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Is the Green Revolution in Sub-Saharan Africa a Fertilizer and Seed Revolution? The Impact of Training and Free Distribution of Fertilizer and Seeds on Agricultural Productivity

Yuko Nakano* and Eustadius Francis Magezi†

Abstract

The Green Revolution in Asia is often considered the "fertilizer and seed revolution." However, it has recently become recognized that Green Revolution is not merely a fertilizer and seed revolution but that good agricultural practices for better water and crop management are also crucial. If so, agricultural training instead of providing fertilizer and seeds for free should effectively increase agricultural productivity in sub-Saharan Africa. This study conducts a randomized control trial to compare the efficacy of agricultural training and the free distribution of a small amount of fertilizer and seeds of a modern variety of rice. Our results show that trained farmers adopted modern varieties and improved agronomic practices more often and achieved higher paddy yield, income, and profit per hectare than the control group. By contrast, neither the paddy yield nor the income of those who received free inputs increased, although they were more likely to adopt modern variety than a control group. The results suggest that proper knowledge transfer is crucial for enhancing agricultural productivity. We also observed that control group farmers learned about new technologies from trained farmers while they did not do so from free-input receiving farmers, suggesting possible knowledge spillover from trained farmers but not from free-input receivers.

Keywords: Technology adoption, Agricultural productivity, Agricultural training, Free-input distribution, Sub-Saharan Africa, Tanzania

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1. Introduction

Technological transformation and increased agricultural productivity are crucial for poverty reduction and food security in sub-Saharan Africa (SSA). Especially, the importance of rice in SSA has continued to grow in the region due to increasing demand and imports. However, paddy yield in SSA has been stagnant and lagged behind Asian countries, awaiting an African version of the Green Revolution (Evenson and Gollin 2003).

The Green Revolution in Asia is often considered to be a "fertilizer and seed revolution" (Carter, Laajaj, and Yang 2021; Gollin, Morris, and Byerlee 2005; Johnston and Cownie 1969; Suri and Udry 2022). Insufficient use of modern inputs, including seeds of improved varieties and chemical fertilizer, is often cited as a significant constraint on transferring the Green Revolution to Africa (Sheahan and Barrett 2017). Previous academic literature has discussed the reasons for low input use, including procrastination and time-inconsistent preferences (Duflo, Kremer, and Robinson 2011), low or heterogenous return on inputs (Ayalew, Chamberlin, and Newman 2022; Beaman et al. 2013; Bird et al. 2022; Burke, Jayne, and Black 2017; Duflo, Kremer, and Robinson 2008; Marenya and Barrett 2009; Suri 2011), high prices of fertilizer due to poor infrastructure (Aggarwal et al. 2022; Minten, Koru, and Stifel 2013; Porteous 2020), the absence of formal credit and insurance markets (Emerick et al. 2016; Karlan et al. 2014; Nakano and Magezi 2020), poor or manipulated quality of inputs (Ashour et al. 2019; Bold et al. 2017; Michelson et al. 2021; 2023), and lack of knowledge about new technology (Abay et al. 2022; Ayalew, Chamberlin, and Newman 2022; Harou et al. 2022). Many African governments have also provided fertilizer and seed subsidies, although the effects of this are doubtful, especially from a cost-benefit perspective (Jayne and Rashid 2013; Ricker-Gilbert, Jayne, and Chirwa 2011)

Recently, it has been argued that Green Revolution is not merely a fertilizer and seed revolution; it also requires the use of good agricultural practices, such as improved water, soil, and crop management (Otsuka, Mano, and Takahashi 2023; Otsuka and Larson 2012; 2016). Empirical studies conducted in SSA show that farmers who adopt these practices, particularly in rice fields, achieve higher yields, and in some cases, higher profits than non-adopters (Nakano, Tanaka, et al., 2018; Kijima, 2022; Takahashi et al, 2019). If this is the case, agricultural training must be an important policy option because farmers require greater knowledge and skills to adopt these technologies as critical parts of an integrated system (Kajisa and Vu 2023). Although studies on the effectiveness of agricultural training have increased (deGraft-Johnson et al., 2014; Kajisa & Payongayong, 2011; Kijima, 2022; Nakano, Tanaka, et al., 2018; Nakano, Tsusaka, et al., 2018; Ragasa & Mazunda, 2018; Takahashi et al., 2019), to the authors' knowledge, no previous studies have compared the effectiveness of free input distribution and agricultural training.

Moreover, recent studies focus on the effectiveness of farmer-to-farmer extension (F2FE), because it is prohibitively expensive to train all the farmers in SSA (Conley and Udry 2010; Emerick and Dar 2021; Fafchamps et al. 2020; Kondylis, Mueller, and Zhu 2017; Liverpool-Tasie and Winter-Nelson 2012; Morgan, Mason, and Maredia 2020). In F2FE, a small number of trained farmers are expected to disseminate new technologies to non-trained farmers. One of the key issues here is to whom we should teach new technologies for wider diffusion to non-trained farmers through information sharing. For example, technologies may diffuse more if we teach them to those who are innovative, outstanding, and have larger social network (Maertens, 2017). On the other hand, technologies may diffuse widely when we train those who have similar socio-economic characteristics with the majority of the farmers because other farmers may feel easier to follow farmers who are similar with themselves (BenYishay and Mobarak 2019). If the latter is the case, the information may be shared even if we select trained farmers randomly (Lee, Suzuki, and Nam 2019; Takahashi, Mano, and Otsuka 2019a; Beaman and Dillon 2018)

This paper aims to contribute to the previous literature by comparing the effectiveness of the free distribution of a small number of inputs (3 kg of fertilizer and 5 kg of seed) and agricultural training to promote technology adoption and increased productivity in rainfed rice cultivating areas in Tanzania. JICA and the Ministry of Agriculture Training Institute (MATI) of Tanzania conducted training on rice cultivation called TANRICE training in 2017. For the training component, several lead farmers were trained to disseminate new technologies to surrounding farmers. Given that the peer-learning was promoted and lead farmers were not selected randomly, it is difficult to evaluate the impact of TANRICE training in their villages.

