Does Training Farmers on Multiple Technologies Deter Adoption? Evidence from a Farm Management Training Program in Bangladesh

Nandini Das
Virginia Tech
nandinidas@vt.edu

Anubhab Gupta
Virginia Tech
anubhab@vt.edu

Binoy Majumder
SCDA Consulting Pvt. Ltd.
Binoy.majumder@hotmail.com

Mahamitra Das
Indian Institute of Technology, Kanpur
mahamitra@iitk.ac.in

Rangaswamy Muniappan
Virginia Tech
rmuni@vt.edu

Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-30, 2024

Does Training Farmers on Multiple Technologies Deter Adoption? Evidence from a Farm Management Training Program in Bangladesh*

Nandini Das Anubhab Gupta Binoy Majumder Mahamitra Das Rangaswamy Muniappan

Abstract

Farmers in low-income countries suffer from several challenges that prevent them from achieving higher yields and generating economic gains. Improved agricultural technology can help remove some of the existing obstacles to high agricultural productivity. This paper evaluates an agricultural intervention that provided groundnut farmers in rural Bangladesh with comprehensive recommendations on Integrated Pest Management (IPM), Good Agricultural Practices (GAP), and agronomical suggestions. Using reduced form econometric analyses, we assess the impact of the training program on input usage and yield. Our findings indicate that when farmers receive training on several technologies together, they tend to adopt only the low-cost ones, making such a training program less effective due to the non-adoption of the potentially more beneficial higher-cost technologies. We find significant changes (based on recommendations) in the usage of traditional inputs, but not in new ones. The adjustments in traditional inputs are easier to remember and cheaper to implement. We construct a simple model to show that the learning costs are high for new inputs, leading to selective adoption. Policy recommendations include simplifying complex training into manageable components and implementing strategies to reduce the learning costs associated with new inputs.

Keywords: Technology adoption, groundnut cultivation, Integrated farm management, training, Bangladesh

JEL codes: Q16, 013, O33

---

* Nandini Das is a Ph.D. candidate in the Department of Economics and Anubhab Gupta is an assistant professor in the Department of Agricultural and Applied Economics, both at Virginia Tech. Mahamitra Das is an assistant professor in the Department of Economic Sciences at the Indian Institute of Technology, Kanpur. Binoy Majumder is a field investigator and researcher at SCDA Consulting Pvt. Ltd. in India. Rangaswamy Muniappan is the program director for the IPM Innovation Lab at Virginia Tech. The authors thank the support from the Virginia Tech Bangladesh team in Dhaka and the ACCS farmers' association in Char Fassion during data collection and monitoring.

Corresponding email: nandinidas@vt.edu

Does Training Farmers on Multiple Technologies Deter Adoption? Evidence from a Farm Management Training Program in Bangladesh

1. Introduction

Farming households in low-income countries suffer from several challenges that prevent them from achieving their potential yields and generating economic gains. Good agricultural practices (GAP), including improved inputs, can help address some of the existing obstacles to achieving high agricultural productivity. Technology adoption remains low due to several factors that vary widely by the technology itself, cultural context, and geography (Ruzzante *et al.* 2021). New technologies may reduce welfare when demand-side (like inelastic demand, lack of infrastructure, absence of export markets, etc.) and supply-side constraints (such as imperfect input markets, liquidity constraints, lack of extension services, etc.) exist (Gupta *et al.* 2018).

An all-composite intervention in the form of a training program was carried out on groundnut farmers in rural Bangladesh. The USAID training program was held to address the major constraints that groundnut farmers face in the region including diseases that affect seeds, plants, and harvest.[1] We evaluate the impact of this program on input usage and yield by employing difference-in-differences (DID) econometric analyses, semi- and non-parametric techniques. Our analyses reveal significant changes in the usage of traditionally used inputs based on the training program's guidelines, but not in the usage of newly recommended inputs.

Learning costs can be higher for complex new inputs (Foster and Rosenzweig, 2010, Emerick and Dar, 2021, Jack, 2013). One of our main findings indicates that farmers predominantly made low-cost adjustments or changes in traditional inputs, while largely disregarding the high-cost recommendations. However, since the high-cost inputs were those that

[1] Among groundnut farmers in Tanzania, Daudi et al. (2018) highlight that pests and diseases were the main production constraints.

could potentially increase yields significantly, their non-adoption resulted in no overall impact of the training program on the farmers' yields and profits.

