intervention on borrowing from other sources. Therefore, there is no substitution or complementary effects of the BCUP program on loans from other credit sources. In panel B, we find the treatment group borrows on average BDT 6,230 (US$78) more from the BCUP program compared to the control group. Like in panel A, we do not find any significant impact of the BCUP program on the amount of borrowing from other credit sources.

[Table 2 here]

Results based on WCB and RI show that the BCUP program increases participation and amount of loan from the BCUP program similar to the DID model. However, results from the ANCOVA model show that BCUP intervention increases the probability of acquiring a loan from banks and Grameen, while reduces the probability of taking loan from other NGOs, although the magnitudes of these coefficients are quite small. During the follow-up survey, we collected self-reported loan utilization information from respondents; participant households spent around 43% of the total loan on crop cultivation, followed by 14% in livestock, poultry, and fisheries. Households also used 13.4% of the total BCUP loan for investment in non-farm business activities. Farmers used a small portion of the BCUP loan in other activities, such as to repay earlier debts (6.7%) and house repairs (5.9%). Around 35% of the participant households reported that they repaid loans from self-employment activities, and 55% reported that they repaid loans from wage, service, or remittance income.

8.2 *Modern Varieties (MV) Rice Adoption and Rice Yield*

Rice comprises 75% of both total crop production and cultivated area in Bangladesh (Talukder et al., 2014). Thus, MV rice adoption and rice yield rate are the main outcomes of interest in this study. There are three rice seasons in Bangladesh: *Aus*, *Amon*, and *Boro*.[7] The importance of the *Aus* season has declined substantially with the availability of MV rice and improvements in irrigation facilities over time. For the study, we estimated the impact of the BCUP program on the yield rate and adoption of HYV and hybrid rice in the *Amon* and *Boro* seasons.

Results are presented in Table 3. Panel A also shows the impact on the adoption of MV rice in the *Amon* and *Boro* seasons. We find that treatment households are 12 percentage points more likely to adopt HYV rice and 6 percentage points more likely to adopt hybrid rice in the *Amon* season, and are 8 percentage points more likely to adopt hybrid rice in the *Boro* season. Results from WCB and RI also confirm findings of the DID model. Impact on HYV adoption in the *Amon* season is 46% of the average adoption rate in the control group. Impact on adoption of hybrid in the *Amon* and *Boro* seasons is more than 100% compared to the mean adoption rate in the control area, but it is important to note that the mean adoption rate in control area is very small during the same time. In fact, our results from the ANCOVA model show that the BCUP intervention has no significant effect on MV rice adoption. Moreover, the coefficient of HYV in *Boro* season is negative and significant at 10% significance level. Thus, impact on MV rice adoption is inconclusive.

[Table 3 here]

Panel B shows the impact of the BCUP program on yield rates in the *Amon* and *Boro* seasons along with the aggregate yield rate. We find that BCUP intervention increases yield rates by 0.66 ton per hectare and 0.47 ton per hectare in the *Amon* and *Boro* seasons, respectively, and 0.50 ton per hectare in the *aggregate*. Compared to the mean of the control group during the same time, increase in yield rates is 53% in the *Amon* season and 15% in the *Boro* season. ANCOVA results show that only the impact on yield rate in the *Amon* season is significant, and it is approximate 46% of the mean yield rate in the control group.

The quantile regression estimation showing the distribution of impacts on yields for both the *Amon* and *Boro* seasons are presented in Annex figure 2. There is very little or no difference in yields between the treatment and control groups until the 70th percentile, which indicates that most of the impacts belong to the upper tail of the distributions of yields in both seasons. Overall, we do not get any precise impact on adoption and yield rate except for the *Amon* season.

8.3 *Income and Expenditures*

We examine the impact of the BCUP program on income and expenditures because both indicators reflect household welfare. Results are presented in Table 4. Panel A shows the impact on household income from different sources, and panel B shows the impact on expenditures. We find that BCUP intervention increases farm income by BDT 4,700 (US$59) and decreases wage income by BDT 5,132 (US$64) in the treatment group compared to the control group. The impact is positive for business income, although it is not statistically significant. There is no impact on total income.

[**Table 4 here**]

As before, the WCB and RI tests confirm the results of the DID model. From the results using the ANCOVA model, we find that BCUP intervention increases farm income by BDT 4,900 (US$61), but it has no significant effect on wage income. Appendix figure 2 shows the distributions of the impact on farm and wage income using quantile regression analysis. We find that the gain in farm income is significantly positive for the entire distribution of farm income, but it is proportionally larger in the upper quantiles. On the other hand, the impact on wage income is significantly negative only around the 40th to 70th quantiles of wage income. There are no significant differences between the treatment and control groups in the lower tail of the wage income distribution, and the point estimates are approximately zero. Panel B shows the effect of BCUP intervention on household food, non-food, and total expenditures. We find no significant effect on any expenditure indicators.

8.4 *Labor Supply*

As most of the farmers in our study are marginal and landless, it would not be surprising if some farmers work additional hours to increase profits in the presence of additional working capital after participating in the BCUP program. At the same time, additional capital can also affect the number of working hours of the other members of a household. From our findings in the previous section, we notice an increase in crop farming income in the treatment group, which could cause the number of working hours in self-employment activities to increase in the treatment group.

Table 5 presents the impact of the BCUP program on the time allocation of household members by age and sex categories. We show results for four household groups: children (ages 5–14), males (ages 15–64), females (ages 15–64), and seniors (over age 64). Results from the DID model shows that the BCUP program has no significant effect on time allocation except that women and older-aged members work more hours in household activity. On the other hand, ANCOVA results show that children and working-aged male and female members work more hours in crop farming activity after the BCUP intervention. We also find that working-aged male members reduce time allocation in non-farm and household activities, while older-aged group increases time allocation in household activity.

[Table 5 here]

8.5 *Landholding and Livestock Assets*

One of the main objectives of the BCUP program is increasing the farming activity of credit constrained farmers. If the BCUP program relaxes credit constraint, we would expect that farmers will engage more in farming activity and hence, their amount of land cultivation is likely to increase. BCUP program can also increase productive asset holding of participant farmers as a livelihood diversification strategies; productive assets can work as buffer stocks in case of financial difficulties or crop failures. In this section, we examine whether the BCUP loan increases household access to land and livestock assets (e.g., cows and goats).

[Table 6 here]

Results are presented in table 6. We do not find any significant effect of the BCUP program on amount of land cultivation, although the point estimates for owned land and rented-in-land are considerably large. We find the BCUP participants hold significantly higher numbers of cows and goats compared to the control group. Once again, WCB and RI methods confirm findings of the DID model. From the ANCOVA model, we find that the BCUP program increases owned land cultivation significantly; a 30% increase compared to the average owned land cultivation in the control group. BCUP intervention also reduces land renting-out to other households and increase holding more cows compared to the control group.

8.6 *Expenditure and Market Sales of Rice*

Our final set of outcome is household expenditure on rice, non-rice crop farming, and business activities. Results are presented in panel A of table 7. We do not find any significant effect of the BCUP program on these variables. All point estimates are positive and quite large in magnitude, especially for business activities. One potential reason for no significant effect on expenditures in farming activities can be the timing of the loan from the BCUP program. If a farmer uses loan money only during the first year of BCUP intervention, we might not see any change in the expenditures as we conduct follow-up survey after two years of the initial BCUP intervention.

[Table 7 here]

Panel B explores whether credit access increases farmers' waiting time to sell their products until they can get a desirable price. This is a critical issue because many farmers acquire loans from informal sources to cover production costs and must sell their products immediately after harvesting at a lower price to repay the loan. We expect that the BCUP credit access relaxes this constraint and helps tenant farmers to wait for desirable prices to sell their crops. Our results show no significant changes between selling within 1 month of harvesting and selling in the next 11 months, although point estimates are positive for sales in the last 11 months and negative for sales within 1 month.