To address this issue, this study conducted a uniquely designed randomized control trial. First, we carefully selected sample villages neighboring the TANRICE villages with similar agroecological and initial technological conditions. After the baseline survey in 2017, we randomly selected farmers in our sample villages to receive TANRICE training and asked them not to disseminate learned technologies in their villages for two years until the completion of our midline survey in 2019. This was to ensure that information spillover to non-trained farmers would be minimal. We also created two other randomly selected groups: free input group who received a small number of free inputs (3kg of fertilizer and 5kg of modern variety seeds) but no training and control group who receive no intervention. By estimating the intention-to-treat (ITT) effects, we compared the effectiveness of agricultural training and the free distribution of inputs.

Our results show that trained farmers increased technology adoption and achieved significantly higher paddy yield, income, and profit. Importantly, although free-input farmers were more likely to adopt modern varieties (MVs), their paddy yield, income or profit were not statistically different from those of the control group, suggesting that the distribution of free inputs alone was not enough to increase productivity. These results support the argument that Green Revolution in Africa should not be considered merely a fertilizer and seed revolution as in Asia, but that disseminating improved agricultural practices is crucial to its achievement. [1]

After our midline survey in 2019, we allowed information to be shared among trained, free input, and control farmers. The results of our dyadic regression on the formation of learning links, based on the data collected in 2022, show that the trained farmers provided information on agricultural technology to the control group, while we did not observe such knowledge transfer from the free-input farmers to the control group farmers. The results imply that randomly selected trained farmers potentially play a role in stimulating the knowledge spillover to control farmers, but free-input farmers may not play such a role.

The structure of the paper is as follows. Section 2 describes the study site, experimental design, and data collection method. In Section 3, we estimate ITT of training and free input by using midline data in 2019. Section 4 investigates if information spills over among trained, free-input, and control farmers by estimating a dyadic regression model on the formation of learning links. Section 5 provides a summary of the main findings and suggestions for future research.

2. Study Site and Data

2.1 Training

The TANRICE training was held from October 2017 to June 2018. The main training components included the adoption of a MV called SARO5, [2] chemical fertilizer use, and transplanting or dibbling in rows (hereafter called planting in rows altogether) for better crop management. In TANRICE training, 16 farmers designated as key farmers in each village were trained in new cultivation technologies at a training institute for 1–2 days before the start of the main crop season of 2017. Key farmers were selected in the village meeting, meaning that the selection of key farmers in TANRICE village was not random. When the season was underway, these TANRICE key farmers, together with officers of

[1] Unlike in SSA, improved cultivation practices—including transplanting in rows, bunding, and land leveling—seem to have been widely diffused during the Asian rice Green Revolution (Abe and Wakatsuki 2011; Otsuka et al. 2023).

[2] The formal name of SARO5 is TXD305, and it was developed in the research institute in Dakawa in 2003. It is the most popular MV in Tanzania.

MATI and the village extension officers, held training sessions at the main demonstration plot in the TANRICE village for three days at the time of sowing and for two days at the time of harvesting. For these in-season training sessions, each key farmer was responsible for inviting four additional farmers, who in turn were expected to later train other non-trained ordinary farmers in TANRICE village. In addition, key farmers were provided with free inputs, including 5 kg of MV seeds and 3 kg of fertilizer, to demonstrate taught technologies to other farmers in their own fields.

2.2 Experimental Design

Due to the promotion of information-sharing and non-random selection of key farmers, the estimates would be biased if we conduct impact evaluation in TANRICE villages. To circumvent this problem, we conducted an experiment in four districts of Tanzania: namely Ulanga, Kilombero, Kyela, and Momba districts, where TANRICE training was conducted.

Appendix Figure 1 shows the timeline of our experiment. First, we selected our sample villages neighboring the TANRICE villages.[3] In each sample village, we invited randomly selected 20 farmers to undertake TANRICE training. They received the same training as TANRICE trainees. More importantly, to avoid information spillover within our sample villages, we requested that trained farmers should not disseminate technologies learned in the training for at least two years. We also asked trained farmers to explain to other farmers that they could not teach new technologies to other farmers until the effectiveness of technologies was confirmed. The training was held only once in 2017 but was not repeated in 2018. Given that it was difficult and not socially desirable to withhold the information for a long time, trained farmers were allowed to disseminate newly learned technologies to other farmers after our midline survey in 2019.

Trained farmers also received the same inputs as TANRICE key farmers (5 kg of MV seeds and 3 kg of fertilizer). Note, however, that the midline survey was conducted in 2019, and data about the cultivation season of 2018 were collected, while the training and free inputs were provided to trained farmers during the training in 2017. This means that trained farmers did not receive free input in the survey year.

In addition, we randomly selected 16 farmers for the free input group, and 16 farmers for the control group, resulting in 208 farmers in our list (52 farmers per village in each of the four villages). We distributed the same amount of free inputs to free-input group as well as the trained farmers in the seasons of both 2017 and 2018, meaning that the free-input

[3] We carefully selected our sample villages so that the information spillover from TANRICE villages to our sample was likely to be limited. For example, we avoided villages where villagers cultivate in the same lowland areas as villagers in TANRICE villages.

farmers were affected by the free-input distribution even in the survey year. In short, we compared the control group that received no treatment, the free input group that received free inputs in both 2017 and 2018, and the trained farmers who received training and free inputs only in 2017.

2.3 Data Collection

The baseline survey was conducted from October to November 2017, and farmers were asked about production during the cultivation season starting from October 2016 to May 2017, which was before the training. Among 80 farmers invited to training, six farmers did not attend, and unfortunately, we failed to interview them. An additional two farmers did not grow rice or were sick. Consequently, out of the 208 farmers in our initial sample, we interviewed 200 farmers who grew rice in 2016–2017 (see Appendix Table 1 for sample size in each district). The absence of the six farmers from our sample could mean our ITT estimates on the impact of training are not free from self-selection bias. As we will discuss later, however, we hardly find significant differences between trained farmers and the control group in terms of the initial degree of technology adoption or household characteristics, suggesting that the omission of these observations did not cause serious bias. Some farmers grew rice in multiple plots, and we obtained detailed information, including technology adoption, input use, and the use of both hired and family labor on all the rice-growing plots. This makes our sample size at baseline 350 plots of 200 households.