Several agricultural development interventions carried out by international agencies, governments, and NGOs do not often lend themselves to rigorous impact evaluation. Such interventions attempt to solve multiple challenges faced by farmers at the same time. These interventions often combine multiple treatments within the program, which leaves the scope for various levels of adoption and allows the adoption of different components. To boost agricultural production, recent studies of technology adoption consistently suggest the adoption of integrated farm management systems. However, one limitation of these studies is the absence of rigorous analysis on the profitability of new composite technologies (Takahashi *et al.* 2019). In this paper, we attempt to fill this gap by evaluating an intervention that includes several farm management recommendations on Integrated Pest Management (IPM), Good Agricultural Practices (GAP), and agronomical suggestions, for groundnut farmers in rural Bangladesh.

We study why the adoption follows such a behavioral pattern where farmers choose to follow low-cost technologies, while not adopting the seemingly higher-cost ones. While learning how to use new inputs can be costly, risk and uncertainty from new technologies prevent their adoption (Chavas and Nauges, 2020). Farmers might also perceive adjusting traditional inputs as less risky than introducing entirely new practices, particularly if the intervention is on their primary crop. Prior evidence suggests that support services are crucial for multiple agricultural technologies (Khonje *et al.*, 2018).

A farmer who is hesitant to adopt all components of the recommendations due to unfamiliarity with the new technology may still implement parts of it by engaging in less costly activities (like setting up sticky traps). There are many low-cost activities that a farmer can choose from. However, having too many low-cost activities that one can choose from might not be a good thing. Too many choices may result in poor decision quality due to the "choice overload"[2] effect. Several experiments show excessive choices result in decision-makers being less motivated to choose, they have difficulty choosing and are unsatisfied with their choices which cumulatively leads to 'decision fatigue'[3] (Iyenger and Lepper 2000, Schewartz 2004). The change in the usage of traditional inputs is relatively easier to remember and cheaper to implement.

However, since starting to use new inputs like biofertilizers and trichocompost (trichoderma bacteria-laced compost to manage soil diseases caused by a fungus) are costly and perceived as risky, adoption is selective due to varying costs to farmers. The lack of adoption aligns with the findings of Rahman *et al.* (2018) and Rao *et al.* (2008), indicating low adoption rates of certain IPM components in Bangladesh and India, respectively. [4] This could be due to several other factors such as increased costs of production and lack of availability of new IPM products in the local markets.

The training program was held to address the major constraints that groundnut farmers face in the region. Integrated pest management can help sustainably combat these issues and generate environmental benefits (Cuyno *et al.* 2001, Birthal *et al.* 2000, Mullen *et al.* 1997, Norton *et al.* 2019, Rahman *et al.* 2018). According to the Environmental Protection Agency, "Integrated Pest Management (IPM) is an effective and environmentally sensitive approach to pest management that relies on a combination of common-sense practices. IPM programs use current, comprehensive information on the life cycles of pests and their interaction with the environment. This information, in combination with available pest control methods, is used to manage pest

[2] term first used in the book, *Future Shock* (1970) by Alvin Toffler.
[3] coined by the social psychologist Roy F. Baumeister
[4] Rao *et al.* (2008) focus on the IPM package adoption on groundnut.

damage by the most economical means, and with the least possible hazard to people, property, and the environment." While it has been a few decades since IPM was introduced, the adoption rate has been very low. Many attribute this to a perceived lack of knowledge supply (Buurma *et al.* 2017, Rao *et al.* 2008, Rahman 2022).

This paper is particularly relevant for policymakers, program implementers, and agricultural and experimental economists. From the policymaker's perspective, the primary objective often centers on maximizing the extensive margin — that is, expanding the reach and number of participants in an intervention. Accordingly, it is common practice in developing countries to bundle multiple recommendations simultaneously within training programs, a strategy that is deemed cost-effective due to its broad coverage.[5] Bundling various agricultural practices and technologies into a single training session appears efficient, reducing logistical costs and ensuring that more farmers receive exposure to new methods and tools.