9 Robustness Checks

We perform additional robustness checks of our impact estimates in three alternatives. First, we estimate the impact of the BCUP program by dropping households that had MFI memberships at the baseline. As we mentioned before, 6% of our sample were MFI members, although we are not supposed to have any microfinance members during the baseline survey. Second, we winsorize values of continuous outcome variables above the 95^{th} percentile with the value at the 95^{th} percentile to reduce the sensitivity of treatment effect by extreme values. Third, one of the concerns for program estimates is whether MV rice adoption and rice yield rate are driven by factors other than microcredit (e.g., extension services). We re-estimate program impacts controlling for access to extension services from other agents (e.g., government extension officers). We control extension indicator as additional control in equation(1).[8]

[**Table 8 here**]

We present robustness results in table 8 for three main sets of outcome variables: adoption rates, yield, and income. Column 1 shows impact estimates from our earlier results using the DID model. When we drop households with MFI membership during the baseline survey, coefficients of MV rice adoption and rice yield rate remain similar, but the magnitude of the coefficients of crop farming income decrease while wage income increase, which implies that pre-MFI treatment households gain more in crop farming activity from BCUP credit program participation. After winsorizing the top 5% extreme values, we find that the impact estimates become smaller consistently, and the impact on income from other sources becomes negative and significant. Finally, we find that exposure to extension services from other sources does not alter program estimates significantly.

10 Heterogeneous Treatment Effect

The heterogeneous treatment effect is often a point of interest to policymakers and other stakeholders alongside the simple average treatment effect. The most common strategy in heterogeneity analysis is to use the subgroup analysis where treatment effects are estimated for each group (e.g., by age or sex of participants). One potential problem with the subgroup analysis is that researchers may purposively choose subgroups with higher treatment effects or report only extreme effects (Assmann et al., 2000; Cook et al., 2004). Moreover, choosing a large number of subgroups can generate overfitting in the model (Chernozhukov et al., 2017). Non-parametric methods (e.g., nearest-neighbor matching, kernel methods or series estimation) work well with a small number of covariates, but those can break down as the number of variable increases (Wager and Athey, 2017). To overcome these shortcomings, a growing number of studies are using ML tools to estimate heterogeneous treatment effects nowadays. ML methods are ideal for estimating treatment heterogeneity when a large number of baseline covariates are available, and researchers have limited guidance on which variables are relevant (Chernozhukov et al., 2017).

We estimate treatment heterogeneity using the Causal Forest (CF) method following Wager and Athey (2017), which is based on an ensemble of causal trees. Causal trees predict the conditional average treatment effect (CATE) for a subgroup such that $x \in R_k$using the average difference between treatment and control outcomes as follows.

$$\hat{\tau}(x) = \hat{\tau}_{R_k} = \frac{1}{N_k(1)} \sum_{i \in R_k(1)} Y_i - \frac{1}{N_k(0)} \sum_{i \in R_k(0)} Y_i, \quad k = 1, 2, ..., k., \tag{3}$$

where $W \in (0, 1)$ showing control or treatment status of households, $R_k(W)$ is the observation set i such that $X_i \in R_k$, and $N_k(W)$ is the corresponding number of observations. Each causal tree is grown using a binary splitting rule that chooses a feature and cutoff yielding a maximum value of $\sum_{i \in R_k} \hat{\tau}(X_i)^2$ that also maximizes the variance of predicted treatment effects $\hat{\tau}(X_i)$. One limitation of such heterogeneity analysis is that we cannot say who had the largest or smallest effect.

In table 9, we present heterogeneous treatment effects for three main sets of outcome variables: MV rice adoption, rice yield rate, and household income. For comparability of ML estimates with non-ML estimates discussed in previous sections, we use the CF method to estimate the average treatment effect as well. Column 1 in table 9 shows the estimated ATE using CF model. We find that treatment effects using the CF method on MV rice adoption and yield rate of rice are very similar in sign and magnitudes to ATE estimates by non-ML methods. The ATE estimate of crop farming income is about half of the non-ML ATE estimate in magnitude, and the ATE of wage income is statistically insignificant. Columns 2 to 6 show average, median, minimum, and maximum values of treatment effects for the same set of outcome variables. In Appendix figures 4 and 5, we show histograms of heterogeneous treatment effects for all variables considered. We find that average and median treatment effects are very similar for all the outcome variables considered. Our results show a substantial heterogeneity in all variables, although treatment effects are mostly positively distributed.

[Table 9 here]

11 Discussion and Conclusion

We estimate the impact of an agricultural microcredit program intended to increase credit access of tenant farmers in Bangladesh. After two years of the BCUP program launching in the treatment area, we find that 20% of eligible farmers acquire at least one loan from the BCUP program and invest about 57% of their total loans in agricultural activities such as crop cultivation, and the livestock, poultry, and fishery sectors. We also find that the BCUP program increases MV rice adoption, rice yield rate, and crop farm income. However, we do not find any significant impact on household total income or total expenditures. Our results show some imprecise positive impacts on more land cultivation, working hours in farming activities, and livestock holdings. Like the literature on general microcredit, we conclude that the BCUP program has a transformative effect on the livelihood of tenant farmers in Bangladesh, but it does not have a significant impact on their overall welfare.

The take-up rate of the BCUP program is only 20%, which is very similar to the take-up rate in general microcredit related studies. Banerjee et al. (2015b) show that participation rate ranges from 17% to 31% in six microfinance studies. Participation rate varies over region, for example, 12.7% in India (Banerjee et al., 2015a), 10% in Morocco (Crépon et al., 2015), 10% in Mexico (Angelucci et al., 2015), and 36% in Ethiopia (Tarozzi et al., 2015). We explore determinants of participation in the BCUP program to examine who did or did not acquire loans. We use simple the mean difference test (T-test) and logit regression model to check whether loan participants and non-participants hold distinct characteristics. Results are presented in Annex tables 6 and 7, respectively. Our results show younger household heads are more likely to participate in the BCUP loan program. Additional wage income and business income increase the probability of loan participation, but more livestock holdings and better household infrastructure (access to sanitary latrine) reduce participation in the BCUP program.

One of the important findings of our study is that credit access increases household farm income but reduces wage income, which accounts for no net effect on total income. This finding is not surprising given other studies with similar findings. Banerjee et al. (2015b) find no statistically significant effect on household income in any of the six studies reviewed. They mention that two out of four studies report a positive business income accompanied by a reduction in wage income. Banerjee et al. (2015b) address such a transformation by microfinance as a positive sign because microfinance gives more freedom in choices and self-reliance for participant households. The impact of the BCUP program on MV rice adoption, rice yield rate, and time allocation can explain our findings of positive crop farm income. We show that the BCUP program has a significant positive effect on MV rice adoption and rice yield rates, and it also helps working-aged household members to spend more time in farming activities. The impact of microcredit on productivity is evident in other studies. For example, Ayaz and Hussain (2011) find positive effects on productivity in Pakistan, and Girabi and Mwakaje (2013) find positive impacts on farm productivity in Tanzania. Similarly, positive effects on time allocation are evident in studies by Attanasio et al. (2015) in Mongolia, and Banerjee et al. (2015a) in India. Our results can be interpreted as follows: an increase in MV rice adoption along with higher time allocation raises production, which increases household income in the crop farming sector.

Insignificant effects of the BCUP program on the overall welfare of farmers have implications for future policies toward financial inclusion of farmers.Foltz (2004) states that better access to the agricultural credit market may increase profits of rich farmers compared to poor farmers; he also states that the low-profit elasticity of credit (0.20) casts doubt on improving credit access in the agricultural sector. Beaman et al. (2014) find a similar result in a field experiment in Mali. Earlier literature indicates that credit may not be the only constraint for farmers. For example, Karlan et al. (2014) show that when cash grants are combined with insurance, farmers are more likely to invest in more risky crops. de Janvry et al. (2016) state that farmers are likely to utilize credit services when superior technology is available along with credit availability, such as flood-tolerant rice in India (Emerick et al., 2016) and contractual arrangement to produce high-value export crops in Kenya (Ashraf et al., 2009). Therefore, there is a need to add other components to the agricultural credit market.

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Notes

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[2] US$1=BDT 80

[3] Average cost of rice production is BDT 38,800 for rice and BDT 29,000 for non-rice per one hectare of land (Source: estimation from the survey data).

[4] We consider all the households from the random assignment in our analyses irrespective of their actual program participation.

[5] Yield rate is estimated as total production per unit of land (e.g., ton of rice per hectare of land).

[6] Normalized differences show the differences in average covariate values by treatment status, scaled by a measure of the standard deviation of the covariates.