The midline survey was conducted from September to November 2019, two years after the TANRICE training.[4] At the midline survey, we found that most farmers had subdivided one plot into two to three plots to apply the new technologies. According to our field observations, this was because farmers were either testing the effects of new technologies or mitigating the risk of adoption.[5] The increased plot number for each household made it difficult to ask in-depth questions, especially about inputs and labor use on all the rice-growing plots. Thus, during the midline survey, we randomly selected two plots: one plot (if any) where either MV or planting in rows was adopted and another plot where these technologies were not adopted. Regarding these two plots, we asked for details, including inputs and labor use. We also asked simple questions about technology adoption and paddy yield for all the cultivated plots. This made our sample size for the analyses on technology adoption and yield 366 plots. The sample size for income and profit became 302 plots of

[4] In the first year of the training, trained farmers were expected to adopt new technologies in a small portion of their plots as a trial. In order to examine the adoption of their main plots, we interviewed farmers two years after the training so that we could ask farmers about the subsequent seasons after the training.

[5] This behavior of sub-dividing plots to adopt new technologies were observed in other study areas in Tanzania (Nakano, Tanka, et al. 2018).

the 187 households, with an attrition rate at the household level of 6.5% (200 households in the baseline and 187 households at the midline).

Due to the COVID-19 pandemic, we conducted the endline survey by phone in 2022. This made it difficult for us to follow all of our sample farmers, and we were only able to interview 115 farmers with about 182 plots. Since it was more difficult to reach farmers in areas with poor phone networks, sample reduction did not occur randomly. In the following analyses, we consider panel attrition in both 2019 and 2022 by using attrition weights. We could only collect relatively simple information, including technology adoption and paddy yield, in the endline survey. Therefore, we cannot calculate costs, income, or profit for 2022.

Moreover, to construct plot-level panel data, farmers needed to recognize which plots they had provided the information on during the base- and mid-line surveys and answer the questions regarding the same plot in the end-line survey. It was, however, impossible for us to explain for which plot we expected them to answer because the survey was conducted over the phone. Thus, we interviewed the same household about a newly selected two plots—one with advanced technology adoption and the other with conventional technologies, as we did in the midline survey. Since we could not follow the same plots, our data is household-level panel data, while the unit of observation for some analyses is the plot.

2.4 Network variables

In all the surveys, we collected the relationship data between each farmer. Specifically, we asked each farmer whether he or she had ever learned any new rice-cultivating technologies from another farmer. To capture the social relationship, we also asked each farmer whether they had any social ties (i.e., relatives, plot or residential neighbors, same church/mosque members, or same social group members) with another farmer. In doing so, we used the "network within sample" method, asking each farmer about their learning and social network links to every other person in the sample. Another approach is "random matching within the sample," where each farmer is matched with a certain number (typically 5 to 10) of randomly drawn individuals from the sample, and for each match, one elicits the details of the relationship (Maertens and Barrett 2013). The problem of random matching within the sample, however, is that omitted variable bias can be substantial if the sample omits a key network node, i.e., someone with many links compared to others. In our case, networks with trained and free-input farmers are especially important,and omitting these key network nodes would cause problems in our analyses. Therefore, we used the network within the sample approach, where the sample includes trained, free-input, and control group farmers.

Before the baseline survey, we prepared a list of randomly selected farmers to interview (e.g., person i). We needed to prefix person j in the questionnaire list so that farmer i could answer a question about their relationship with person j. We listed the same person i for person j so that the relationship data would be symmetric. During the survey, however, we failed to meet some of the interviewees (e.g., person i) and replaced them with another randomly selected farmer. Because of this, those who were actually interviewed (person i) and person j became different and our relationship data is no longer symmetric.[6] To avoid a reduction in sample size, we include the combination of i and j for the analyses as long as the data on information exchange between farmer i and j and basic household characteristics of i and j are available. In addition, there is a sample reduction of farmer i over time. To mitigate the attrition bias, we calculate attrition weight at the individual level rather than the nodes level (i.e., the attrition dummy takes 1 if individual i is attritted, rather than the node of i and j, and this dummy is regressed on household characteristics and village fixed effects). This is because the attrition of sample over time mainly arises from the attrition of individual i.

2.5 Descriptive Analyses

Table 1 shows household-level technology adoption, where adoption takes 1 if a farmer adopts new technologies in one of their plots. We also calculated the average paddy yield at the household level. The asterisks show that there are significant differences between each category of farmers and the control group in the t-test of mean comparisons. In 2017, before the training, we did not observe significant differences in paddy yield and technology adoption between trained and control farmers or between free-input and control farmers, except for a slightly lower adoption rate of planting in rows for the trained farmers than the control farmers. This suggests that our randomization was largely successful.

In 2019, after the training, each farmer cultivated 2.0 plots on average. The household-level adoption rate of MV for trained farmers rose to 66.7%, and the ratio of plots adopting MV among adopters was 52.1%, meaning that 66.7% of trained farmers adopted MV in at least one of their plots, and they grew MV in about half of their plots. The household-level adoption rate of planting in rows (54.5%) and chemical fertilizer (28.8%) for trained farmers were also significantly higher than those for the control group, with these technologies adopted in 48.5 to 64.0% of their plots. We observed that farmers did not

[6] For example, in the original list, we selected farmers A, B, and C to be interviewed. We intended to ask farmer A about their relationship with B and C. We also asked person B about their relationship with persons A and C. Then, the relationship data become symmetric (3 by 3 vector). However, we sometimes failed to find farmer A and therefore replaced person A with person A'. Since person j's list in the questionnaire is pre-fixed (farmers A, B, C), in this case, we asked farmer A' about their relationship with A, B, and C. This makes the list of farmer i different from farmer j and our relationship data has become asymmetric.

adopt new technologies in all of their plots immediately. This was partly because farmers tried to mitigate the risk of adopting unknown technologies and partly because they preferred the taste of local varieties, especially for home consumption. As a result of higher technology adoption, trained farmers achieved significantly higher yields (2.6 tons per hectare) than the control group (1.9 tons per hectare).

The household-level adoption rate of MV was 60.3% for the free input group, significantly higher than that of the control group in 2019. Some farmers were skeptical about the effectiveness of chemical fertilizer based on their view that the use of chemical fertilizer causes soil degradation in their fields. Also, growing MV requires different knowledge and techniques from the traditional variety. Thus, some farmers did not adopt MV or chemical fertilizer even after they received the free inputs. It is important to note that the adoption of other technologies or paddy yield of the free-input group was not statistically different from those of the control group, suggesting that only receiving free input was not enough to increase the adoption of other technologies and improve productivity.

