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To What Extent Do Improved Practices Increase Productivity of Small-Scale Rice Cultivation in A Rain-fed Area? : Evidence from Tanzania

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Abstract

This paper investigates the impact of training provided by a large-scale private farm on the performance of surrounding small-scale rice farmers in a rain-fed area in Tanzania. We found that the training effectively enhances the adoption of improved rice cultivation practices, paddy yield, and profit of rice cultivation by small-holder farmers. In fact, the trainees achieve paddy yield of 5 tons per hectare on average, which is remarkably high for rain-fed rice cultivation. Our results suggest high potential of small-scale rain-fed lowland rice cultivation and extension services by private large scale farms.

Keywords: Green Revolution, Sub-Saharan Africa, Food Security, Lowland Rice, Rain-Fed Cultivation

JEL Classification: O12, O13, O33, O55, Q12, Q16, Q18

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1. Introduction

Agriculture development is indispensable for poverty reduction and food security in Sub-Saharan Africa (SSA). Among other crops, rice is considered one of the most important and promising crops to achieve a Green Revolution similar to Asia, which lead to a drastic increase in paddy yield due to the diffusion of modern varieties and chemical fertilizer use (Otsuka and Larson, 2013; Seck et al., 2010). In fact, fertilizer-responsive modern varieties developed in Asia have exhibited high yield potential especially in irrigated areas in SSA (Kajisa and Payongayong, 2011; Otsuka and Larson, 2013; Nakano et al., 2013). However, the irrigation ratio in SSA is much lower than in Asia (Hayami and Godo, 2005; Johnson, et al., 2003). Since it takes time and resources to develop irrigation infrastructure, whether SSA can achieve a rice Green Revolution in near future critically depends on the strategy for the development of rain-fed rice cultivation even though the importance of irrigation development will remain unchanged in the long run (Nakano et al., 2014; Nhamo et al., 2013).

Recent case studies have shown that intensive training on rice cultivation can effectively enhance the adoption of new technologies including modern variety, chemical fertilizer and improved agronomic practices such as dibbling, and productivity of rice cultivation both in irrigated and rain-fed area in SSA (De Graft Johnson et al., 2014; Kijima et al., 2012; Nakano et al., 2014). However, improved rice cultivation technologies are not widely adopted partly because of weak public extension system (Nakano et al., 2014). One possible solution for this problem is to utilize private sector's resource in extension activities in the form of contract farming (World Bank, 2008). In contract farming, an agribusiness firm manages processing and marketing but contracts for farm products from peasant farmers. The firm provides technical guidance, credit and other services to peasants in return for their pledged production to the firm (Hayami and Godo, 2005).

In order to examine the potential of improved practices in rain-fed rice cultivation, authors conducted a survey in Kilombero district in Tanzania, the largest rice producing country in East Africa. In our study site, Kilombero Plantation Limited (KPL), which is a large-scale private rice farming company, provides training on improved rice cultivation practices to surrounding small-scale farmers. Although KPL's attempt to operate contract farming is still at its initial stage, this study would provide an opportunity to examine the potential of private extension services to small-scale farmers in the form of contract farming as well.

The training was called SRI (System of Rice Intensification) and main contents of the training included the adoption of modern varieties (MV), chemical fertilizer use, and straight-raw dibbling or transplanting with the spacing of 25cm by 25cm. Note that SRI here is a modified and simplified version of the well-known SRI developed in Madagascar, which does not require a new variety nor additional external inputs. [1] Thus, we call the package of technologies adopted in our study site as modified SRI (or shortly denote as MSRI).

We collected two types of data: first one is plot-level recall data on paddy yield and the adoption of technologies for the past 4 years, which include both before and after the training. The second one is cross-sectional plot-level data on rice cultivation, which include detailed information on the use of current, labor, and capital inputs in 2013. It is relatively easy for the farmers to recall their technology adoption

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1 The main components of SRI include (1) early transplanting of seedling that are 8-12 days old; (2) shallow planting (1-2 cm) of one or two seedlings; (3) sparse planting in a square grid (more than 20×20 cm); and (4) intermittent irrigation (Moser and Barrett, 2006; Stoop et al., 2002; Takahashi and Barrett, 2014).

and harvest for the past few years, while it is very difficult for them to remember all the detail on input use. Thus, we construct a recall panel data for the former and cross section data for the latter. The very unique feature of our data set is that some of our sample households cultivate rice in more than two plots by adopting MSRI technologies in a plot and by not doing so in others. This enables us to examine the impact of technology adoption on paddy yield and profit of rice cultivation by controlling innate household characteristics by using both our panel and cross-section data.

The paper is organized as follows. Section 2 explains the study sites and data collection method, followed by the descriptive analyses in Section 3. Section 4 shows the regression analyses on the impact of training on the adoption of improved rice cultivation technologies and paddy yield by using panel data. In section 5, we examine the impact of technology adoption on costs and profit of rice cultivation by using propensity score matching methods and sub-sample analysis with household-fixed effect with our cross section data. Section 6 concludes the paper.

2. Data and Study Site

2.1 Study Site

The survey was conducted in the nearby villages of a large-scale rice farming company called Kilombero Plantation Limited (KPL). KPL was established in 2008 as a private company, with the capital from England and the U.S., in Kilombero Valley, Kilombero district, Morogoro Region. The Kilombero Valley is about 400 km to the east of the country's main city, Dar es Salaam, and covers an area of about 11,600 square kilometers. Rice cultivation is very popular among farmers in the valley and they produced about 9% of all rice produced in Tanzania in 2003 (Kato, 2007). KPL cultivates 5000 ha of paddy field, of which 215 hectare is irrigated by using sprinkler. According to the manager of KPL, the average paddy yield in rain-fed area of the farm is from 3.1 to 3.5 tons per hectare, while that in irrigated area is 7 tons per hectare.