[7] Aus is the pre-monsoon rice cultivation season, where rice is seeded April-May and harvested July-August. Amon is the rain-fed monsoon production period, where rice is seeded April-May and harvested November-December. Finally, Boro is the irrigation intensive dry-season rice production period, where rice is seeded December-February and harvested April-May. Rice was mainly local and HYV varieties until early 2000, when hybrid rice was introduced in Bangladesh. Hybrid rice, a type of rice bred from two very different parents, can significantly out-yield other rice varieties. The main differences between HYV and hybrid rice is that farmers cannot save seeds of the hybrid variety for future cultivation, and hybrid rice cultivation is highly irrigation intensive.

[8] During the baseline and follow-up surveys, we ask households if they meet any extension worker in their community or in any other palaces in the last year. These two variables are exogenous to BCUP intervention. We check whether BCUP intervention has any effect on these two variables and find no significant effect (results are not presented here). Therefore, these two variables are not post-treatment variables and we can control these variables in equation (1).

Table 1: Baseline Summary Statistics

	Control group	Treatment group	Mean difference	Normalized Differences	P-value (mean Diff)
	(1)	(2)	(3)	(4)	(5)
A. Household Composition					
Number of dependents	1.72	1.90	0.18	0.10	0.121
Number of working age members	3.02	3.03	0.00	0.00	0.959
Household size	4.75	4.93	0.18	0.07	0.296
Head's education	3.05	3.22	0.18	0.04	0.583
Head's age	44.51	45.11	0.60	0.04	0.373
Female head	0.05	0.08	0.03	0.08	0.124
B. Infrastructure					
Concrete floor (yes=1)	0.14	0.12	-0.02	-0.04	0.489
Use sanitary latrine (yes=1)	0.16	0.14	-0.02	-0.04	0.496
C. Access to credit					
Microfinance member (Yes=1)	0.07	0.05	-0.02	-0.06	0.070
Amount of Microfinance loan (BDT)	1502	919	-583	-0.05	0.109
Have informal loan (Yes=1)	0.04	0.02	-0.02	-0.06	0.160
Informal loan amount (BDT)	1773	1639	-134	-0.01	0.884
D. MV Adoption and Rice yield rate					
HYV adoption in *Amon* (Yes=1)	0.30	0.36	0.06	0.10	0.580
Hybrid adoption in *Amon* (Yes=1)	0.02	0.01	-0.01	-0.03	0.679
HYV adoption in *Boro* (Yes=1)	0.68	0.70	0.02	0.03	0.891
Hybrid adoption in *Boro* (Yes=1)	0.04	0.04	0.00	0.01	0.879
Yield rate in *Amon* (Ton/Hectare)	1.51	1.86	0.35	0.15	0.340
Yield rate in *Boro* (Ton/Hectare)	3.78	3.43	-0.35	-0.11	0.526
E. Income (BDT/year)					
Wage labor	33060	40108	7048	0.10	0.094
Crop farming	15004	11678	-3326	-0.10	0.184
Non-crop farming	6827	7474	647	0.02	0.451
Non-farm business	12039	15938	3899	0.06	0.158
Other sources	24374	32818	8445	0.05	0.272
F. Expenditure(BDT/year)					
Food	55453	58580	3127	0.09	0.254
Non-food	41343	39505	-1839	-0.04	0.498
G. Asset holdings					
Owned land (in Decimal)	38.83	37.66	-1.17	-0.02	0.726
Rented in land (in Decimal)	51.33	51.51	0.18	0.00	0.981
Rented out land (in Decimal)	7.77	8.42	0.66	0.02	0.574
Cow(Yes=1)	0.58	0.58	0.00	0.01	0.923
Goat (Yes=1)	0.26	0.18	-0.07	-0.12	0.158
H. Input use and market transaction					
Total rice cost (BDT/yearly)	14471	15631	1160	0.05	0.543
Total non-rice crop cost (BDT/yearly)	5180	2830	-2350	-0.11	0.250
Total business investment (BDT/yearly)	9749	7373	-2376	-0.02	0.587
Rice sale with 1 month (BDT/yearly)	10415	6448	-3967	-0.06	0.374
Rice sale in last 11 months (BDT/yearly)	2288	1556	-732	-0.06	0.421
Non-rice crop sale with 1 month (BDT/yearly)	8322	7110	-1212	-0.04	0.561
Non-rice crop sale in last 11 months (BDT/yearly)	6307	6271	-36	0.00	0.972

Notes: Number of households are 2155 and 2146 in treatment and control groups, respectively. Standa differences are clustered at the branch level. Normalized difference in column (4) is computed as the d means in treatment and control villages divided by the square root of the sum of the variances in column in column (5) is for the mean difference test between the treatment and control groups.

Table 2: Impact on Access to Credit

	BCUP	Bank & Cooperative	Grameen Bank	Other NGOs	Informal
	(1)	(2)	(3)	(4)	(5)
Panel A. Access to credit (1=Yes, 0=No)					
DID	0.201***	0.014	0.011	-0.013	0.011
	(0.027)	(0.013)	(0.015)	(0.014)	(0.012)
Wild Cluster P-Value	0.000	0.313	0.561	0.336	0.386
RI- P*	0.018	0.342	0.544	0.348	0.394
ANCOVA	0.119***	0.015**	0.015**	-0.029**	-0.002
	(0.019)	(0.007)	(0.007)	(0.012)	(0.008)
Control mean (Follow-up)	0	0.0353	0.0507	0.103	0.0387
Panel B. Credit amount (BDT)					
DID	6229.4***	386.7	391.7	-392	1516.2
	(885.7)	(901.1)	(450.5)	(864.7)	(2209.3)
Wild Cluster P-Value	0.000	0.670	0.462	0.656	0.647
RI (P*)	0.000	0.682	0.436	0.659	0.662
ANCOVA	3451.1***	347.8	498	-1158.5	3448.5*
	(621.0)	(468.0)	(313.7)	(968.2)	(1870.8)
Control mean (Follow-up)	0	2030.4	1206.4	3767	2197.5

Notes: N= 8282 in all specifications. Cluster-robust standard errors are in parentheses. Columns 1–5 report the probability of having one loan from the respective source in last year. The corresponding columns in panel B report the credit amount. "Informal lender" includes moneylenders and friends/family. Asterisk (*), double asterisk (**), and triple (***) denote variable significant at 10%, 5%, and 1%, respectively. RI- β P* test sharp null hypothesis of no treatment effect on any observations. Wild cluster p-value and RI- β P are estimated based on 5000 replications.

Table 3: Impact on Modern Variety Adoption and Yield Rate

Panel A. Modern variety adoption (1=Yes, 0=No)				
	Amon		*Boro*	
	HYV	Hybrid	HYV	Hybrid
DID	0.117**	0.059***	0.059	0.077***
	(0.049)	(0.013)	(0.041)	(0.023)
Wild Cluster P-Value	0.020	0.000	0.162	0.002
RI- P*	0.033	0.000	0.194	0.002
ANCOVA	0.066	0.065	-0.127*	0.0428
	(0.058)	(0.041)	(0.074)	(0.034)
Control mean (Follow-up)	0.256	0.003	0.505	0.033
Panel B. Yield rate (Ton/hectare)				
		Amon	*Boro*	Agg. Yield
DID		0.660**	0.472**	0.502**
		(0.247)	(0.181)	(0.207)
Wild Cluster P-Value		0.020	0.014	0.029
RI- P*		0.018	0.013	0.051
ANCOVA		0.572*	-0.173	-0.114
		(0.318)	(0.367)	(0.345)
Control mean (Follow-up)		1.243	3.145	3.203

Notes: N= 8,282 in all specifications. Cluster-robust standard errors are in parentheses. Adoption indicator is estimated based on whether a household adopts of that category rice seed in any plots in that season. Aggregate yield in column 4 in panel B is calculated as total production divided by total land cultivated in the Amon and Boro rice seasons. Asterisk (*), double asterisk (**), and triple (***) denote any variable significant at 10%, 5%, and 1%, respectively. RI- β P* test sharp null hypothesis of no treatment effect on any observations. Wild cluster p-value and RI- β P are estimated based on 5000 replications.