In 2022, the adoption rates of MV and planting in rows for trained farmers remained high, with about 67.9% and 58.5% of trained farmers continuing to use MV and planting in rows, respectively—even five years after the training. The adoption rate of MV for free-input farmers (50.0%) also was significantly higher than the control group (29.0%), suggesting that free-input farmers continued to use MV even when they did not receive free inputs. However, their paddy yield was not significantly higher than the control group.

Table 2 compares the mean of plot-level technology adoption, paddy yield, income, and profit among trained, free-input, and control groups before and after the training. Income is defined as the gross output value minus paid-out costs for fertilizer and agrochemicals, hired labor, and rental costs of machinery and animals. Profit is income minus imputed costs of family labor and owned animals and machinery.[7,8] As discussed above, farmers cultivated multiple plots. The plot-level adoption was consistent with the household-level adoption shown in Table 1. For example, the household-level adoption rate of MV for trained farmers in 2019 was 66.7%, and farmers adopted MV in 52.1 % of plots, consistent with the plot-level adoption rate of 37.2% in 2019.

In 2017, we did not observe any significant differences in technology adoption and farm performance between trained and control farmers, except that the adoption rate of planting

[7] In the calculation of gross-output value, we used the median price of paddy at the village level to evaluate the value of the total harvest, including self-consumed products. We imputed the costs of family labor and owned machinery and animals by using village-level median wage and rental rate of machinery and animals.

[8] The average exchange rate in 2019 was 1 USD = 2307.0 Tanzanian shillings.

in rows was lower for the trained group than the control group. As we discussed earlier, we failed to interview six farmers who were invited but did not join the training. However, this did not cause any upward bias of initial technology adoption for trained farmers. Despite the random selection of free-input farmers, they used significantly larger amounts of chemical fertilizer, and their paddy yield (2.1 tons per hectare) was significantly lower than the control group (2.5 tons per hectare). We will take care of the initial differences between free-input and control farmers by controlling for the outcome variables at baseline in the following ITT estimation.

In Appendix Table 2, we also compared the baseline household characteristics of three categories of farmers. Again, we observed no significant differences between trained and control groups, suggesting that our randomization for trained farmers was largely successful. Free-input group, however, were more educated and had a larger amount of assets than the control group, and the differences were statistically significant at 10%. We will also control for baseline household characteristics in our following estimation to mitigate this imbalance.

As shown in Panel B of Table 2, in 2019, the adoption rate of technologies and productivity of trained farmers increased and became significantly higher than the control group. The plot-level adoption rate of MV for trained farmers became 37.2%, while that of control farmers was 8.3%. The adoption rate of chemical fertilizer is 24.8%, and the average chemical fertilizer use for trained farmers was 14.5kg per hectare. The adoption rate of planting in rows for trained farmers became 33.1%, while that of control farmers was 6.4%. As a result, trained farmers achieved a significantly higher yield of 2.8 tons per hectare than control farmers, who yielded 2.1 tons per hectare. Trained farmers also achieved significantly higher income and profit than control farmers, suggesting the effectiveness of training for productivity enhancement. In Appendix Table 3, we showed the factor share of rice cultivation for each category of farmers. The results indicated that the significant difference in income and profit between trained and control farmers was a result of higher revenue for trained farmers, and there were no significant differences in the production costs between the two.

In contrast, free-input farmers' performance was not significantly different from the control group, except that they were more likely to adopt MV and chemical fertilizers. Free-input farmers did not achieve higher productivity in terms of yield, income, or profit than control farmers, suggesting that distributing free inputs was not effective in improving productivity.

It Is important to note that the technology adoption of control group farmers and their productivity did not increase much from 2017 to 2019, except that their adoption rate of

MV increased from 0.0% to 8.3%. Although we need to admit that the possibility of the spillover from trained or free input to control farmers was not zero, it was not significant to the extent that it did not increase control farmers' productivity from 2017 to 2019. This is important because the impact of training or free-input distribution should not be underestimated when 2019 data is used.

In 2022, the adoption rate of MV for trained farmers was 46.9% and that of planting in rows was 40.7%, and both are statistically significantly higher than those of control farmers. As a result, trained farmers achieved a higher yield of 3.5 tons per hectare while control farmers' yield was 2.7 tons per hectare, suggesting a sustained impact from agricultural training. This also indicates, however, that the spillover effects to control farmers were not large, showing that the difference between trained and control farmers did not disappear over time due to the catch-up of control farmers (see also Nakano, Tsusaka, et al. 2018). The adoption rate of MV for free-input farmers was 37.5%, showing that free-input farmers adopted MV even when they did not receive free inputs. The free-input farmers' yield, however, was not statistically higher than that of the control farmers.

3. The impact of training and free input distribution

3.1. Estimation methods

This section investigates the effects of training and free-input distribution on the adoption of technologies and the productivity of rice cultivation. Since the information spillover was restricted in 2019 but not in 2022, we estimate intention-to-treatment (ITT) effects based on the following model by using our sample only in 2019.

$$Y_{ik2019} = \alpha + \beta Training_{i2019} + \gamma Free\ input_{i2019} + \delta X_{i2017} + \theta Y_{i2017} + u_{ik2019} \quad (1)$$

where Y_{ik2019} denotes the outcome variable of individual i's plot k, including a dummy variable that takes 1 if a farmer adopts MV, a dummy for the adoption of planting in rows, chemical fertilizer use (kg/ha), paddy yield (tons/ha), income (thousand Tsh/ha), and profit (thousand Tsh/ha) in 2019. $Training_{i\ 2019}$ is a dummy variable that takes 1 for trained farmers while $Free\ input_{i\ 2019}$ is a dummy variable taking 1 for free-input farmers. We control for Y_{i2017}, pre-training outcome variables of individual i to account for the differences in the initial performance; that is, we estimate ANCOVA models (McKenzie 2012). Since our data is not plot-level panel data, we calculate the household-level adoption of technologies and the average chemical fertilizer use, yield, income, and profit at base year if farmers cultivate multiple plots. The baseline household characteristics X_{i2017} include the number of adult household members, female-headed household dummy, the age and the years of education of the household head, the value of household assets in millions of Tanzanian shillings (TSh), the number of bulls owned, and landholdings in hectares. U_{ik2019} is an error term.