However, it might be undesirable if farmers do not fully comprehend the recommendations and opt for the "easier" changes over more complex, but potentially more beneficial, ones. For program implementers, understanding the dynamics of technology adoption is crucial. Effective training programs must balance the depth and breadth of content to ensure that farmers can internalize and implement the practices being taught. Implementers must recognize that without ongoing support and follow-up, the initial training might not lead to sustained adoption of the recommended practices. Additionally, evaluating the impact of such programs is challenging. Consequently, the literature on rigorous economic impact evaluations

[5] Some examples are as follows. The Integrated Pest Management Lab at Virginia Tech (funded by USAID) training modules for different crops have several recommendations (IPM IL n.d.). Otsuka and Larson (2016) discuss training modules prepared by Japan International Cooperation Agency (JICA) which included several recommendations on "seed selections, seedling preparation, transplanting, fertilizer use, water management, and animal traction."

of similar training packages (or IPM packages) is scarce. This paper contributes by providing important lessons for agricultural interventions and offering insights into the effectiveness and limitations of bundling multiple recommendations within training programs.

The rest of the paper is organized as follows: Section 2 provides details on the background of the study region in Bangladesh and about the training program. In Section 3 we discuss the baseline data which throws some light on the economic behaviors of the farming households in our study. In Section 4, we discuss the empirical strategy. The results are discussed in Section 5, which is followed by a final Section 6 that concludes.

2. Setting

Bhola district is situated in the Barisal Division of south-central Bangladesh.[6] Agriculture remains the primary economic activity. Main crops include rice, potatoes, onions, chilies, and garlic. Fishing is also significant, given Bhola's proximity to the Bay of Bengal. Groundnut cultivation in southern Bangladesh, as in other low-income countries, suffers from several challenges that prevent farmers from achieving their potential yields and higher income from groundnut farming. The prevalent issues fall into two categories: (a) unpredictable adverse shocks like pests, diseases, and weather calamities, and (b) systematic poor traditional agricultural practices such as excessive use of certain inputs and pesticides, and inadequate spacing between plants. (Akter *et al.* 2010, Binam *et al.* 2004, Begum *et al.* 2011, Miah and Mondal, 2017, Suraya *et al.* 2018).

To address these issues, the integrated pest management activities (IPMA) training program supported by the United States Agency for International Development's (USAID) Bangladesh mission and carried out by Virginia Tech was implemented in Char Fassion *upazila*

[6] Administratively, Bangladesh is divided into divisions and further subdivided into districts. Each district is segmented into *Upazilas*, which are then divided into unions, and finally, unions are broken down into wards.

(subdistrict) of Bhola district in the Barisal division. The primary goal of the training program along with several demonstrations was aimed at strengthening activities around groundnut farming in the 2022-23 *Dhulot* (December 2022 to May 2023) season. The training program aimed to tackle these issues by introducing IPM activities, which is a collection of sustainable eco-friendly strategies for pest control, and GAP, a set of standard practices established to ensure secure and sustainable cultivation of crops. Thus, there were multiple informational nudges, each of which, if adopted by itself and in combination, is expected to impact agricultural yields and other outcomes of interest positively. The interactive effects of these changes are also expected to be positive.

A total of 200 farmers were invited to participate in the training program that happened in November 2022, before the 2023 *Dhulot* planting season (January – June 2023). The training program was held over 5 days. About 30-40 farmers were trained each day from 9-5. The training was interactive and was conducted in the local language, Bengali. There were 3 components to the training program: information on Integrated Pest Management (IPM), Good Agricultural Practices (GAP), and agronomical suggestions. The session on IPM included understanding the existing pests and diseases of groundnut in the area and providing eco-friendly solutions to these problems. Some of the suggestions were preemptive, while others were provided as responses if certain pests showed up. For example, since root rot was reported to be a major problem in the area, the usage of trichocompost was recommended. Another example includes the setting up of sticky traps to capture insects, instead of chemical pesticides. The farmers were also explained the life cycle of certain common pests in the area so that they could respond accordingly. In the session on GAP, practices like cleaning diseased plants from the field, making proper water-draining channels, and maintaining enough space between plants while planting were discussed. Finally, certain agronomical suggestions were made based on the local government's recommendations regarding the amount of usage of fertilizers like urea, boron, and gypsum among others.