Table 4: Impact on Household Income and Expenditures

Panel A: Income (Yearly/BDT)						
	Crop-Farm	Wage	Non-crop Farm	Non-farm Business	Other	Total
	(1)	(2)	(3)	(4)	(5)	(6)
DID	4704.3**	-5141.3**	-854.5	2769.7	-3259	-1780.8
	(1971.6)	(2506.4)	(2040.3)	(2772.0)	(6408.7)	(7695.1)
Wild Cluster P-Value	0.022	0.061	0.710	0.321	0.638	0.835
RI-P*	0.026	0.066	0.697	0.347	0.636	0.827
ANCOVA	4936.3*	-1370.8	-1642.2	6534.2	-5235.9	4821.3
	(2443.8)	(2379.2)	(2935.3)	(4366.4)	(12902.8)	(12399.1)
Control mean (Follow-up)	18,146	47,967	12,864	13,698	37,019	129,694
Panel B: Expenditure (Yearly/BDT)						
	Food	Non-food	Total			
DID	782	3921.3	4703.3			
	(4406.9)	(6362.5)	(10181.2)			
Wild Cluster P-Value	0.844	0.532	0.650			
RI- P*	0.869	0.550	0.656			
ANCOVA	335.2	885	987.4			
	(4194.7)	(5155.2)	(9399.6)			
Control mean (Follow-up)	80,941	66,566	147,507			

Notes: N= 8282 in all specifications. Cluster-robust standard errors are in parentheses. All the values show yearly BDT amount. Asterisk (*), double asterisk (**), and triple (***) denote variable significant at 10%, 5%, and 1% respectively. RI- β P* test sharp null hypothesis of no treatment effect on any observations. Wild cluster p-value and RI- β P are estimated based on 5000 replications.

Table 5: Impact on Working Hours by Age Group

	Wage	Farm	Non-farm	Household Activity	Wage	Farm	Non-farm	Household activity
	Children (age 5 to 14)				Male Working member (age 15 -64)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DID	-0.0424	0.0492	0.00172	-0.0126	0.358	0.33	0.0168	-0.407
	(0.0311)	(0.0402)	(0.0486)	(0.0892)	(0.354)	(0.349)	(0.309)	(0.345)
Wild Cluster P-Value	0.196	0.258	0.978	0.903	0.336	0.384	0.957	0.278
RI- P*	0.224	0.269	0.970	0.893	0.356	0.350	0.958	0.264
ANCOVA	-0.0581	0.0267*	-0.0331	-0.0391	0.128	0.958***	-0.706***	-0.614***
	(0.0427)	(0.0155)	(0.0735)	(0.0929)	(0.281)	(0.337)	(0.212)	(0.222)
Control mean (Follow-up)	0.0616	0.0358	0.0537	0.224	2.223	0.86	2.186	1.017
	Female Working member (age 15 -64)				Aged group (age >64)			
DID	-0.00558	-0.0104	-0.0665	1.277*	0.00955	-0.00204	-0.033	0.155**
	(0.0395)	(0.0557)	(0.158)	(0.633)	(0.0172)	(0.0372)	(0.0417)	(0.0760)
Wild Cluster P-Value	0.891	0.876	0.678	0.070	0.605	0.946	0.466	0.041
RI- P*	0.892	0.864	0.681	0.071	0.627	0.962	0.468	0.052
ANCOVA	-0.0217*	0.165***	0.0047	-0.286	0.0216	0.0148	0.00831	0.168**
	(0.0128)	(0.0441)	(0.117)	(0.513)	(0.0153)	(0.0565)	(0.0401)	(0.0815)
Control mean (Follow-up)	0.0237	0.0821	0.134	7.779	0.0079	0.0495	0.0421	0.22

Notes: N= 2526 in all specifications. Cluster-robust standard errors are in parentheses. All the values s Asterisk (*), double asterisk (**), and triple (***) denote variable significant at 10%, 5%, and 1% respe test sharp null hypothesis of no treatment effect on any observations. Wild cluster p-value and RI- β based on 5000 replications.

Table 6: Impact on Access to Land and Asset Holdings

	Own cultivation	Rented in	Rented out	Cow	Goat	Chicken
	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.514	5.789	-0.394	0.041*	0.045*	-0.016
	(2.509)	(3.867)	(1.060)	(0.021)	(0.023)	(0.030)
Wild Cluster P-Value	0.862	0.147	0.690	0.076	0.061	0.620
RI-P*	0.842	0.133	0.721	0.056	0.073	0.623
ANCOVA	10.16***	7.482	-2.712**	0.049**	0.024	-0.034
	(2.849)	(4.693)	(1.313)	(0.018)	(0.024)	(0.026)
Control mean (Follow-up)	34.17	44.64	11.16	0.54	0.22	0.81

Notes: N= 8282 in all specifications. Cluster-robust standard errors are in parentheses. Columns 1–3 show land amount in decimals and columns 4–6 show number of respective assets. Asterisk (*), double asterisk (**), and triple (***) denote variable significant at 10%, 5%, and 1%, respectively. RI- β P* test sharp null hypothesis of no treatment effect on any observations. Wild cluster p-value and RI- β P are estimated based on 5000 replications.

Table 7: Impact on Investment and Sale

Panel A. Input investment (BDT/Per hectare)				
	Rice	Non-rice crop	Nonfarm business	
	(1)	(2)	(3)	(4)
DID	702.7	506	3373.6	4582.3
	(1716.3)	(1288.2)	(4408.7)	(5097.8)
Wild Cluster P-Value	0.706	0.719	0.499	0.438
RI- P*	0.694	0.711	0.513	0.442
ANCOVA	3634.5	-1078.8	668.2	2689.4
	(2733.0)	(809.1)	(1859.6)	(5109.1)
Control mean (Follow-up)	15310	6272	3332	24913
Panel B. Market sale (BDT)				
	Rice		Non-rice crop	
	Within 1 month	11 months	Within 1 Month	11 months
DID	-56.97	53.26	-2006	872.1
	(98.92)	(106)	(2151)	(2283)
Wild Cluster P-Value	0.598	0.646	0.406	0.726
RI- P*	0.576	0.641	0.396	0.725
ANCOVA	-56.97	53.26	-2006.7	872.1
	(98.92)	(106.0)	(2152.7)	(2283.6)
Control mean (Follow-up)	490	651	9051	11907

Notes: N= 8282 in all specifications. Cluster-robust standard errors are in parentheses. Asterisk (*), double asterisk (**), and triple (***) denote variable significant at 10%, 5%, and 1% respectively. RI- β P* test sharp null hypothesis of no treatment effect on any observations. Wild cluster p-value and RI- β P are estimated based on 5000 replications.

Table 8: Robustness analysis

	(1)	(2)	(3)	(4)	(5)
	Original	No MFI	Winsorize	Meet	Last meet
	(1)	(2)	(3)	(4)	(5)
HYV in *Amon* (Yes=1)	0.117**	0.114**		0.110**	0.111**
	(0.049)	(0.050)		(0.047)	(0.047)
Hybrid in *Amon* (Yes=1)	0.059***	0.059***		0.058***	0.058***
	(0.013)	(0.012)		(0.013)	(0.013)
HYV in *Boro* (Yes=1)	0.059	0.059		0.053	0.054
	(0.041)	(0.042)		(0.041)	(0.041)
Hybrid in *Boro* (Yes=1)	0.077***	0.078***		0.076***	0.076***
	(0.023)	(0.022)		(0.023)	(0.023)
Yield in *Amon* (Ton/Hectare)	0.660**	0.641**	0.573**	0.639**	0.641**
	(0.247)	(0.249)	(0.230)	(0.248)	(0.248)
Yield in *Boro* (Ton/Hectare)	0.472**	0.472**	0.382**	0.439**	0.443**
	(0.181)	(0.185)	(0.171)	(0.178)	(0.176)
Total yield (Ton/Hectare)	0.502**	0.494**	0.401**	0.472**	0.75**
	(0.207)	(0.210)	(0.198)	(0.209)	(0.208)
Crop farm income	4704.3**	3983.2**	3840.6***	4470.6**	4488.3**
	(1971.6)	(1843.2)	(1415.3)	(1950.2)	(1939.6)
Wage labor income	-5141.3**	-5725.7**	-4401.6**	-4918.1*	-4875.4*
	(2506.4)	(2467.6)	(2057.4)	(2583.7)	(2604.7)
Non-crop farm income	-854.5	-588	-327.8	-989.7	-984.2
	(2040.3)	(2058.5)	(1199.5)	(1997.9)	(1995.2)
Non-farm business income	2769.7	2662.9	1733.9	2697.4	2661.4
	(2772.0)	(2647.0)	(1851.2)	(2757.7)	(2761.3)
Income from other sources	-3259	-3931.7	-4103.6**	-3698	-3690.9
	(6408.7)	(6614.4)	(1964.3)	(6508.9)	(6510.8)
Total income	-1780.8	-3599.3	-4786.2	-2437.8	-2400.8
	(7695.1)	(7754.3)	(4461.9)	(7666.2)	(7654.1)