The land acquired by KPL used to belong to an estate. Around 1985, Korea Tanzania Cooperation Limited (KOTACO), state owned company of Tanzania and North Korea, was established in the area. However, due to their management problem, they closed their operation by the mid 1990's. KPL started their operation in 2008 and extension services to local small scale farmers in the surrounding villages in 2009, in response to the request of Tanzanian government.

SRI office, which was established as a section of KPL, is in charge of extension services to the local farmers. They started their operation by training 15 farmers as trainers in a neighboring village in 2009. They trained 25 farmers in a village in 2010, and expanded their extension service to 1350 farmers in 2011, 2850 farmers in 2012, and 2250 farmers in 2013. Currently, they are financially supported by USAID and operate in surrounding 10 villages.[2]

When they start the training program, SRI officers call for a village meeting and ask those who are interested to form a group of 25 farmers. The criteria for the participants are that he or she must be a resident in the villages, must be a farmer, and has not been trained by SRI office before. Participants need to provide a piece of land of quarter acre as a group, which is called a demo-plot. The extension officers, who are qualified agronomists hired by KPL and USAID, provide training in the demo-plot during the season. During the training, participants are provided with 26 kg of

[2] Out of these 10 villages, KPL occupies the land in Mkangawaro, Lukolongo, and Mngeta villages.

chemical fertilizer and 4kg of seeds of MV (the variety called SARO5), which are recommended amounts for a quarter acre, and are obliged to cultivate a quarter acre of their own land following the technology taught in the demo-plot.

One year after they receive training, trainees no longer receive any training or free inputs but are eligible to receive in-kind credit of chemical fertilizer and seed from NGOs which are associated with SRI office. NGOs provide the credit of 440,000 Tanzanian Shilling (Tsh) for an acre in cash before the cultivation starts. Out of this 440,000 Tsh, 200,000 Tsh is deducted for the purchase of 100 kg of chemical fertilizer, 12 kg of seeds, and the rental cost of a rotary weeder, with 240,000 Tsh remaining at the hand of the farmers. Farmers are obliged to repay 15,000 Tsh every two weeks during the cultivation season for 5 months, resulting in 10 installments. In addition, farmers need to sell 6 bags (approximately 600kg) of paddy at the agreed price to KPL at the time of harvest, so that KPL can repay remaining balance to lender NGO.

However, this credit service was not popular among farmers. Firstly, it is difficult for the farmers to repay the loan during the cultivating season as they receive most of their cash income at the harvesting season. Furthermore, there was confusion on the agreement of selling price of the paddy between farmers and KPL. For example, some farmers refused to sell paddy at the agreed price to KPL in 2012, when they observed that market price was higher than the agreed price at the time of the harvest. On the other hand, in 2013, due to the government ban on rice export, the price of paddy decreased significantly at the harvesting season, which caused serious loss to KPL. Such fluctuation in paddy price caused confusion between farmers and KPL, and this credit service (or "contract farming" of KPL) seemed not to be as widely accepted as expected by the farmers. In fact, only 11 eligible farmers out of 281 sample households in our data set received the loan from KPL in 2013.

2.2 Sampling

In order to examine the impact of the program, we selected 3 villages where training was held (we call them training village hereafter). We also covered 2 nearby villages, where there was no training held (we name them non-training village). Training villages and non-training villages are neighboring and in a similar agro-ecological condition. In training villages, we interviewed on average 37 training participants and 35 non-participants per village. In addition, we interview on average 35 farmers per village in non-training village, generating the total sample size of 283 households.[3]

During the interview, we asked farmers to list each of their farming plots. Among those listed, we selected 2 paddy plots for plot-level analysis. Note that in our study sites even trainees clearly differentiate the use of plots where they adopt modified SRI technologies as a package and do not adopt these technologies at all. We call the plots, where trainees adopt new technologies, modified SRI plot (or denote as MSRI plot) here after. For farmers who grow rice with MSRI technologies, we automatically selected that MSRI plot and selected another plot randomly where rice is grown with traditional cultivation method. For farmers who do not grow rice with MSRI technologies, we randomly selected up to two plots where rice is grown. We interviewed detailed rice cultivation practices and input use in the sample plots for the

[3] We targeted to interview 40 participants and non-participants in each village. The reduction of sample size is caused by the absence of the farmers in the list on the interview date.

cultivation season of 2013, generating 406 sample plots of 283 households. After dropping households and plots with missing values in key variables, total sample size became 396 plots of 281 households. We also collected recall data on paddy yield and the adoption of key technologies from 2010 to 2013 so that we can construct a panel data before and after the training. The sample size of our panel data becomes 396 plots of 281 households for 4 years, generating the total sample size of 1329 plots. Note that our sample is not balanced because some farmers do not grow rice in some years.[4]

Out of 110 training participants in our sample, no farmers were trained before 2011, 25 farmers were trained in the season of 2012, and 85 farmers in 2013. This implies that 85 trainees in 2013 received free inputs for quarter acres from KPL while 25 trainees in 2012 were eligible for the KPL credit program in the cultivating season of 2013. Since trainees in 2012 and 2013 received different services from KPL in 2013, we separately analyze the impact of the training for trainees in each year in our following analyses. Note that the impact of the SRI training for trainees in 2012 partially includes the impact of the credit service. As only 11 out of 25 eligible farmers joined credit program, it is difficult for us to statistically distinguish the effects of training and credit.