3.2. Results

Table 3 shows the ANCOVA estimates of the impact of the training and free-input distribution on technology adoption and land productivity using plot-level data. We only report the coefficient of the main variables of interest for brevity. The coefficient of being a trained farmer is positive and significant for the adoption of MV and planting in rows, paddy yield, income, and profit. The adoption rate of MV for trained farmers is higher by about 26% point, that of planting in rows by 22% point, and paddy yield by 0.56 tons per hectare. As a result, trained farmers achieved a higher income by 334 thousand Tanzanian shillings (about USD 144.7) and profit by 340 thousand Tanzanian shillings (about USD 247.3) per hectare than control farmers. These findings suggest that training was not only effective for technology adoption but also for the improvement of productivity and profitability.

Importantly, the coefficient of being the free input group is significant only for the adoption of MV. We do not observe any significant impact of free-input distribution on other technology adoption, yield, income, or profit. This indicates that free input distribution increased the adoption of MV but did not increase paddy yield, income, or productivity, suggesting the limitations of free input distribution as a means for productivity improvement.

Appendix Table 4 shows the estimation results of the ANCOVA models for the factor share of rice cultivation. Due to the high yield, trained farmers achieved higher revenue than the control group. At the same time, there were no significant differences in production costs, and thus, trained farmers achieved higher income and profit than the control group. In Appendix Table 5, we estimate the same models for the labor costs for each cultivation activity, including land preparation, planting, weeding, and harvesting. We observed positive coefficients of being trained farmers for hired and family labor costs for planting and negative coefficients for the family labor costs for weeding and harvesting. These results are consistent with our expectations, as planting in rows is labor intensive while it reduces the weeding and harvesting labor. All the differences, however, are statistically insignificant.

4. Formation of information link

This section examines the information flows among different categories of farmers using dyadic regressions from the network data collected between 2017 to 2022. Following

Fafchamps and Gubert (2007) and Mekonnen et al. (2018), we estimate the following equation:

$$L_{ijt} = \alpha + \beta_m Treatment\ status_i \times Treatment\ status_j * Year_t + \gamma_n\ Treatment\ status_{i0} \times Treatment\ status_{j0} + \delta(zi - zj) + \theta(zi + zj) + \mu Relation_{ij} + \omega_{v+} u_{ijt} \qquad (3)$$

where L_{ijt} is equal to one if respondent i has ever learned any new rice cultivating technologies from person j by year t. Since person i can cite j without j citing i, L_{ijt} is directional. z_i and z_j are baseline household characteristics of individuals i and j. We control for the subtraction and summation of basic household characteristics as well as baseline average paddy yield at the household level to control for the innate ability of farmers. We include the set of interaction terms between the training status of i, that of j, and *year* dummies as well as those in the base year. We have different coefficients β_m and γ_n for each combination of the training status of i and j, with the base category of the information exchange between control and control farmers in 2017. For example, the interaction term of $trained_i$, $free\text{-}input_j$, and $year_{2019}$ indicates the likelihood that trained farmer i learned new rice cultivation technology from j in $year_{2019}$ compared to the information exchange between control and control farmers in 2017. We estimate our models with and without relationship variables between i and j, such as being a relative, plot neighbors, residential neighbors, same church or mosque members, or same social group members, and control for village fixed effects ω_v in both models.

We found no link between households across villages. Thus, there is no point in including pairs of individuals from different villages in the estimation. For this reason, we only include pairs that come from the same village. Following Attanasio et al. (2012) and Takahashi et al. (2019), we use clustered standard error at the village level to allow for possible correlations not only within dyadic pairs but also across all dyads in the same village.

Table 4 shows the summary statistics of network data, showing the probability that person i knows person j; of person i ever having learned new technologies from person j; that person i identifies person j as their relative, same religious group member, plot neighbor, same social group member, or residential neighbor in 2017, 2019, and 2022 respectively. The probability that person i knows person j increased from 46% in 2017 to 77% in 2022. Importantly, the probability of person i ever having learned new technology from person j was 0.0% in 2017 and 1.0% in 2019, suggesting that the information exchange did not occur before or just after the training, and our strategy of asking trained farmers not to disseminate technologies was successful. This probability significantly increased to 20%

in 2022, implying that active information exchange took place between farmers after we allowed them to do so. The probability of person *i* having social relationships with person *j*, such as relatives, neighbors or same group members ranged from 2.7 to 7.3 % at the baseline.

Table 5 shows the estimation results for the dyadic regression on the learning link formation. We only show the estimated coefficients of the interaction terms of the training status of person *i* and *j* and the *year* dummy, although we include other covariates shown in equation (3) and interaction terms of treatment status in the base year. The training status of *i* is indicated on the left and that of *j* on the right in regard to a specific factor. For example, the term $trained_i$ *x* $input_j$ *x 2019* means that the trained farmer (i) learned any new technology from a free input farmer (j) by the year 2019. We show the results with and without relationship variables between *i* and *j* in Columns (1) and (2), and the results are largely the same for both models.

First, the interaction terms between each category of farmers in 2019 are insignificant, except for marginal significance among the free-input and control farmers. Although we need to admit that we could not fully control the information exchange, the coefficient of this interaction term is as low as 0.002. suggesting that our strategy of requesting trained farmers not to disseminate technologies was largely successful.

In contrast, the interaction terms between the $year_{2022}$ dummy and $free\text{-}input_i$ and $trained_j$ dummy, and that of $free\text{-}input_i$ and $free\text{-}input_j$ dummy are positive and significant, implying that there was an increase in information exchange among free-input farmers and from trained to free-input farmers in 2022. Distribution of free inputs might increase the demand for knowledge on how to grow MV, and information exchange was stimulated among free-input farmers and from trained farmers to free-input farmers. Importantly, the interaction term of $control_i$, *trained* $farmer_j$, and the $year_{2022}$ dummies has a positive and significant coefficient of 0.10. This means that the probability of information exchange from trained to control farmers in 2022 is 10.1% point higher than between control and control group farmers in 2017. This demonstrates that the information was transmitted from trained to control farmers once the restriction on information flow was no longer in place in 2022. Instead, the coefficient of the interaction term of $control_i$, $free\text{-}input_j$, and $year_{2022}$ dummies was insignificant, suggesting some limited information flow from free-input to control farmers.