When organizations design training programs, their objective is to maximize farmer adoption of the technology. As a result, they often target areas where farmers are not credit-constrained or where households belong to higher-income groups, given their greater likelihood of adoption. However, this targeting approach complicates the task of evaluating the causal impact of training programs on farming outcomes, as finding a comparable control group becomes difficult.

Similarly, in this project, the training program was chosen to be made available to farmers in regions where higher adoption rates were anticipated. In response to this case, the multi-arm control design was developed to evaluate the impact of the training program as discussed in the Introduction. 350 farmers were invited to the training, but only 200 attended. From these 200 attendees, 150 farmers were randomly selected to form our "treatment" group. Technically speaking, the farmers who complied with the treatment assignment and attended the training program are known as "compliers". However, we will refer to them as the "Treatment" group for simplicity. Those who were invited but did not attend the training program will be referred to as non-compliers (NC). These two groups are comprised of farmers within the same union. We collected data on the non-compliers as well.

The first control group comprised farmers from the same sub-district but a distinct union, while the second control group consisted of farmers from a neighboring sub-district with similar characteristics to where the intervention took place. The location of the first control group is about an hour away from the location of the treatment farmers (about 11 miles) and the second is about an hour and a half away (about 30 miles)[7]. A baseline survey was carried out before the start of the season in December 2022, which was followed up with another survey on the same sampled households after the groundnut harvest in July 2023. The two waves of groundnut household surveys created a panel dataset of more than 500 households for evaluating the impact of the training program on groundnut cultivation.

[Figure – 1 here]

Essentially, the issue can be viewed as a three-stage decision problem: first, the decision to adopt a new technology; second, determining the number of technologies to adopt; and third, selecting which ones to adopt. (See Figure 1). Our analysis suggests that when providing informational nudges on multiple technologies, farmers are likely to choose the ones perceived as "easier" or less costly, while wrongly assuming all technologies bring equal benefits. Consequently, there is a lower likelihood of adopting technologies requiring "high effort." If this holds, training farmers simultaneously on high-cost and low-cost technologies may deter farmers from adopting “more” profitable, but perceivably riskier, technologies. During a single training session, it becomes challenging for farmers to assess the individual benefits of each technology. However, costs are a well-defined factor that affects farmers in the short term, making them more inclined to decide on adoption based on cost considerations.

3. Data

The treatment group consists of 150 farmers (compliers) randomly selected farmers from the 200 farmers who chose to come to the training program. The other farmers who did not comply comprise the group of non-compliers. The farmers who were invited for the training program were

[7] The travel times are approximate times required to travel in public transport, which is the main mode of travel in the area. Very few individuals own personal vehicles in these areas.

from 4 wards in Char Madras union, Char Fasson *Upazila*, Bhola district.[8] [See Table 1] 112 and 127 farmers were selected from 4 wards in the Osmanganj union and 8 wards from the Tazumuddin *Upazila*[9], respectively as controls. Throughout the paper, T, NC, and C will be used to denote Treatment (Compliers), Non-compliers, and Control groups, respectively. There has been an attrition of only 2 farmers for the follow-up in the treatment group.

[Table 1 here]

While we provided training to the farmers, we are treating this initiative as an intervention for their households. In certain households, when the main decision-maker regarding groundnut (mostly the male head of the household[10]) was not present, the spouse of the main decision-maker was sent for the training. Also, in groundnut cultivation, the entire family is involved in labor-intensive components. Hence, we focus on the household-level variables for our analysis and not the farmer's demographic variables. Table 2 represents the means of the three groups and differences in household demographic variables between treatment and non-compliers, and treatment and control groups. There are no highly significant differences between the groups, except that the household heads in the treatment group are, on average, about four years younger than those in the control group.