3. Descriptive Analyses

This section descriptively examines the impact of the training on the adoption of MSRI technologies and productivity of rice farming. Table 1 compares the adoption of modern inputs and improved practices by trainees in 2012, trainees in 2013,

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4 We confirmed that the main results of our analyses would not change even when we use the balanced panel data by omitting those households who did not cultivate rice in any single year within four years.

non-trainees in training villages, and farmers in non-training villages in 2013. The most important finding is that trainees, regardless of their training year, achieve as high yield as 5 tons per hectare on average in their MSRI plots. This yield is remarkably high given that the average paddy yield in other rain-fed areas in Tanzania is 1.8 tons per hectare (Nakano et al., 2014) and non-trainees' yield in the training village is 2.6 tons per hectare, suggesting the high potential of improved technologies in rain-fed areas.

This high yield may be attributed to the high adoption rate of new technologies by trainees on their MSRI plots. The adoption rate of MVs is as high as 97.1%, that of straight row dibbling 82.5%, and that of wide spacing 59.2%. Trainees apply much more chemical fertilizer (91.8 kg per hectare) on MSRI plot than their non-SRI plots (11.5 kg per hectare). Note also that there is no significant difference between the performance of trainees in 2012 and 2013, suggesting that this high yield and high rate of technology adoption continues even after KPL stops providing free input. Another important finding is that we do not observe significant difference between average yield before training (2009-2010) in the MSRI plots and other categories of the plots, suggesting that farmers do not necessarily select plots of good quality to adopt MSRI technologies. Lastly, the adoption of technologies and yield do not differ much between non-SRI plots of trainees and non-trainees in training villages or between non-SRI plots of trainees and farmers in non-training villages. These results suggest that there is limited spill-over effect from trainees to non-trainees even in training villages and also from MSRI plots of trainees to their non-SRI plots.

In order to examine differences in factor use among farmers, we show factor payments by training status in Table 2. We define income as gross output value minus paid-out costs of current inputs, hired labor, and rental costs of machinery and draft animals. Profit is defined as income minus imputed costs of family labor and owned capital, evaluated at the village median wage and rental rate, and it can be interpreted as the return to land and management efficiency.

Trainees earn much higher gross output value in their MSRI plots than in their non- SRI plots. Furthermore, their gross output value is much higher than that of non-trainees or farmers in non-training villages. Since MSRI technologies are labor and input intensive, trainees pay higher labor and input costs in their MSRI plots. Especially, imputed family labor cost is much higher in the MSRI plots of trainees than other categories of the plots. This suggests that MSRI technology is more family-labor intensive as it requires more care than traditional cultivation methods. Despite the increase in labor and other input costs, the increase in gross output value exceeds that in costs and, hence, trainees achieve higher income and profit per hectare in MSRI plots than other categories of the plots. Note also that there is no significant difference in income and profit between non- SRI plots of trainees and non-trainees in training villages, which is denoted as (d) - (g) in the Table 2. Income and profit in non-SRI plots of trainees are also not higher than that in non-training villages.

4. Impact of Training on Technology Adoption and Paddy Yield

4.1. Methodology and Variable Construction

In this section, we estimate the impact of the training on the adoption of rice cultivation technologies and paddy yield by using recall panel data. The dependent variables are paddy yield (tons/ha) and the sets of technology adoption variables including the dummy variable which takes one if a farmer adopts MV, chemical fertilizer use (kg/ha), and dummy variables which take one if a farmer adopts dibbling or transplanting in rows, or recommended spacing of 25 cm by 25 cm. The base model is;

$$y_{vijt} = \tau(MSRI_{vij} * trainee_{vit} * After) + \delta(trainee_{vit} * After) + \theta Year + p_{vij}\gamma + u_{vijt} \quad (1),$$

where

y_{vijt}: the outcome variable of individual i's plot j in the village v at time t,

$MSRI_{vij}$: time invariant dummy variable which takes 1 if the plot is used as modified SRI plot in any single year,

$trainee_{it}$: dummy variable which takes 1 if the cultivator of the plot has attended MSRI training in either 2012 or 2013,

After: year 2012 and 2013 dummies,

Year: year dummies,

p_{vij}: plot specific time-invariant characteristics, and

u_{vijt}: error term.

The main independent variable is the interaction terms of MSRI plot, trainee dummy, and After dummy. Note that MSRI plot dummy here is a time invariant dummy variable which takes one if a plot is used as MSRI plot in any single year. We include After dummies which are year 2012 and 2013 dummies because trainees has attended the training by these years. Since there are only three households who gave up MSRI technologies after they adopted it, we consider the coefficient τ as the estimator of the impact of the training. In order to examine the differential impact of the training in 2012 and 2013, we constructed three interaction terms: namely, the interaction term of MSRI plot dummy, 2012 trainee dummy and year 2012 dummy, the interaction term of MSRI plot dummy, 2012 trainee dummy and year 2013 dummy, and the interaction term of MSRI plot dummy, 2013 trainee dummy and year 2013 dummy.

We also include the interaction terms of the trainee dummy and the After dummy. The coefficient δ captures the potentially negative impact of the training on productivity and technology adoption in non-SRI plots of the trainees due to their labor reallocation from non-SRI plots to MSRI plots or the positive spill-over effect of the training to the non-SRI plot of trainees. Again, in order to estimate the impact of training on the trainees in 2012 and 2013 separately, we include the interaction term of 2012 trainee and year 2012 dummy, that of 2012 trainee and year 2013 dummy, and that of 2013 trainee and year 2013 dummy. We estimate this model using the plot fixed effect model.[5,6] By estimating the plot fixed effect model, we can control for plot specific time-invariant characteristics (p_{vij}) which may affect farmer's endogenous selection of MSRI plot.