5. Conclusions

This paper compares the effectiveness of agricultural training and free distribution of a small number of inputs on the technology adoption and productivity in rainfed rice-growing areas of Tanzania. For that purpose, we conducted a uniquely designed randomized control trial. We found that training effectively enhanced the adoption of MV and planting in rows which led to increased paddy yield, income, and profit. We also observed that free input distribution increased the adoption of MV for the recipients. However, neither the adoption of other technology nor productivity increased among free-input farmers. These results suggest that the free-input distribution alone is not effective in improving agricultural productivity and that knowledge transfer by providing training is critically important.

Our findings are consistent with the argument that African Green Revolution should not be merely considered to be a seed and fertilizer revolution, but that the adoption of agronomic practices also plays an important role (Otsuka and Larson, 2012; Otsuka, Mano et al., 2023). This has important implications, especially in the current situation whereby many SSA governments are heavily subsidizing fertilizer and seeds, requiring significant budget expenditures (Jayne and Rashid, 2013). Such interventions may not be useful unless appropriate knowledge is transferred through agricultural trainings.

Second, our dyadic regression analyses showed that there was information exchange among the free-input farmers, and from trained farmers to free-input farmers. This could be because the free input distribution stimulated the demand for knowledge on how to grow MV, and farmers started to exchange their knowledge. Importantly, the results of our dyadic regression showed that information was transferred from trained farmers to the control group, implying that trained farmers can stimulate knowledge spillover to non-trained farmers. In contrast, we did not find such information exchange from free-input farmers to control group farmers, suggesting that the free distribution of inputs did not stimulate knowledge spillover to control farmers. One interesting finding is that the information was exchanged even when trained farmers were selected randomly. This is consistent with the findings of Takahashi et al. (2019) and Lee, Suzuki and Nam (2019), who found positive spillover effects from randomly selected trained farmers.

A notable finding is that the adoption of technologies and productivity of control farmers did not increase much, even after the information exchange was allowed. One exception to this was that the adoption of MV increased from 8.3% in 2019 to 17.8% in 2022. This finding seems to contradict the fact that the information was shared by trained to control farmers. One possible reason is that control farmers may have found it difficult to adopt new technologies simply by receiving information from trained farmers, even when we select “average farmers” as trainees. Recently, greater attention has been paid to the effectiveness of F2FE. Further investigation is needed not only on finding effective ways to promote information spillover from trained to non-trained farmers but also on how to promote technology adoption by non-trained farmers. Also, examining whether this process would be enhanced by selecting different types of trained farmers is an interesting topic for future research (Takahashi, Muraoka, and Otsuka 2020).

Another concern is access to qualified seeds. According to our field observation, the seed market is not well-developed in our study sites and qualified seeds are seldom available in markets. Although rice is self-pollinated, and farmers can produce their own seeds from the distributed seeds of MV, the quality of seeds deteriorates over some years. For the positive effects of training to be continuous, assistance for seed market development, such as training for qualified seed production, may be needed. This is an important issue that should be investigated in the future.

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Table 1: Household-level technology adoption by treatment status (2017–2022)

	Training	Free input	Control
Panel A: 2017			
Number of plots cultivated	1.8	1.8	1.7
Household-level adoption rate of MV (%)	1.4	0.0	0.0
Household-level adoption rate of chemical fertilizer (%)	9.7	11.1	4.6
Household-level chemical fertilizer use (kg/ha)	3.8	3.3	3.2
Household-level adoption rate of planting in rows (%)	1.0*	3.2	7.7
Household-level yield (ton/ha)	2.65	2.35	2.54
Observations	72	63	65
Panel B: 2019			
Number of plots cultivated	2.2	1.9	1.8
Household-level adoption rate of MV (%)	66.7***	60.3***	15.9
Household-level adoption rate of chemical fertilizer (%)	28.8**	29.3**	11.1
Household-level chemical fertilizer use (kg/ha)	9.9	5.7	3.7
Household-level adoption rate of planting in rows (%)	54.5***	15.5	7.9
Household-level yield (ton/ha)	2.62***	1.9	1.9
Ratio of plots adopting MV among adopters (%)	52.1	56.7	44.2
Ratio of plots adopting chemical fertilizer among adopters (%)	64.0	82.9	63.1
Ratio of plots adopting planting in rows among adopters (%)	48.5	41.8	73.3
Observations	66	58	63
Panel C: 2022			
Household-level adoption rate of MV (%)	67.9***	50.0*	29.0
Household-level adoption rate of chemical fertilizer (%)	35.8	19.4	22.6
Household-level chemical fertilizer use (kg/ha)	14.9*	7.4	5.1
Household-level adoption rate of planting in rows (%)	58.5***	25.0	22.6
Household-level yield (ton/ha)	3.4*	2.7	2.7
Observations	50	36	29

Source: Authors' calculations

Note: *** p<0.01, ** p<0.05, * p<0.1 in *t*-tests comparing each category and control group

Table 2: Plot-level technology adoption and productivity of rice cultivation by treatment status (2017–2022)

	Training	Free input	Control
Panel A: 2017			
Adoption rate of MV (%)	0.8	0.0	0.0
Adoption rate of chemical fertilizer (%)	9.5	11.2*	4.6
Chemical fertilizer use (kg/ha)	5.2	5.6	5.4
Adoption rate of planting in rows (%)	0.8**	2.6	5.6
Paddy yield (tons/ha)	2.6	2.1*	2.5
Income ('000Tsh/ha)	1491.9	1074.0**	1384.8
Profit ('000Tsh/ha)	296.3	159.7	149.6
Observations	126	116	108
Panel B: 2019			
Adoption rate of MV (%)	37.2***	33.9***	8.3
Adoption rate of chemical fertilizer (%)	24.8***	24.1***	10.1
Chemical fertilizer use (kg/ha)	14.5***	6.1	4.5
Adoption rate of planting in row (%)	28.2***	8.9	6.4
Paddy yield (tons/ha)	2.8***	2.1	2.0
Income ('000Tsh/ha)	1271.2***	892.8	823.4
Profit ('000Tsh/ha)	713.21***	332.5	282.8
Observations	145	112	109
Observations for income and profit	118	93	91
Panel C: 2022			
Adoption rate of MV (%)	46.9***	37.5**	17.8
Adoption rate of chemical fertilizer (%)	24.7	16.1	17.8
Chemical fertilizer use (kg/ha)	18.9	7.9	8.6
Adoption rate of planting in row (%)	40.7***	19.6	13.3
Paddy yield (tons/ha)	3.5**	2.7	2.7
	81	56	45

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1 in *t*-tests comparing each category and control group. '000Tsh/ha stands for thousand Tanzanian Shillings per hectare.