Notes: Column 1 controls baseline characteristics (number of age-dependent members (age <15 and age>64), the number of working-aged family member (age 15 to 64), household head's education and age, and the amount of land owned). Column 2 controls baseline characteristics and district-level fixed effect, column 3 use wild bootstrap-t procedure to estimate standard errors instead of regular cluster-robust standard errors, column 4 presents results from ANCOVA estimation, Column 5 presents results excluding baseline NGO client, and column 6 presents results after winsorizing. We control household baseline characteristics in all columns. District-level fixed effects are included in all columns except 1. Asterisk (*), double asterisk (**), and triple (***) denote variable significant at 10%, 5%, and 1%, respectively. N=7808 in column 2 and 8282 for rest of the specifications. Cluster-robust standard errors are in parentheses.

Table 9: Heterogeneous Impact Analysis

	ATE	Heterogeneous treatment effect				
		Mean	Std. Dev.	Median	Min.	Max.
	(1)	(2)	(3)	(4)	(5)	(6)
HYV (Amon)	0.14 (0.013)	0.13	0.07	0.13	-0.15	0.36
Hybrid (Amon)	0.05 (0.005)	0.04	0.04	0.03	-0.04	0.19
HYV(Boro)	0.07 (0.01)	0.06	0.08	0.05	-0.17	0.43
Hybrid(Boro)	0.09 (0.008)	0.09	0.05	0.08	-0.02	0.29
Yield rate (Amon)	0.76 (0.053)	0.80	0.51	0.86	-0.65	1.98
Yield rate (Boro)	0.38 (0.071)	0.40	0.39	0.38	-0.90	1.78
Crop-farming income	2,460 (887)	2422.83	3094	2350.19	-18212	12828
Wage labor income	-198 (1724)	180.65	6490	-7.94	-36030	30226

Notes: Baseline covariate set (X) includes number of dependent and working-aged members in household; age and education of household head; own, rented-in, and rented-out land; number of cows and goats; farming wage, and other income; adoption and yield rate of rice in the *Amon* and *Boro* seasons; expenditures in rice and non-rice farming; and household distance to Upazila. Parentheses in column 1 consist of standard error. Number of trees is 10,000 and honest splitting is used in the ATE estimation. For heterogeneous effect, we estimate $E(Y|X = x)$ and $E(W|X = x)$and run the CF on residuals.

Appendix

Wild Cluster Bootstrap

Let's consider equation (1) again,

$$Y_{it} = \alpha + \beta_1 T_i + \beta_2 W_t + \beta_3 (T_i \times W_t) + \mu X' + \eta_d + \varepsilon_{it}$$

We would like to test β_3=0. The wild cluster bootstrap by Cameron et al. (2008) can be performed using following steps,

1. Estimate equation (1) using the OLS model and calculate t-statistics for β_3=0 using cluster robust standard error, t_3.

2. Re-estimate equation (1) with a restriction of β_3=0 and obtain restricted residual, $\tilde{\varepsilon}$, and coefficients, $\tilde{\beta}$.

3. For each bootstrap replication j, generate cluster level weight, v_{ig}^{*j} , from the set {-1,1} for each observation i corresponds to $g(i)$ and estimate new dependent variable y_{ig}^{*j} as follows,

$$y_{ig}^{*j} = X_{ig}\tilde{\beta} + \tilde{\varepsilon}_{ig} v_{ig}^{*j}$$

4. For each bootstrap replication estimate equation (1) by substituting Y_{it} by y_{ig}^{*j} and estimate t-statistics, t_3^{*j}.

5. Calculate a two-sided bootstrap p-value as follows,

$$\hat{P}_s^* = \frac{1}{B} \sum_{j=1}^{B} \mathrm{I}(|t_3^{*j}| > |t_3|)$$

Randomization inference (RI)

Randomization inference (RI) uses treatment assignment as a random draw while keeping all other aspects of the experiment fixed. Let's consider equation (1) again,

$$Y_{it} = \alpha + \beta_1 T_i + \beta_2 W_t + \beta_3 (T_i \times W_t) + \mu X' + \eta_d + \varepsilon_{it}$$

In case of sample samples, clustered treatment assignment, or non-standard treatment assignment, we can perform Ri test to examine whether the observed realization of the BCUP program impact,β_3, is observed by chance or not. RI can be done on coefficient (β_3) or t-statistics of treatment effect. Although there is no clear preference on test statistics, HeB (2018) mentions that RI based on t-statistics can be beneficial in some cases. The null hypothesis is zero treatment effect for all observation that is $y_i(T = 1) = y_i(T = 1)$ for all i=$1, 2, ...n$. To test this, we use following steps,

1. Compute test statistics for each permutation of the treatment assignment. We have 40 total clusters with 20 treatment branch; therefore, we will have $40C_{20}$ number of alternatives. In estimation, we randomly draw 1000 out of $40C_{20}$ combinations.

2. Examine the test statistics, $\hat{\beta}_3$, with its distribution from 1000 draws as follows,

   $rk = \sum_{m=1}^{M} \mathrm{I}(\dot{\beta}_m \leq \hat{\beta}_3)$ or $rk = \sum_{m=1}^{M} \mathrm{I}(|\dot{\beta}_m| \leq |\hat{\beta}_3|)$

   Where $\dot{\beta}_m$ are the M i.i.d. draws from permutation list.

3. Use a two-sided test to compute P-value by ranking the test statistics as follows, $P^{two-sided} = \frac{1}{M} rk^{abs}$.