In order to estimate the spill-over effect of training to non-trainees in training village, we also estimate equation (1) without controlling any fixed effect. In these models, we further include the interaction terms of MSRI plot and 2012 and 2013 trainee dummies to control for farmer's endogenous selection of MSRI plots. We also include the 2012 and 2013 trainee dummies. The coefficient of trainee dummy would capture the trainee's innate characteristics. We control training village dummy and, thus, the base category is plots in non-training villages. The coefficient of SRI village

[5] In some cases, farmers split one plot (let it be plot A) into two and adopt MSRI technologies in one plot (plot A') and do not in the other (A'') after they attend MSRI training. In this case, we consider the plots A' and A'' as two different plots. We use the information for plot A as yield and technology adoption in pre-training years for both plots A' and A'' when we construct panel data.
[6] For the robustness check, we also estimate the model by using household fixed effect to control household specific characteristics (x_{vi}), which may include farmers' innate ability or motivation. The main result does not change. The estimated results are available for readers upon request.

dummy would capture the spill-over effect from trainees to non-trainees in training villages compared with that to non-training villages, while year dummies capture the general trend including non-training villages.

4.2. Regression Results

Table 3 shows the regression results with plot fixed effects. All three interaction terms of MSRI plot dummy, trainee dummy, and After dummy have positive and significant coefficients in all the regressions, suggesting the effectiveness of the training. Compared to those of the non-trainees' plots, the trainees' adoption rates in MSRI plot increase by 0.6-0.9 for modern variety, 0.4-0.9 for transplanting/dibbling in rows, and by 0.3-0.6 for recommended spacing. The trainees also increase chemical fertilizer application by 86-98 kg per hectare after they attend the training. As a result, trainees' paddy yield increases by 1.6-2.1 tons per hectare in MSRI plot. Note that the estimated coefficients of the interaction terms of MSRI plot dummy, trainee dummy, and After dummy on paddy yield and other technology adoption in 2013 are not statistically significantly different for 2012 trainees (indicated as b) and 2013 trainees (indicated as c) in 2013, suggesting that the training is effective even after KPL stops providing free inputs.

Table 4 shows the estimation results without controlling any fixed effect. The interaction terms of MSRI plot dummy dummies, trainees in 2012 and 2013 dummies, and After dummies have positive and significant coefficients in all the models, suggesting the effectiveness of SRI training on the adoption of technologies and paddy yield in the MSRI plot of trainees. Training village dummy has positive and significant coefficient for the adoption of MVs, suggesting that there is slight spill-over effect from trainees to non-trainees in training village. This may be because the availability of seed of MVs in training villages would improve when trainees start cultivating MVs as the seed of rice can be self-produced. Note, however, that coefficient of training village dummy has no significant coefficient for paddy yield and the adoption of other technologies. On the other hand, year dummy of 2012 and 2013 has positive and significant coefficient on paddy yield and the adoption of technologies. These results suggest that spill-over effect from trainees to non- trainee in training village is no larger than that from trainees to farmers in non-training villages. However, new technologies taught in the training has diffused overtime even to non-SRI villages, though the estimated coefficients are small.

5. Impact of Technology Adoption on Costs and Profit

5.1 Methodology

In this section, we estimate the impact of the adoption of improved technologies on paddy yield, costs, and profit of rice cultivation by using our cross-section data in 2013. We apply two estimation methods: average treatment effect on the treated (ATT) by using Propensity Score Matching (PSM) and sub-sample analyses by using the plot-level variation of the adoption of MSRI technology (Wooldridge, 2010; Takahashi and Barrett, 2014).

First, we estimate the Average Treatment Effect on Treated of the adoption of MSRI technologies on paddy yield, costs, and profit of rice cultivation. Let y_{1j} denote an outcome of interest in plot j with MSRI adoption, and y_{0j} the outcome in the same plot without adoption. Let the variable D_j be a binary treatment indicator, where $D_j = 1$ denotes being MSRI plot and $D_j = 0$ otherwise. ATT can be defined as:

$$ATT = E(y_{1j} - y_{0j} \mid D_j = 1) = E(y_{1j} \mid D_j = 1) - E(y_{0j} \mid D_j = 1), \qquad (2)$$

where $E(\cdot)$ denotes an expectation operator. A fundamental problem here is that we cannot observe both y_{1j} and y_{0j} as a plot cannot be in both states.

As it is well known, simple comparison between MSRI plot and non-SRI plot would result in a biased estimator due to the endogeneity of technology adoption. In order to circumvent this problem, this paper relies on Propensity Score Matching (PSM) method, proposed by Rosenbaum and Rubin (1983). PSM relies on an assumption of conditional independence, which means that conditional on the probability of using MSRI on a plot given observable covariates, an outcome of interest in the absence of treatment y_{0j} and MSRI adoption D_j are statistically independent. Another important assumption is called overlap assumption and can be expressed as $0 < \Pr(D_j = 1 \mid x_{ij}) < 1$, where $\Pr(D_j = 1 \mid x_{ij})$ denotes the probability of being MSRI plot given household- and plot- level observable characteristics x_{ij} (Wooldridge, 2010). If these two assumptions hold, then we can consistently estimate

$$ATT^{PSM} = E\left[y_{1j} \mid D_j = 1, p(x_{ij})\right] - E\left[y_{0j} \mid D_j = 0, p(x_{ij})\right] \qquad (3).$$

The major limitation of PSM is that if unobservable factors affect adoption decisions, estimated ATT may be biased by selection of those unobservable factors. It is virtually impossible, however, to control for all the unobservable characteristics. Therefore, we test whether unobservables might affect our estimated results by using sensitivity tests (Rosenbaum, 2002). Furthermore, we also check the robustness of our results by estimating ATT by using both Kernel matching and biased-corrected Nearest Neighbor matching methods.

As we discussed earlier, some households in our sample utilize some of their plots for growing rice by using MSRI technologies and other plots for growing rice in a traditional manner. In order for us to control for the unobserved household characteristics that cannot be controlled in the PSM estimation, we utilize this variation at the plot level to estimate the impact of the adoption of MSRI technologies on paddy yield, costs, and profit of rice cultivation by controlling household fixed effect. The advantage of this method is that we can control household innate characteristics which may affect both adoption of MSRI technologies and outcome variables, resulting in endogeneity bias in estimated coefficients. The drawback, however, is that we need to restrict our sample to 72 trainees whose data for both MSRI and non-SRI plots in 2013 is available.