Table 3： ANCOVA estimates on the impact of training and distribution of free inputs on technology adoption and paddy yield (2019)

VARIABLES	Adoption of MVs (=1)	Chemical fertilizer use (kg/ha)	Planting in rows (=1)	Paddy yield (tons/ha)	Income ('000Tsh/ha)	Profit ('000Tsh/ha)
Training	0.264*	9.763	0.220**	0.558*	334.275***	340.618***
	[0.110]	[5.766]	[0.051]	[0.218]	[114.343]	[106.759]
Free input	0.237*	3.930	0.027	0.058	47.990	7.318
	[0.094]	[3.842]	[0.061]	[0.232]	[118.189]	[112.507]
Constant	0.182**	19.219**	0.107	1.765***	737.494**	583.321**
	[0.043]	[4.392]	[0.081]	[0.139]	[323.902]	[252.729]
Observations	366	366	366	366	302	302
R-squared	0.143	0.146	0.151	0.249	0.224	0.191

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1. We control for baseline household characteristics including the number of adult household members,female-head household dummy, age of household head, years of education of household head, the value of the household asset (thousand Tanzanian Shillings), number of bulls owned, and size of owned land. Village fixed effects and baseline outcome variables are also controlled. Robust standard errors are in brackets. '000Tsh/ha stands for thousand Tanzanian Shillings per hectare.

Table 4: Summary statistics of network variables

	2017	2019	2022
Person *i* knows person *j*	0.46	0.51	0.77
Person *i* have ever learned new technologies from person *j*	0.00	0.01	0.20
Person *i* identify person *j* as relative	0.05	-	-
Person *i* identify person *j* as same religious group member	0.07	-	-
Person *i* identify person *j* as plot neighbor	0.03	-	-
Person *i* identify person *j* as same social group member	0.03	-	-
Person *i* identify person *j* as residential neighbor	0.06	-	-
Observations	8264	7750	6312

Source: Authors' calculations.

Table 5: Dyadic regression results for the formation of learning link (2017–2022)

	(1)	(2)
VARIABLES	Learning link	Learning link
$Trained_i$ x $trained_j$ x 2019	0.009	0.009
	[0.009]	[0.009]
$Trained_i$ x $input_j$ x 2019	-0.000	0.000
	[0.002]	[0.002]
$Trained_i$ x $control_j$ x 2019	0.002	0.002
	[0.001]	[0.001]
$Input_i$ x $trained_j$ x 2019	0.006	0.006
	[0.003]	[0.003]
$Input_i$ x $input_j$ x 2019	-0.001	-0.000
	[0.002]	[0.002]
$Input_i$ x $control_j$ x 2019	-0.004	-0.004
	[0.003]	[0.003]
$Control_i$ x $trained_j$ x 2019	0.002	0.001
	[0.002]	[0.002]
$Control_i$ x $input_j$ x 2019	0.002	0.002*
	[0.001]	[0.001]
$Control_i$ x $control_j$ x 2019	-0.007	-0.007
	[0.005]	[0.005]
$Trained_i$ x $trained_j$ x 2022	0.421	0.421
	[0.190]	[0.189]
$Trained_i$ x $input_j$ x 2022	0.226	0.227
	[0.126]	[0.125]
Trainedi x $control_j$ x 2022	0.164	0.164
	[0.102]	[0.102]
$Input_i$ x $trained_j$ x 2022	0.228*	0.228*
	[0.082]	[0.082]
$Input_i$ x $input_j$ x 2022	0.156*	0.156*
	[0.060]	[0.060]
$Input_i$ x $control_j$ x 2022	0.094	0.093
	[0.054]	[0.054]
$Control_i$ x $trained_j$ x 2022	0.101*	0.100*
	[0.035]	[0.034]

$Control_i$ x $input_j$ x 2022	0.089	0.089
	[0.042]	[0.042]
$Control_i$ x $control_j$ x 2022	0.068	0.067
	[0.048]	[0.048]
Relative		0.006
		[0.019]
Same religious group		0.042*
		[0.016]
Plot neighbor		0.029
		[0.013]
Same social group		0.014
		[0.008]
Residential neighbor		0.032
		[0.014]
Constant	-0.089	-0.086
	[0.057]	[0.057]
Observations	20,984	20,984
R-squared	0.220	0.225

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1. The baseline interaction term of training status of *i* & *j* are controlled. Summation and subtracts of basic household characteristics (the number of adult household members, female-headed household dummy, age of household head, years of education of household head, the value of household assets (thousand Tanzanian Shillings), number of bulls owned, and size of owned land, household average paddy yield in 2017) are also controlled. Village fixed effects are controlled and clustered standard errors at village level are shown in brackets.

Appendix Figure 1: Timeline of the survey and interventions

	Aug2017 – Sept 2017	Oct 2017 – May 2018	Oct 2018 – May 2019	Aug-Sept 2019	March 2022
Training group	Baseline survey	Training & free input	-	Midline survey	Endline survey
Free input group		Free input	Free input		
Control		-	-		

Appendix Table 1: Sample size in each district and by training status

District	Trained	Free-input	Control
Kilombero	19	16	16
Ulanga	16	16	16
Kyela	18	16	16
Momba	19	16	16

Appendix Table 2: Balancing test of baseline characteristics

	Training	Free-input	Control
Number of adult household members	2.9	2.8	2.8
=1 if female-headed household	0.1	0.2	0.2
Age of household head	46.0	47.1	45.2
Years of education of household head	6.2	6.5*	5.6
Value of asset (million Tanzanian Shillings)	1.2	1.0*	0.7
Number of bulls owned	1.1	1.4	1.3
Size of owned land (ha)	2.9	2.4	2.1
Observations	72	63	65

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1 in *t*-tests comparing each category and control group.