[Table 2 here]

Table 3 represents the means of the three groups and differences in groundnut cultivation variables between treatment and non-compliers, and treatment and control groups. While the experience of the main decision-maker is not different between the three groups, the households

[8] Administratively, Bangladesh is divided into divisions and further subdivided into districts. Each district is segmented into *Upazilas*, which are then divided into unions, and finally, unions are broken down into wards.
[9] 4 wards each from unions Chandpur and Chanchra, in Tazumuddin *Upazila*.
[10] While the role of females as the main decision maker regarding groundnut is not commonplace, there are some crops where the women in the household make the major decisions.

in the control group seem to have been engaged in groundnut farming for a significantly longer period. Groundnut is also considered to be a main source of income by more farmers who received the training than the other groups. In this region, plot sizes vary significantly and are often specialized for specific crops, which may restrict farmers from cultivating their preferred crops on their own land. Consequently, farmers frequently engage in leasing transactions — leasing out their less suitable plots while leasing in plots that are more conducive to their preferred crops. This practice helps explain the observed discrepancy between average land ownership and the extent of land used for groundnut cultivation.

From Table 3, we can see that farmers in the treatment group have cultivated significantly more land than the other two groups, despite owning similar or even smaller amounts of land, facilitated by these leasing opportunities. The treated farmers also have significantly more plots and areas for groundnut cultivation. However, yield is higher in the control group, which points to the inverse relationship between plot size and productivity (See Table 4) (Helfand and Taylor 2021, Rada and Fuglie 2019). The yield is, however, similar in treatment and the non-complier groups (See Table 3). The higher yields observed in the control group could be due to more efficient farming practices or better soil conditions in their area.

[Table 3 here]

Table 4 represents the means of the three groups and differences in groundnut agricultural characteristics and practices between treatment and non-complier, and treatment and control groups. This table provides some explanations for the above evidence. We observe farmers in our treatment group use a much lower quantity of seeds per acre. Additionally, the soil in the area is also perceived to be more saline than the control group. The agricultural practices among the three groups are largely similar, with the notable exception of removing dead plants. This difference may stem from varying disease incidence rates across the groups. Specifically, the treatment and non-complier groups likely experience higher rates of plant diseases compared to the control group, reducing the necessity for them to engage in cleaning dead plants.

[Table – 4 here]

The evidence suggests that the program was implemented in an area where a higher proportion of farmers consider groundnut cultivation their primary source of income, and thus possibly allocate more resources to it. Additionally, the area possibly has a higher incidence of plant diseases, which results in lower yields. Table 5 shows the baseline input usage of inputs (in kg/acre). Focused group discussions were held and depending on their current usage levels and local soil conditions, the farmers were recommended to adjust the levels of inputs they use, as shown in Table 5.

[Table – 5 here]

5. Empirical strategy

First, we investigate the uptake of new IPM inputs, followed by the change in fertilizer usage following the training. We estimate the change in the amount of each fertilizer, caused due to the training, using the Difference-In-Difference estimation (DID) (Angrist and Pischke 2009, Card and Krueger 1994) strategy for each input:

$$Y_{it} = \alpha + \mu_i + \lambda_t + \beta_1 T_i * t + \epsilon_{it} \qquad (1)$$

where Y_{it} is the dependent variable, the amount of input (fertilizer) used, β_1 is the coefficient of interest which measures the Average Treatment Effect on the Treated. T_i is the dummy variable that equals 1 if the observation is in the treatment group and 0 otherwise. t is the time variable which is equal to 0 in baseline and 1 in the follow-up. λ_t captures the time-fixed effects to account for unobserved characteristics specific to both the periods, μ_i captures the household-level fixed effects, and ϵ_{it} is an idiosyncratic stochastic error term. This strategy allows us to account for time-invariant unobservable differences between treatment and control groups.

After studying the impact of the training program on agronomical input use, we study the impact on yields. We present equation (1) for yields and estimate it again after incorporating controls for additional household-level demographic variables, along with cultivation and agricultural characteristics.

$$Y_{it} = \alpha + \lambda_t + \mu_i + \beta_1 D_{it} + \boldsymbol{\delta} X_{it} + \epsilon_{it} \qquad (2)$$