5.2 Regression Results for Average Treatment Effect on Treated of Modified SRI adoption

In order for us to estimate the ATT of MSRI adoption, we first estimate the plot-level MSRI use by using probit estimation method, although the results are not shown here. Using the estimation results of probit model, we compute the propensity score for each plot. Note that we dropped 4 observations, which do not satisfy the overlap assumption.[7]

[7] We also conduct balancing tests on the differences in means. Although results are not shown, no covariates is significantly different between MSRI plots and non-SRI plots after matching, suggesting that our matching procedure is successful in generating relevant comparison groups (Takahashi and Barrett, 2014) Estimated results for probit estimation and balancing tests are available upon request.

Table 5 shows the ATT estimates of the impact of being MSRI plot on productivity, production costs, and profit. For robustness check, we show the estimated results based on Kernel matching and biased-corrected Nearest Neighbor matching methods. We use an Epanechnikov kernel with a band width of 0.06 and obtain standard error by bootstrapping with 500 replications for our Kernel matching estimation. The estimated coefficients are largely the same regardless of the matching methods, suggesting the robustness of our results. Yields in MSRI plots are higher than non-SRI plots by 2.3-2.4 tons per hectare. The family labor costs are higher in MSRI plots than in non-SRI plots while there is no significant difference in hired labor costs, suggesting that MSRI technologies are more labor intensive and require care than traditional cultivation methods. Despites its high input and labor cost, the increase in gross output value exceeds that in costs and, hence, cultivators achieve higher income and profit in MSRI plots than in non-SRI plots. ATT estimation results show that the profit in MSRI plots is higher than that in non-SRI plots by 277.1 – 292.7 USD per hectare.

In Table 5, we also report the results for Rosenbaum bounds tests for sensitivity analysis (Rosenbaum, 2002). We report the value of odds ratio of MSRI use, which alter the results of our statistical inference at 10% level. Although there is no clear-cut critical threshold that distinguishes existence and non-existence of hidden bias, the larger the critical value is, the less sensitive to bias based on selection-on unobservables our estimated results are (Rosenbaum, 2002; Takahashi and Barett, 2014). Our results show that odds ratio to alter the inference is from 2.0 to 8.2, suggesting that our results are not sensitive to unobserved characteristics.

5.3 Regression Results for Household Fixed Effect Models on Impact of Modified SRI

Table 6 shows the estimation results of sub-sample analyses with household fixed effects on the impact of MSRI adoption on paddy yield, costs, and profit of rice cultivation in 2013. We separately include the interaction term of trainee in 2012 dummy and MSRI plot dummy, and that of trainee in 2013 dummy and MSRI Plot dummy. Note that the sample is restricted to trainees who cultivate both MSRI plots and non-SRI plots in 2013. The results show that the adoption of MSRI increases the paddy yield by 2.6-2.8 tons per hectare. Although total labor costs and input costs increases, the increase in gross output value exceeds that of costs, and trainees earn higher income by 449-736 USD and profit by 286-625 USD per hectare in MSRI plots than in non-SRI plots. Note that family labor cost is significantly higher while hired labor cost is lower in MSRI plots than in non-SRI plots. This result suggests that farmer cannot rely on hired labor to adopt MSRI technologies probably due to its care intensive feature and high monitoring cost of agriculture labor in general (Otsuka, 2007).

Furthermore, the estimated coefficients on paddy yield and profit are higher for trainees in 2012 than trainees in 2013, suggesting that 2012 trainees achieve higher yield and profit than those in 2013. This result suggest that training is effective even after KPL stop providing free inputs probably because trainees in 2012 enjoy being eligible for credit program and probably because of the learning effect as well.

6. Conclusion

This paper examined the impact of the training provided by a private company in a rain-fed rice cultivating areas in Kilombero district in Tanzania. The most important finding is that a high productivity and profitability of improved technologies in rain-fed rice cultivation. The farmers who applied recommended MSRI technologies achieve as high yield as 5 tons per hectare on average. Given that the average paddy yield in other rain-fed areas of the country is merely 1.8 tons per hectare (Nakano et al., 2014) and the average yield without new technology adoption in the study sites are 2.6 tons per hectare, this is a remarkably high yield. Note also that, the paddy yield in the large scale farm of KPL is about 3 tons per hectare. Our results also imply that the small scale farmers are more productive than a large scale farm as long as they are provided with proper technologies.

We observe that the training effectively enhances the technology adoption by small-scale farmers and increases the paddy yield by 1.8 -2.6 tons per hectare and the profit by 277.1- 625.9 USD per hectare, even though family labor costs increases probably due to labor and care intensive features of MSRI technology. Judging from the much higher income as well as profit per hectare in MSRI plots than in non-SRI plots, the technologies have potential to be disseminated rapidly and widely to many peasant farmers in Kilombero Valley. If that happens, it is not a dream that the Kilombero Valley, which is as large as 11,600 km^2, becomes the center of rice production in East Africa. However, since this project is at its inception stage, it is too early to judge the scalability of the MSRI. Indeed, it is extremely labor intensive, particularly for planting and weeding, which many farmers want to avoid.

Our results also suggest that private extension service by a large scale farm can effectively enhance the productivity of small scale rice farmers. However, we also have to be careful in judging the sustainability and scalability of this type of private extension to other areas. As we discussed earlier, the intension of credit service (or “contract farming”) by KPL was not widely accepted by farmers because of the fluctuation in the market paddy price. Currently, the extension service is financially supported by USAID. Whether other private companies would have incentive to provide qualified extension services critically depends on if they can develop mutually beneficial relationship with small-scale farmers. We need to further examine if this mutually beneficial collaboration will be expanded to other vast but under-utilized rain-fed areas with the due caution regarding the land use rights of local farmers to achieve a rice Green Revolution in rain-fed areas in SSA.