Appendix Table 3: Mean comparison of factor share of rice cultivation by treatment status (2017–2019)

Variable	Training	Free input	Control
Panel A: 2017			
Revenue from rice ('000Tsh/ha)	1696.7	1398.8*	1669.1
Paid-out costs for purchased input ('000Tsh/ha)	29.2	35.0	30.6
Paid-out costs for labor ('000Tsh/ha)	121.9	210.6	171.3
Imputed costs for family labor ('000Tsh/ha)	1091.9	805.5**	1087.8
Paid-out costs for machinery and animals ('000Tsh/ha)	57.0	75.7	70.4
Imputed costs for owned machinery and animals ('000Tsh/ha)	108.7	79.2**	133.7
Income ('000Tsh/ha)	1491.9	1074.0**	1384.8
Profit ('000Tsh/ha)	296.3	159.7	149.6
	126	116	108
Panel B: 2019			
Revenue from rice ('000Tsh/ha)	1582.9**	1137.3	1081.1
Paid-out costs for purchased input ('000Tsh/ha)	47.1	33.0	35.5
Paid-out costs for labor ('000Tsh/ha)	159.2	136.9	137.2
Imputed costs for family labor ('000Tsh/ha)	438.6	475.6	434.8
Paid-out costs for machinery and animals ('000Tsh/ha)	81.7	81.9	83.8
Imputed costs for owned machinery and animals ('000Tsh/ha)	94.8	76.4	99.5
Income ('000Tsh/ha)	1271.2***	892.8	823.4
Profit ('000Tsh/ha)	713.21***	332.5	282.8
	118	93	91

Source: Authors' calculations.
Note: *** p<0.01, ** p<0.05, * p<0.1 in *t*-tests comparing each category and control group.
'000Tsh/ha stands for thousand Tanzanian Shillings per hectare.

Appendix Table 4： ANCOVA estimates on the impact of training and distribution of free inputs on factor share of rice cultivation (2019)

VARIABLES	Revenue from rice ('000Tsh/ha)	Paid-out costs for purchased input ('000Tsh/ha)	Paid-out costs for labor ('000Tsh/ha)	Imputed costs for family labor ('000Tsh/ha)	Paid-out costs for machinery and animal ('000Tsh/ha)	Imputed costs for owned machinery and animal ('000Tsh/ha)	Income ('000Tsh/ha)	Profit ('000Tsh/ha)
Training	399.814***	9.171	44.449	2.391	14.760	-7.115	334.275***	340.618***
	[113.058]	[7.389]	[28.777]	[61.587]	[13.602]	[18.030]	[114.343]	[106.759]
Free input	58.227	1.497	-0.951	53.604	0.852	-17.051	47.990	7.318
	[116.664]	[6.382]	[26.580]	[59.854]	[14.000]	[16.502]	[118.189]	[112.507]
Constant	977.321***	84.781***	84.974	221.426*	70.565**	58.049	737.494**	583.321**
	[326.296]	[17.056]	[72.692]	[133.387]	[29.938]	[40.701]	[323.902]	[252.729]
Observations	302	302	302	302	302	302	302	302
R-squared	0.216	0.276	0.138	0.202	0.359	0.329	0.224	0.191

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1. We control for baseline household characteristics including the number of adult household members, female-head household dummy, age of household head, years of education of household head, the value of the household asset (thousand Tanzanian Shillings), number of bulls owned, and size of owned land. Village fixed effects and baseline outcome variables are also controlled. Robust standard errors are in brackets. '000Tsh/ha stands for thousand Tanzanian Shillings per hectare.

Appendix Table 5: ANCOVA estimates on the impact of training and distribution of free inputs on labor costs for different activities (thousand Tanzanian Shillings per hectare)

VARIABLES	Paid-out costs of labor for land preparation	Paid-out costs of labor for planting	Paid-out costs for hired labor for weeding	Paid-out costs for hired labor for harvesting	Imputed costs of family labor for land preparation	Imputed costs of family labor for planting	Imputed costs for family labor for weeding	Imputed costs for family labor for harvesting
Training	13.650	21.265	10.078	32.616	16.834	9.953	-4.110	-16.307
	[18.208]	[18.370]	[9.173]	[23.499]	[15.002]	[5.189]	[26.933]	[65.815]
Free input	-0.918	11.686	3.001	-19.129	4.888	6.739	26.772	3.451
	[1.860]	[14.969]	[9.988]	[17.877]	[14.240]	[2.940]	[34.097]	[77.664]
Constant	25.228	12.563	47.424***	-70.125	67.057	-35.667	134.822**	88.384
	[15.811]	[5.851]	[5.324]	[114.342]	[36.758]	[16.000]	[29.225]	[71.657]
Observations	302	302	302	302	302	302	302	302
R-squared	0.113	0.088	0.078	0.053	0.102	0.186	0.146	0.206

Source: Authors' calculations.

Note: *** p<0.01, ** p<0.05, * p<0.1. We control for baseline household characteristics including the number of adult household members, female-head household dummy, age of household head, years of education of household head, the value of the household asset (thousand Tanzanian Shillings), number of bulls owned, and size of owned land. Village fixed effects and baseline outcome variables are also controlled. Robust standard errors are in brackets.

Abstract (in Japanese)

要　約

アジアにおける緑の革命は「近代品種と化学肥料の革命」と考えられてきた。しかし、近年アフリカで緑の革命を起こすためには、近代品種と化学肥料に加えて、水及び作物管理のための栽培技術の普及が重要であることが認識されつつある。そのような状況においては、農業技術研修が農業生産性の向上にとって重要な政策となるだろう。本研究はランダム化比較実験を用いてコメの農業技術研修と少量の化学肥料と種子の無料配布の効果を検証する。その結果、技術研修を受けた農家は近代品種及び栽培技術をより多く採用し、籾米の単位面積当たりの収量、所得、利潤が増加した。それに対して、肥料と種子の無料配布を受けた農家は、近代品種の採用を増やすものの、その他の技術や生産性は向上しなかった。このことは技術研修が技術採用と生産性の向上にとって重要であることを示唆している。また技術研修を受けた農家は介入を受けなかった農家に技術の情報を伝えているが、無料配布を受けた農家からは情報の伝達は起こらなかったという結果も得られた。

キーワード：技術採用、農業生産性、農業技術研修、肥料と種子の無料配布、サブサハラ・アフリカ、タンザニア