If the parallel trends assumption is violated, the DID estimate will be biased. According to the parallel trends assumption, the trends would be the same in both groups in the absence of training. In baseline, the yield in the treatment group (compliers) is 76 kg/acre, for non-compliers it is 85 kg/acre, for control it is 107 kg/acre. In the follow-up, it is 125 kg/acre, 118 kg/acre and 147 kg/acre respectively. The household and groundnut agriculture characteristics are significantly different in the treated and control groups. Time-varying confounding factors and the potential sensitivity of the assumption to the chosen functional form of the outcome can undermine the validity of the parallel trends assumption. Since it is uncertain which specific functional form would ensure parallel trends in our analysis, we may question the validity of this assumption. It is possible that the parallel trends assumption does not hold. If we assume that the training had no effects on yield, there seems to be some other factor/factors that affected the yields positively for all these 3 groups. The question is whether that has impacted the treatment and control groups equally. We can condition on covariates and assume that parallel trends hold conditional on those covariates (Roth *et al*. 2023). The overlap condition (also known as the positivity condition) needs to hold. This ensures that for each treated unit with covariates X_i, there are some untreated units in the population with the same value of X_i (Roth *et al*. 2023, Khan and Tamer, 2010). This is a strong assumption. Since certain non-parametric or semi-parametric methods provide consistent estimation of the ATET under conditional parallel trends under weaker assumptions, we will use them for robustness check. Each of these ATETs carries the same meaning as the parameters in a two-period, two-group difference-in-differences (DID) analysis. Since there are multiple DID parameters involved, we describe them as heterogeneous treatment effects or heterogeneous DID. This approach differs from estimating a single ATET, which assumes uniformity over time and across cohorts. We also conduct the RA, IPW, and the doubly robust AIPW (Callaway and Sant'Anna 2021). We also conduct the Propensity Score Matching (PSM) and Nearest Neighbor Matching (NN).

6. Results

6.1 Input usage

First, we discuss the adoption of IPM inputs due to the training program. We summarize the impact of the training on IPM-recommended inputs such as trichocompost, Dynamic, Lycomax, and other practices recommended during the training in Table 6. After training, only 8, 16, 4, and 11 out of the 148 farmers began implementing Trichoderma compost, Dynamic, Lycomax, and other IPM practices, respectively. Boron was utilized by 10 farmers during the baseline study, and this increased to 11 after training. In the case of bio-fertilizer, the number of farmers using it increased from 24 in the baseline to 66 after the IPMA training. Chemical pesticides remain widely used, as one would expect, particularly in the comparison villages. We cannot analyze the effect on the quantity of chemical pesticides since its unit is not well defined because of various undefined units such as bottles, which could be of various sizes.

[Table 6 here]

Table 7 presents the change in price of the major agronomical inputs from baseline to follow-up for all the farmers in our dataset. Hence, broadly speaking, prices of all inputs went up except for TSP and Gypsum. The price of TSP remained the same, but the price of Gypsum fell in the follow-up. Table 8 presents the DID estimates capturing the changes in the quantity of an input used per acre after the treatment. The amount of Urea used by the farmers in the treatment group has marginally gone up by about 1 kg per acre and it is significant. The amount of TSP usage has also gone up by about 3 kgs per acre by the treated households. We find no evidence that the usage of other inputs has changed.

[Table 7 here]

[Table 8 here]

6.2.1 Yield

Table 9.1 reports the impact on groundnut yield per acre. We estimate an average treatment effect on the treated (ATET) estimator using DID estimation strategy, which gives the average impact of providing the IPMA training program on groundnut farmers that received the training program (T vs C). We present four columns, one estimated without adding any baseline variables in the regression analysis; second, where we estimate with the household (HH) characteristics (HH head age, HH head female, HH Head years of education, HH size) as controls; next, along with the HH characteristics, we add the cultivation and agricultural variables as controls (own land holding, total number of plots, plot size, if treated seed, soil salinity, drain channel, if used power tiller, space between saplings, and clean dead plants). Finally, in the fourth specification, we add the groundnut agricultural characteristics as controls. Because of multicollinearity, some of these variables were dropped. The magnitude of the increase in yield is positive, however it is not statistically significant when we add controls. We find no evidence that there is a positive effect of the IPMA training program on yields in the farmers who received the training. In Table 9.2, we also add the first principal component[11] of shocks faced by the farmers in both years as a control to specification (3) and see that there is no change.