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Table 1: Yield, modern inputs, and the adoption of improved practices in the sampled rice plots[1] in 2013 by MSRI training participation

	Training village							Non-training village	Average	Difference[2]					
	Trainee						Non-trainee								
	MSRI Plot in 2013			Non-SRI Plot in 2013											
	Average	2012 trainee	2013 trainee	Average	2012 trainee	2013 trainee				(a)-(d)	(d)-(g)	(g)-(h)	(d)-(h)	(b)-(c)	(e)-(f)
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)							
Paddy yield in 2013 (tons per hectare)	5.1	5.3	5.0	2.8	2.7	2.8	2.6	2.9	3.3	2.3***	0.2	-0.3**	-0.1	0.3	-0.1
Average paddy yield before training (2009-2010) (tons per hectare)	2.7	2.8	2.7	2.6	2.6	2.6	2.3	2.3	2.5	0.2	0.3	0.0	0.3	0.1	0.0
Modern inputs use in 2013															
Share of modern variety plots (%)	97.1	95.7	97.1	9.5	10.0	9.4	5.6	2.4	29.5	87.6***	3.9	3.2	7.1*	-1.4	0.6
Chemical fertilizer use (kilograms per hectare)	91.8	104.1	88.3	11.5	21.0	8.5	2.5	2.5	27.7	80.3***	9.0**	0.0	9.0*	15.8	12.5
SRI adoption / Improved practices in 2013															
Share of straight row dibbling plots (%)	82.5	82.6	82.5	1.2	5.0	0.0	0.8	2.4	22.5	81.3***	0.4	-1.6	-1.2	0.1	5.0*
Share of straight row transplanting plots (%)	7.8	8.7	7.5	0.0	0.0	0.0	0.8	1.2	2.5	7.8***	-0.8	-0.4	-1.2	1.2	0.0
Share of plots adopting spacing of 25cm x 25cm or more (%)	59.2	60.9	58.7	1.2	5.0	0.0	1.6	2.4	16.7	58.0***	-0.4	-0.8	-1.2	2.2	5.0*
Paddy plot size (ha)	0.4	0.5	0.4	1.0	1.2	1.0	0.9	1.2	0.9	-0.6***	0.1	-0.3*	-0.2	0.1	0.2
Observations (plots)	103	23	80	84	20	64	126	83	396						
Observations (households)	110	25	85				100	71	281						

Note: 1. We asked farmers to list the usage of each of their farming plots. Among those listed, we selected 2 paddy plots for plot-level analysis. For farmers who grow MSRI rice, we automatically selected that plot where MSRI rice is grown and selected another plot randomly where traditional rice is grown. For farmers who do not grow MSRI rice, we randomly selected up to two plots where rice is grown. 2. *** denotes significant at 1%, ** significant at 5%, and * significant at 10% in t-test comparing between the labeled categories.

Table 2: Factor payments in the sample rice plots in 2013 by MSRI training participation

	Training village							Non-training village	Difference[2]				
	Trainee						Non-trainee						
	MSRI Plot in 2013			Non-SRI plot in 2013									
	Average	2012 trainee	2013 trainee	Average	2012 trainee	2013 trainee			(a)-(d)	(d)-(g)	(g)-(h)	(d)-(h)	(b)-(c)
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)					
Gross output value (USD/ha) [1]	1061.9	1202.2	1021.5	622.3	621.4	622.6	618.1	732.6	439.6***	4.2	-114.5*	-110.3*	180.7
Paddy Price (USD/kg)	0.203	0.208	0.202	0.224	0.218	0.225	0.236	0.225	-0.021	-0.012	0.011	-0.001	0.006
Hired labor cost (USD/ha)	173.6	215.1	161.7	235.3	347.3	200.3	149.6	140.3	-61.7	85.7**	9.3	95.0**	53.4
Imputed cost of family labor (USD/ha)	346.5	308.1	357.5	165.1	146.8	170.8	242.5	188.3	181.4***	-77.4**	54.2	-23.2	-49.4
Rented machine or animal cost (USD/ha)	82.8	90.7	80.6	41.1	34.5	43.2	91.2	89.9	41.7***	-50.1***	1.3	-48.8***	10.1
Imputed cost of owned machine or animal (USD/ha)	10.1	20.7	7.0	61.8	61.5	61.9	19.8	24.1	-51.7***	42.0***	-4.3	37.7***	13.7
Inputs cost (USD/ha)	118.1	124.4	116.3	53.5	61.1	51.2	70.2	59.8	64.6***	-16.7	10.4	-6.3	8.1
Seeds (USD/ha)	37.8	27.3	40.8	32.4	33.3	32.1	48.3	28.8	5.4	-15.9	19.5*	3.6	-13.5
Chemical fertilizer (USD/ha)	59.4	70.8	56.1	7.1	12.8	5.3	2.0	2.0	52.3***	5.1*	0.0	5.1	14.7
Marketing and Milling cost (USD/ha)	18.0	77.3	0.9	6.8	16.2	3.9	43.1	26.8	11.2	-36.3	16.3	-20.0*	76.4**
Rice Income (USD/ha)	687.1	713.2	679.6	309.6	180.6	349.9	302.7	434.7	377.5***	6.9	-132.0**	-125.1**	33.6
Rice Profit (USD/ha)	312.8	366.2	297.5	58.5	-46.0	91.2	1.7	203.4	254.3***	56.8	-201.7***	-144.9**	68.7
Observations (plots)	103	23	80	84	20	64	126	83					
Observations (households)	110	25	85				100	71					

1. The exchange rate used is USD 1 = TZS 1,583 (year 2013). 2. *** significant at 1%, ** significant at 5%, and * significant at 10% in t-test comparing between the labeled categories.