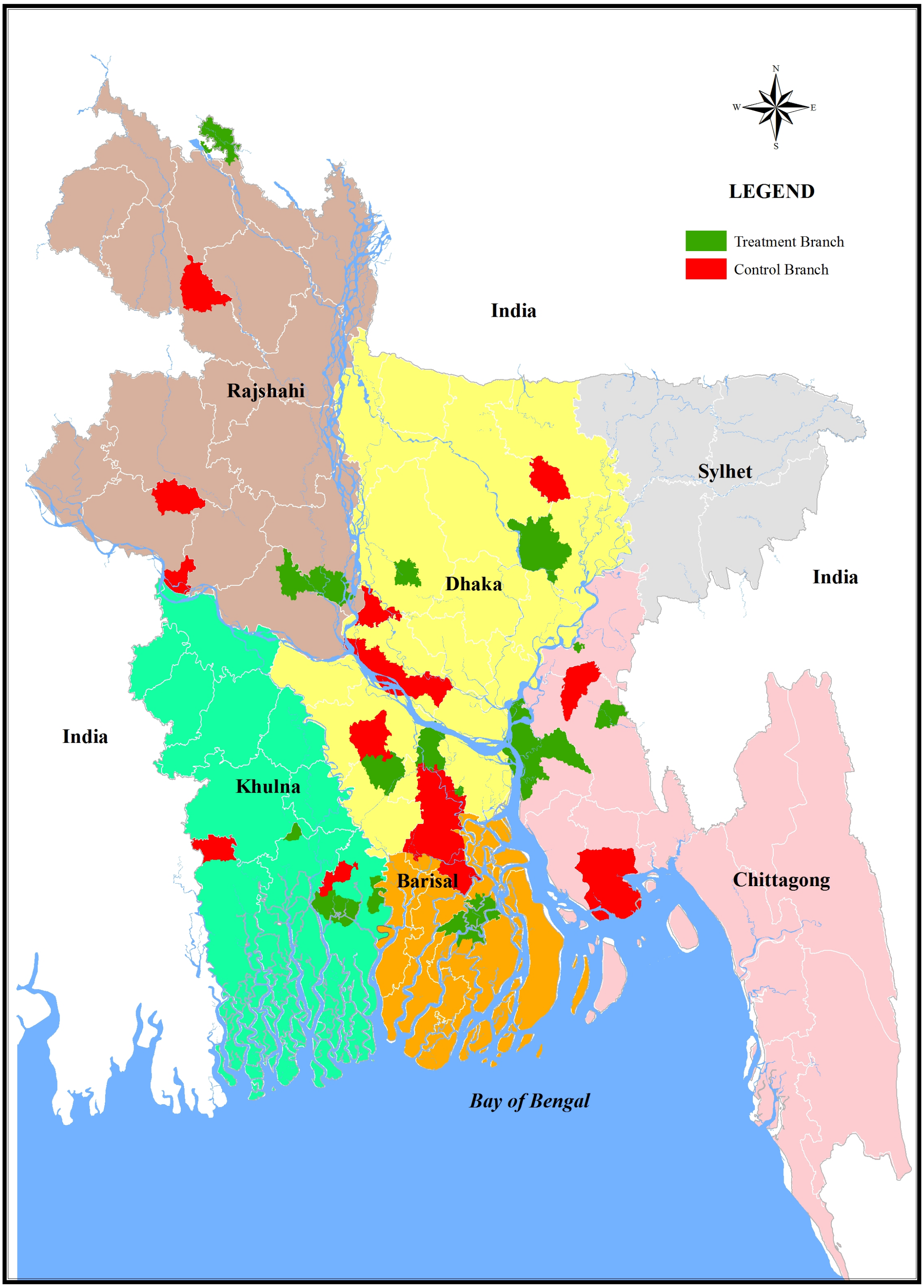

Figure 1: Study Area Map

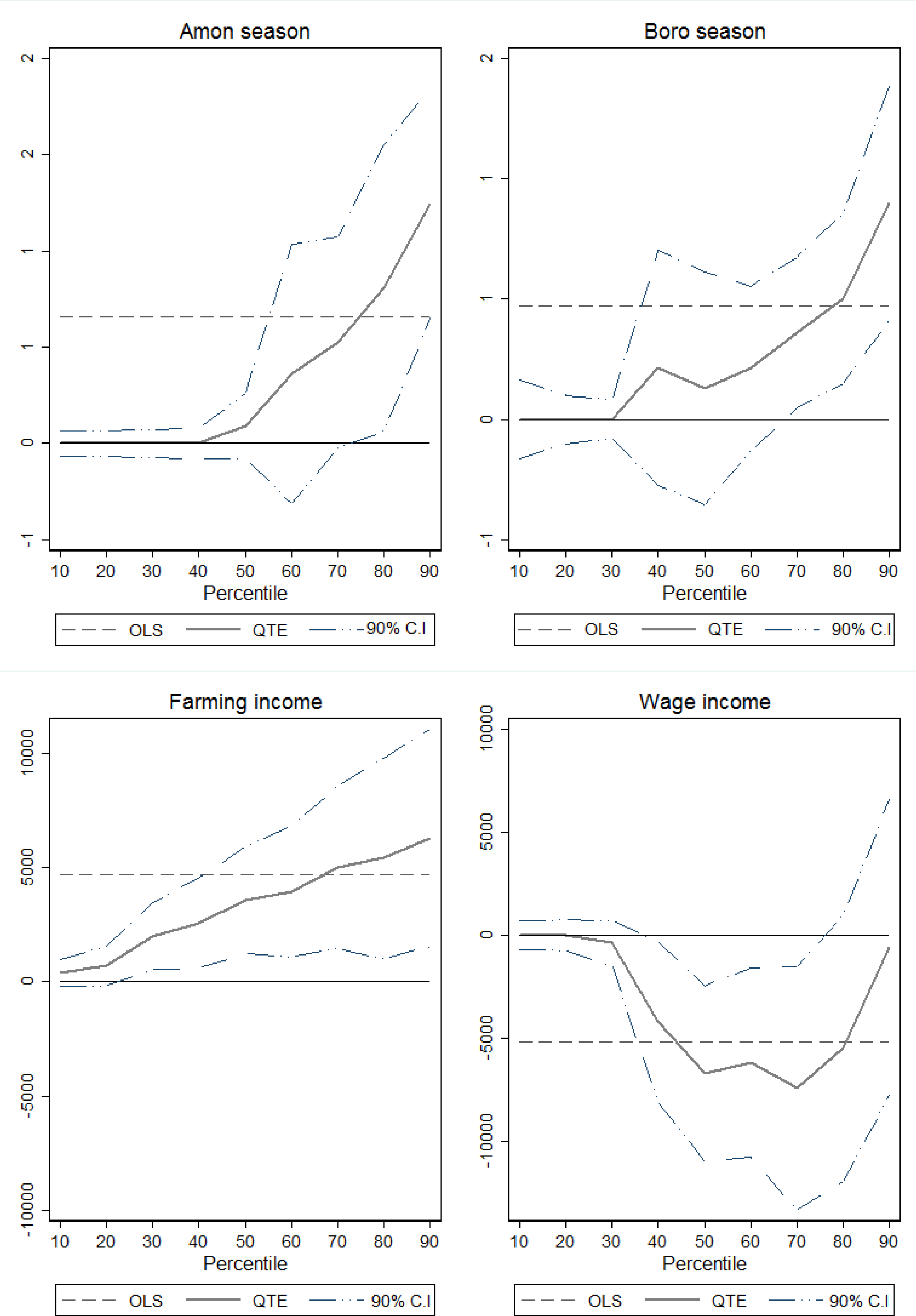

Figure 2: Quintile treatment effect on Rice Yield rate and Income

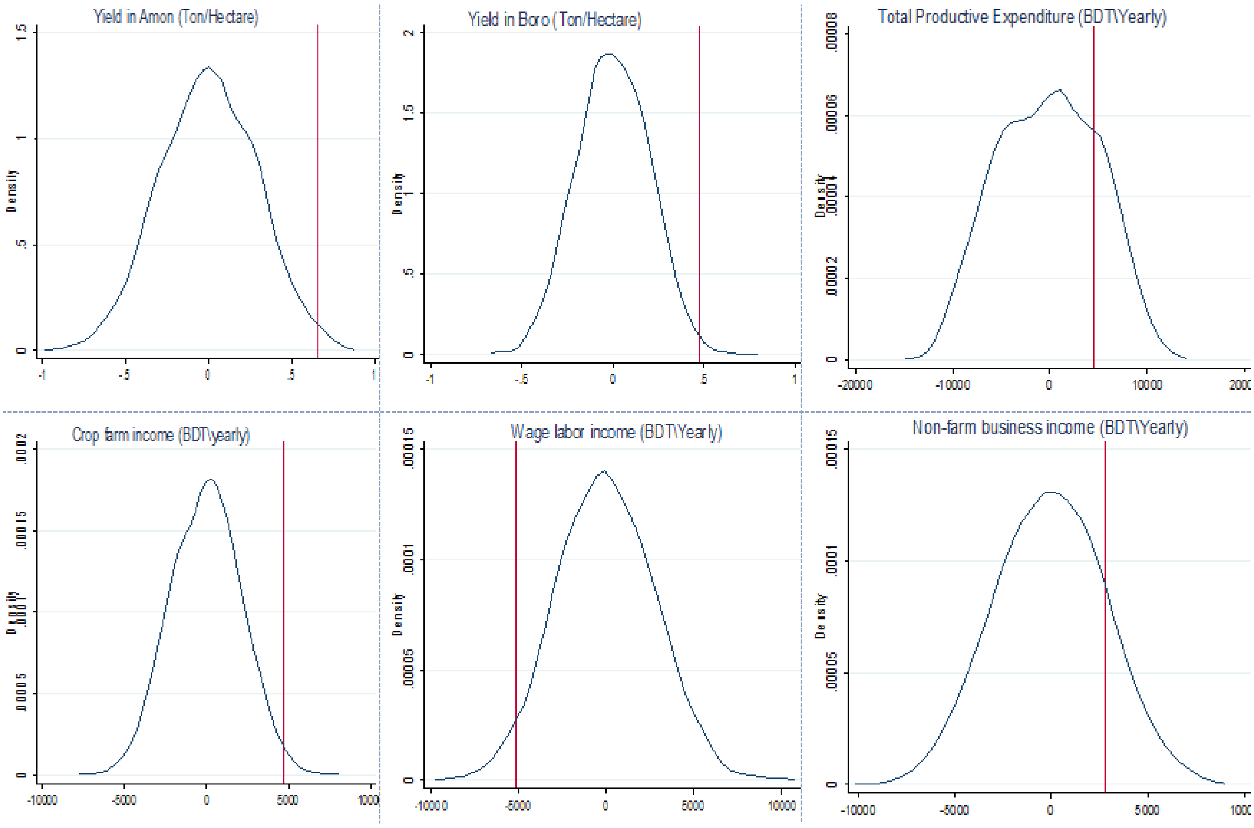

Figure 3: Randomization inference results

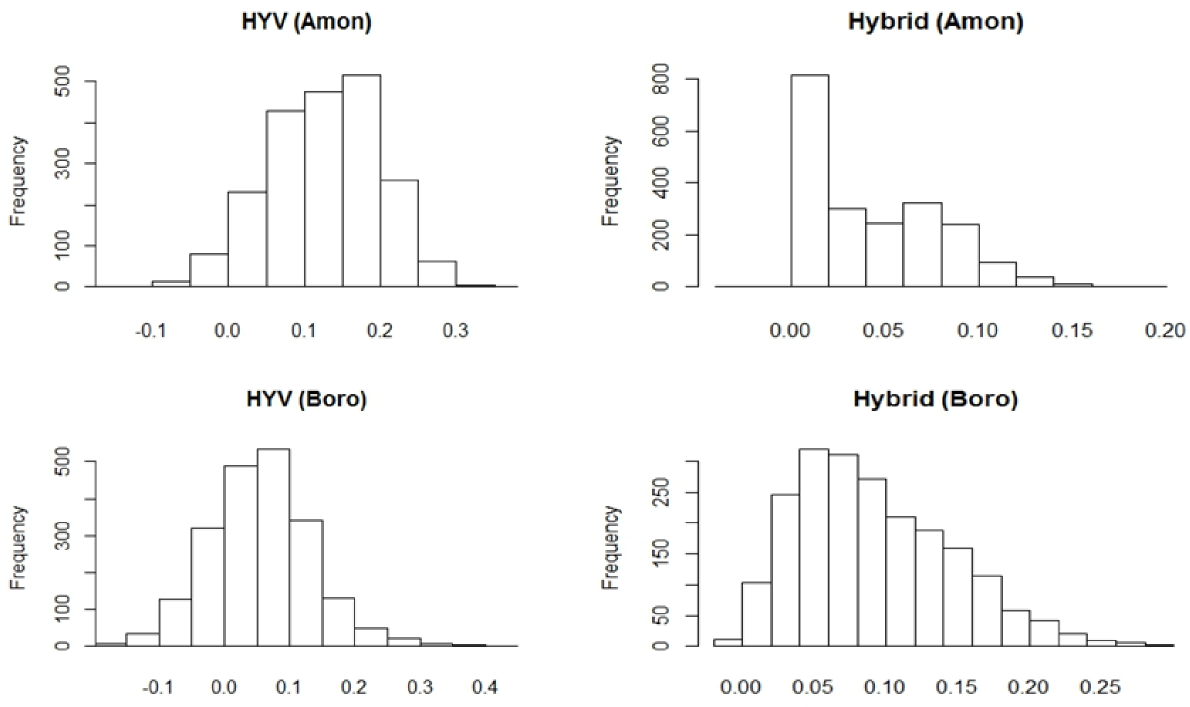

Figure 4: Heterogeneous treatment effect on adoption rate of Rice

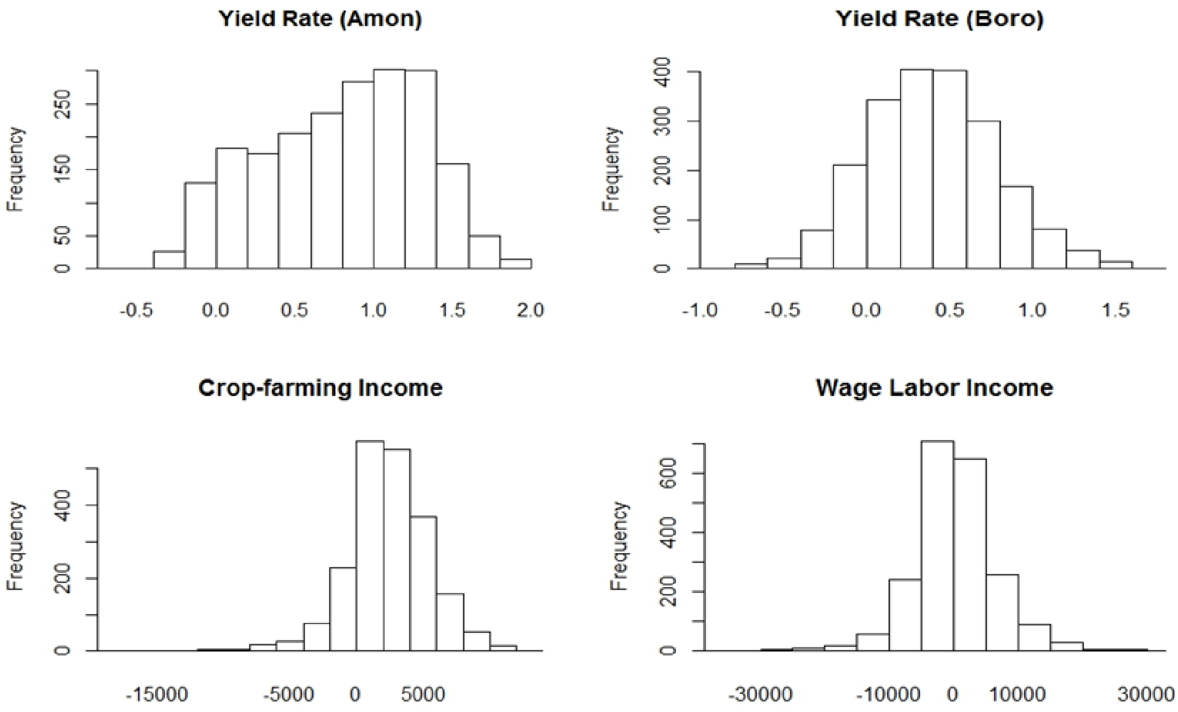

Figure 5: Heterogeneous treatment effect on Yield rate of Rice and Income

Annex table 1: Comparison of microfinance and non-microfinance households

	Non-microfinance	Microfinance	Difference	P value
Household size	4.66	4.96	0.30	0.00
Number of Children less than 5	0.46	0.51	0.05	0.00
Years of permanent residency	50.93	46.82	-4.11	0.00
Age	47.47	45.34	-2.13	0.00
Education	4.56	3.54	-1.03	0.00
Cultivated land	41.25	23.37	-17.88	0.00
Rented in	24.79	31.18	6.40	0.00
Amount from NGOs	0.00	18330.31	18330.31	0.00
Amount from Bank	3237.93	2593.74	-644.19	0.31
Amount from informal sources	2151.26	2120.27	-30.99	0.95

Notes: Number of households are 35,201 and 26,121 in non-microfinance and microfinance group, respectively. Standard errors of differences are clustered at the branch level. P-value is for the mean difference test between the treatment and control groups.

Annex table 2: Comparison of eligible study and non-study households

	Non-study eligible sample	Study Sample	Difference	P value
Household size	4.92	4.98	0.06	0.18
Number of Children less than 5	0.47	0.49	0.01	0.46
Years of permanent residency	50.58	49.67	-0.91	0.34
Age	42.51	42.87	0.36	0.20
Education	3.10	2.95	-0.15	0.10
Cultivated land	36.62	38.82	2.19	0.07
Rented in	55.59	55.19	-0.40	0.84
Amount from NGO	0.00	0.00	0.00	.
Amount from Bank	1359.15	1918.03	558.88	0.21
Amount from informal sources	2699.39	3108.31	408.92	0.37

Notes: Number of households are 3,262 and 4,301 in non-study eligible and study group, respectively. Standard errors of differences are clustered at the branch level. P-value is for the mean difference test between the treatment and control groups.