Table 3: Difference-in-difference estimator of impact of MSRI training on yield, the adoption of modern inputs, and improved practices in 2010-2013 (Plot Fixed Effect – unbalanced panel)

VARIABLES		Paddy Yield (tons/ha)	Modern Variety (=1)	Chemical Fertilizer (kg/ha)	Dibbling/Transplanting in Row (=1)	Recommended Spacing (=1)
		(1)	(2)	(3)	(4)	(5)
Effect on MSRI plot						
MSRI plot x	(a)	1.608***	0.563***	17.120	0.386**	0.336**
2012 Trainee x year2012 dummy		(2.75)	(4.96)	(1.60)	(2.54)	(2.20)
MSRI plot x	(b)	2.078***	0.852***	86.392***	0.875***	0.563***
2012 Trainee x year2013 dummy		(3.99)	(10.36)	(3.20)	(12.77)	(4.79)
MSRI plot x	(c)	1.635***	0.779***	97.853***	0.867***	0.530***
2013 Trainee x year2013 dummy		(5.00)	(13.69)	(7.40)	(19.37)	(8.14)
Effect on non-SRI plot						
2012 Trainee x year2012 dummy		-0.133	-0.012	6.453	0.072	0.086
		(-0.75)	(-0.40)	(1.19)	(0.70)	(0.84)
2012 Trainee x year2013 dummy		-0.297	0.078	22.418	0.010	0.015
		(-0.99)	(1.09)	(1.40)	(0.24)	(0.35)
2013 Trainee x year2013 dummy		-0.258	0.074*	2.529	-0.026**	-0.023**
		(-1.36)	(1.85)	(0.72)	(-2.49)	(-2.23)
Year dummy						
2011		-0.032	0.017*	0.382*	0.001	-0.001
		(-0.54)	(1.67)	(1.81)	(1.19)	(-1.02)
2012		0.177**	0.055***	2.005**	0.034**	0.019
		(2.24)	(2.80)	(2.23)	(2.35)	(1.54)
2013		0.462***	0.034**	2.573***	0.031***	0.025**
		(4.15)	(2.17)	(2.75)	(2.77)	(2.31)
Constant		2.516***	0.008	-0.022	0.000	0.001
		(55.84)	(0.98)	(-0.02)	(0.04)	(0.20)
R-squared		0.230	0.667	0.521	0.742	0.451
No. of observation		1329	1329	1329	1329	1329
No. of plots		396	396	396	396	396
No. of households		281	281	281	281	281
Equality of coefficients test F-statistics [1]						
(a)=(b)		0.36[0.54]	4.72[0.03]	9.75[0.00]	11.57[0.00]	2.86[0.09]
(b)=(c)		0.52[0.47]	0.54[0.46]	0.15[0.70]	0.01[0.92]	0.06[0.80]
(a)=(c)		0.00[0.96]	2.90[0.09]	22.48[0.00]	9.22[0.00]	1.37[0.24]

Note: 1. P-values in brackets. MSRI plot dummy =1 if the plot is used to cultivate MSRI rice at the time of the MSRI training and thereafter. t-statistics in parenthesis. ***p<0.01, **p<0.05, *p<0.1. Base year is 2010. Inverse probability weights included to account for attrition. For columns (6) to (10), only farmers with both MSRI and non-SRI plots are included.

Table 4: Difference-in-difference estimator of impact of MSRI training on yield, the adoption of modern inputs, and improved practices in 2010-2013 (unbalanced panel)

VARIABLES	Paddy Yield (tons/ha)	Modern Variety (=1)	Chemical Fertilizer (kg/ha)	Dibbling/Transplanting in Row (=1)	Recommended Spacing (=1)
Effect on MSRI plot					
MSRI plot x	1.938**	0.597***	32.133***	0.360**	0.326*
2012 Trainee x year 2012 dummy	(2.52)	(5.45)	(3.24)	(2.07)	(1.87)
MSRI plot x	2.358***	0.868***	94.333***	0.889***	0.599***
2012 Trainee x year 2013 dummy	(4.26)	(11.66)	(3.65)	(14.07)	(5.47)
MSRI plot x	1.715***	0.791***	90.917***	0.855***	0.529***
2013 Trainee x year 2013 dummy	(4.44)	(14.65)	(7.17)	(19.18)	(8.21)
Effect on non-SRI plot					
2012 Trainee x year 2012 dummy	-0.327	-0.043**	-1.823**	0.103	0.118
	(-0.81)	(-2.16)	(-2.21)	(0.76)	(0.87)
2012 Trainee x year 2013 dummy	-0.416	0.057	18.279	-0.001	0.010
	(-1.13)	(0.92)	(1.31)	(-0.04)	(0.27)
2013 Trainee x year 2013 dummy	-0.212	0.062*	5.413	-0.030***	-0.021**
	(-0.84)	(1.65)	(1.23)	(-2.68)	(-2.27)
MSRI plot dummy					
MSRI plot x 2012 Trainee dummy	0.252	0.000	0.527	0.000	0.000
	(0.98)	(0.09)	(1.01)	(0.08)	(0.08)
MSRI plot x 2013 Trainee dummy	0.133	0.074***	1.839**	0.036**	0.021*
	(0.85)	(3.22)	(2.20)	(2.57)	(1.75)
Trainee dummy					
2012 Trainee dummy	0.277	-0.014	0.470	0.015***	0.009*
	(1.33)	(-1.28)	(1.18)	(2.76)	(1.83)
2013 Trainee dummy	0.327**	-0.021**	0.179	0.010**	0.005
	(2.37)	(-2.19)	(0.55)	(2.33)	(1.59)
Training village dummy	0.109	0.028***	0.102	-0.007	-0.004
	(1.02)	(3.01)	(0.16)	(-1.07)	(-0.63)
Year dummy					
2011	-0.042	0.018	0.074	0.000	0.000
	(-0.39)	(1.52)	(0.62)	(0.17)	(0.18)
2012	0.136	0.053***	1.863**	0.036***	0.021*
	(1.07)	(2.71)	(2.25)	(2.59)	(1.75)
2013	0.425***	0.040***	2.954***	0.036***	0.025**
	(2.85)	(2.71)	(2.70)	(3.03)	(2.47)
Constant	2.251***	-0.023**	-0.612	-0.008	-0.005
	(19.89)	(-2.56)	(-1.30)	(-1.27)	(-0.96)
R-squared	0.184	0.652	0.478	0.732	0.454
No. of observation	1329	1329	1329	1329	1329
No. of households	281	281	281	281	281
Equality of coefficients test F-statistics[1]					
(a)=(b)	0.23[0.63]	4.20[0.04]	5.06[0.02]	8.12[0.00]	1.76[0.18]
(b)=(c)	0.91[0.34]	0.71[0.40]	0.01[0.90]	0.20[0.65]	0.30[0.58]
(a)=(c)	0.07[0.79]	2.53[0.11]	13.36[0.00]	7.53[0.01]	1.19[0.27]

Base year is 2010. Base group is plots in non-training villages. Standard errors are clustered at household level. t-statistics in parenthesis.***p<0.01,**p<0.05,*p<0.1. SRI plot dummy =1 if the plot is used to cultivate SRI rice at the time of the MSRI training and thereafter. Note: 1. P-values in brackets. Inverse probability weights included to account for attrition

Table 5: Estimated Plot-level Impact of MSRI (Average Treatment Effect by Kernel and Bias-Corrected Nearest Neighbor Matching)

		Kernel Matching[1)]					Nearest Neighbor Matching (Bias-Corrected)[2)]	
		MSRI plot	Non-SRI plot	ATT	s.e.	Rosenbaum bounds critical level of odds ratio[3)]	ATT	s.e.
Paddy Yield	(tons/ha)	5.14	2.69	2.42***	0.24	8.2	2.33***	0.24
Value of Production	(USD/ha)	1073.9	635.3	438.6***	62.5	5.7	448.9***	51.3
Rice Income	(USD/ha)	696.0	314.0	382.0***	62.0	3.7	389.7***	65.0
Rice Profit	(USD/ha)	321.2	44.0	277.1***	63.7	2.6	292.7***	62.7
Total Cost	(USD/ha)	752.8	591.3	161.5***	42.9	2.4	156.1***	52.4
Total Labor Cost	(USD/ha)	525.1	387.0	138.2***	39.0	2.0	96.8*	53.9
Hired Labor Cost	(USD/ha)	179.3	185.2	-5.9	28.0	-	-57.2	47.9
Family Labor Cost	(USD/ha)	345.9	201.7	144.1***	33.7	2.0	154.0***	30.0
Total Paid Cost	(USD/ha)	377.9	321.3	56.6	39.6	-	59.1	49.6
Input Cost	(USD/ha)	115.9	62.0	53.9***	12.4	2.2	64.8***	11.7

Note: *** p<0.01, **p<0.05, *p<0.1.

1. We use an Epanechnikov kernel matching with bandwidth of 0.06 and obtain standard errors by bootstrapping with 500 replications.
2. We use one-to-two matches with robust standard errors.
3. We report the value of odds ratio of MSRI use, which alter the results of our statistical inference at 10% level based on Rosenbaum (2002).

Table 6: Sub-sample analysis of the impact of MSRI-training on rice performance (2013) (Household Fixed Effect)

VARIABLES	Paddy Yield (tons/ha)	Value of Production (USD/ha)	Rice Income (USD/ha)	Rice Profit (USD/ha)	Total Cost (USD/ha)	Labor Cost (USD/ha)	Hired Labor Cost (USD/ha)	Family Labor Cost (USD/ha)	Paid Cost (USD/ha)	Input Cost (USD/ha)
=1 if MSRI plot x trainee in 2012 (a)	2.824***	630.987***	735.525***	625.896***	5.091	-50.544	-204.704**	154.160**	-104.538	64.283***
	(5.41)	(5.60)	(5.67)	(5.09)	(0.05)	(-0.51)	(-2.29)	(2.53)	(-1.13)	(3.80)
=1 if MSRI plot x trainee in 2013 (b)	2.631***	494.194***	448.938***	286.399***	207.795***	187.290***	-39.024	226.314***	45.256	41.067***
	(9.22)	(61.56)	(6.33)	(4.26)	(3.83)	(3.49)	(-0.80)	(6.81)	(0.89)	(4.44)
Constant	2.878***	648.334***	325.758***	68.703	579.631***	414.701***	248.137***	166.564***	322.577***	54.522***
	(16.26)	(38.206)	(7.41)	(1.65)	(17.22)	(12.44)	(8.18)	(8.07)	(10.27)	(9.50)
R-squared	0.614	0.571	0.501	0.379	0.169	0.147	0.075	0.423	0.028	0.322
No. of plots	148	148	148	148	148	148	148	148	148	148
No. of households	74	74	74	74	74	74	74	74	74	74
Equality of coefficients test F-statistics[1]										
(a)=(b)	0.11[0.74]	1.33[0.29]	3.76[0.06]	5.86[0.02]	3.21[0.08]	4.51[0.04]	2.64[0.11]	1.08[0.30]	2.01[0.16]	1.45[0.23]

This analysis uses the observation of plots cultivated by 74 trainees (among 110 trainees) for whom we have both MSRI plots and non-SRI plots data.