Annex table 3: Attrition rate

Dependent variable: Household not found at the end line			
Treatment	0.003	0.003	-0.028
	(0.007)	(0.007)	(0.019)
Household size		-0.002	-0.006***
		(0.002)	(0.002)
Female headship		0.028	0.06
		(0.018)	(0.036)
Head's education		0.002*	0.001
		(0.001)	(0.001)
Own cultivated land		0.000	0.000
		(0.000)	(0.000)
Household income		0.000	0.000
		(0.000)	(0.000)
Household size X Treatment			-0.054
			(0.040)
Female headship X Treatment			0.001
			(0.002)
Head's education X Treatment			0.000
			(0.000)
Own land X Treatment			0.007**
			(0.003)
Household income X treatment			0.000
			(0.000)
Constant	0.036***	0.036***	0.052***
	(0.005)	(0.010)	(0.009)
Observations	4,301	4,301	4,301
R-squared	0	0.003	0.006
F test	0.131	1.248	2.73
Prob>F	0.719	0.303	0.0103

Notes: Coefficients show probability of attrition. Cluster-robust standard errors are in parentheses. Asterisk (*), double asterisk (**), and triple (***) denote variable significant at 10

Annex table 4: Households' characteristics by headship and treatment status

	Female headed			Male headed		
	Control Mean	Diff.	P-Val	Control Mean	Diff.	P-Val
Household size	3.88	0.30	0.36	4.80	0.20	0.25
Head's education	2.62	0.78	0.07	3.07	0.13	0.70
Head's age	44.50	-1.82	0.37	44.51	0.82	0.24
Yield in *Amon* (Ton/Hectare)	1.22	0.59	0.16	1.53	0.34	0.36
Yield in *Boro* (Ton/Hectare)	3.90	-0.06	0.89	3.77	-0.38	0.50
HYB in *Amon* (Yes=1)	0.21	0.18	0.12	0.30	0.06	0.63
Hybrid in *Amon* (Yes=1)	0.01	0.00	0.78	0.02	-0.01	0.70
HYB in *Boro* (Yes=1)	0.71	0.10	0.33	0.68	0.01	0.95
Hybrid in *Boro* (Yes=1)	0.03	-0.02	0.28	0.04	0.01	0.81
Food Expenditure	45450	7263	0.05	56030	3088	0.27
Non-food expenditure	36616	7536	0.16	41616	-2538	0.36
Wage income	27650	-318	0.97	33372	7908	0.06
Crop farm income	8397	1529	0.36	15385	-3547	0.17
Non-crop farm income	6614	-677	0.68	6839	776	0.40
Non-farm business income	5214	864	0.77	12432	4409	0.12
Income from other sources	52717	40052	0.01	22740	4582	0.48

Notes: Number of households is 1,656 and 416 in non-participant and participant group, respectively. Standard errors of differences are clustered at the branch level. P-value is for the mean difference test between the treatment and control groups.

Annex table 5: Comparison of households by tenancy and treatment status.

	Owner			Mixed			Pure tenant		
	Control Mean	Diff.	P-Val	Control Mean	Diff.	P-Val	Control Mean	Diff.e	P-Val
Household size	4.66	0.31	0.13	5.05	0.09	0.64	4.65	0.14	0.51
Head's education	33.12	-0.72	0.87	37.09	1.07	0.84	48.31	-1.08	0.82
Head's age	45.00	1.27	0.14	45.59	1.12	0.19	42.95	0.34	0.73
Female head	0.08	0.06	0.04	0.03	0.02	0.21	0.04	0.02	0.40
Yield in *Amon* (Ton/Hectare)	1.54	0.29	0.45	1.63	0.28	0.52	1.41	0.47	0.17
Yield in *Boro* (Ton/Hectare)	4.03	-0.71	0.25	3.88	-0.36	0.56	3.60	0.01	0.98
HYB in *Amon* (Yes=1)	0.30	0.03	0.81	0.34	0.03	0.82	0.27	0.14	0.20
Hybrid in *Amon* (Yes=1)	0.02	-0.01	0.28	0.02	0.00	0.76	0.01	0.00	0.93
HYB in *Boro* (Yes=1)	0.71	-0.02	0.87	0.72	0.00	0.98	0.67	0.07	0.54
Hybrid in *Boro* (Yes=1)	0.03	0.00	0.90	0.05	0.00	0.99	0.04	0.00	0.99
Food Expenditure	55334	3925	0.15	60691	1917	0.60	50541	3350	0.24
Non-food expenditure	42415	1004	0.71	46012	-2808	0.44	36129	-4259	0.16
Wage income	32498	3666	0.52	29501	10295	0.05	39194	6367	0.15
Crop farm income	16284	-4575	0.13	19592	-4050	0.20	7860	-1059	0.50
Non-crop farm income	7796	1021	0.27	8311	118	0.95	4125	920	0.39
Non-farm business income	15910	2306	0.46	9913	5547	0.14	7140	5727	0.02
Income from other sources	30229	13380	0.37	24296	6829	0.30	18500	5110	0.51

Notes: Number of households are 1,423, 1,325, and 1,282 for owner, mixed, and pure tenant house respectively. Standard errors of differences are clustered at the branch level. P-value is for the mean diffe test between the treatment and control groups.

Annex table 6: Balance between BCUP program participant and non-participant

	Non-participant	Participant	Mean Difference	P- Value
Number of dependents	1.91	1.90	0.00	0.97
Number of working age members	3.05	2.95	-0.10	0.12
Household size	4.96	4.86	-0.11	0.43
Head's education	3.09	3.68	0.59	0.01
Head's age	45.90	42.90	-3.00	0.00
Female head	0.09	0.06	-0.02	0.17
Own land (in Decimal)	37.94	35.59	-2.35	0.43
Rented in land (in Decimal)	51.50	51.74	0.24	0.97
Rented out land (in Decimal)	7.81	10.05	2.25	0.32
Cow(Yes=1)	0.62	0.48	-0.14	0.00
Goat (Yes=1)	0.18	0.20	0.02	0.56
Chicken (yeas=1)	0.72	0.70	-0.02	0.55
Concrete floor (yes=1)	0.12	0.13	0.01	0.79
Use sanitary latrine (yes=1)	0.15	0.12	-0.04	0.15
Wage income	40,216.54	42,634.35	2,417.81	0.40
Farm income	11,169.35	10,871.45	-297.89	0.81
Non-farm income	7,818.11	5,724.06	-2,094.05	0.07
Business income	13,428.19	27,484.74	14,056.55	0.01
Income from other sources	35,279.50	21,004.68	-14,274.82	0.04

Notes: Number of households is 1,656 and 416 in non-participant and participant group, respectively. Standard errors of differences are clustered at the branch level. P-value is for the mean difference test between the treatment and control groups.

Annex table 7: The probability of BCUP program participation.

	Took loan from BCUP (yes=1)	
Number of dependent in HH	0.0344	-0.0323
	(0.0415)	(0.0446)
Number of working aged member in HH	-0.0881*	-0.0606
	(0.0511)	(0.0555)
Head's education	-0.0014	-0.0010
	(0.0013)	(0.0014)
Head's age	-0.0134***	-0.0209***
	(0.0050)	(0.0056)
Female head	-0.0053	-0.2957
	(0.2169)	(0.2304)
Own land	0.0008	0.0001
	(0.0012)	(0.0013)
Cow(Yes=1)	-0.3619***	-0.4322***
	(0.1091)	(0.1167)
Wage income	0.0000***	0.0000**
	(0.0000)	(0.0000)
Farm income	-0.0000	0.0000
	(0.0000)	(0.0000)
Non-farm income	-0.0000	-0.0000*
	(0.0000)	(0.0000)
Business income	0.0000***	0.0000***
	(0.0000)	(0.0000)
Income from other sources	-0.0000	-0.0000
	(0.0000)	(0.0000)
Concrete floor (yes=1)	0.1215	0.2215
	(0.1679)	(0.1805)
Use sanitary latrine (yes=1)	-0.4151**	-0.3146*
	(0.1763)	(0.1864)
Constant	-1.3620***	-0.1089
	(0.2350)	(0.2598)
Observations	4,141	2,072

Notes: Coefficients show probability of participation using all households and only households in the treatment area. Standard errors are in parenthesis