[Table 9.1 here]

6.2.2 Robustness checks for the results on yield

Here, we present the heterogenous/augmented TWFE model which considers interactions between treatment-time cohorts and time (Wooldridge 2021) along with RA, IPW, and the doubly robust AIPW (Callaway and Sant'Anna 2021) (Table 9.2). We present the Propensity Score Matching (PSM) and Nearest Neighbor Matching (NN) in Table 9.3.

[Table – 9.2 here]

[Table – 9.3 here]

7. Conclusion

This paper evaluates the impact of a training program that provided comprehensive recommendations, including information on Integrated Pest Management (IPM), Good Agricultural Practices (GAP), and agronomical suggestions, to groundnut farmers in rural Bangladesh. We provide a detailed summary of the individual and household-level agricultural and groundnut cultivation characteristics of the farmers in the study area.

We observe changes in the usage amounts of traditional inputs aligning with the recommendations; however, the adoption rates of new inputs (IPM inputs) are very low. Consequently, we find no evidence that there has been an impact on yields and profits. Our findings indicate that when farmers receive training on a mix of low-cost and high-cost technologies, they

[11] The first principal component is the linear combination of the independent variables that captures the greatest variance, accounting for the maximum possible variation in the data

are more inclined to adopt only the low-cost ones, making the training program less effective for promoting the adoption of high-cost technologies.

The concept of cost here extends beyond market price to include learning costs. Without ongoing extension services, it is challenging for farmers to absorb and implement all the information provided in a short period, as was the case with our one-day training program. This suggests that for training programs to be more effective in encouraging the adoption of high-cost technologies, they need to be supplemented with continuous support and follow-up to help farmers overcome both financial and educational barriers.

Adopting technology in agriculture in developing countries is a challenging task due to various factors. While several reasons have been identified, the potential for choice overload has not been adequately considered. Choice overload can occur when farmers are presented with multiple technologies simultaneously. As discussed, many implementing agencies bundle all recommendations together, resulting in training packages with numerous instructions. Low literacy rates may further complicate the ability of farmers to assimilate all this information in a single session. Therefore, it is crucial to assess the cognitive capabilities of farmers before implementing any intervention and to provide after-training support and extension services in properly structured manageable portions. This ensures that farmers who are willing to adopt new technologies can do so effectively. The future course of study will focus on understanding how to reduce these steep learning costs. Existing literature highlights the role of extension workers and peer effects in facilitating learning. We aim to explore the extent to which these additional supports can aid in reducing learning costs by reducing the burden of choice and improving technology adoption in subsequent work.

References

Abadie, A. (2003). Semiparametric instrumental variable estimation of treatment response models. *Journal of econometrics*, *113*(2), 231-263.

Akter, M., Miah, M. A. M., Rahman, M. S., & Khurram, M. M. H. (2010). Adoption and relative profitability of groundnut (Arachis hypogaea L.) cultivation in char areas of Bangladesh. *Bangladesh J. of agri*, *35*(1), 85-95.

Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Begum, M. E. A., Islam, M. N., Alam, Q. M., & Hossain, S. B. (2011). Profitability of some BARI released crop varieties in some locations of Bangladesh. *Bangladesh Journal of Agricultural Research*, 36(1), 111-122.

Binam, J. N., Tonye, J., Nyambi, G., & Akoa, M. (2004). Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food Policy*, 29(5), 531-545.

Birthal, P. S., Sharma, O. P., & Kumar, S. (2000). Economics of integrated pest management: Evidences and issues. *Indian Journal of Agricultural Economics*, *55*(4), 644-659.

Buurma, J. S., & Van Der Velden, N. J. A. (2017). New approach to Integrated Pest Management research with and for horticulture. A vision from and beyond economics. *Crop protection*, 97, 94-100.

Callaway, B., and P. H. C. Sant'Anna. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225, 200–230.

Chavas, J. P., & Nauges, C. (2020). Uncertainty, learning, and technology adoption in agriculture. *Applied Economic Perspectives and Policy*, *42*(1), 42-53.

Daudi, H., Shimelis, H., Laing, M., Okori, P., & Mponda, O. (2018). Groundnut production constraints, farming systems, and farmer-preferred traits in Tanzania. *Journal of Crop Improvement*, *32*(6), 812-828.

Emerick, K., & Dar, M. H. (2021). Farmer field days and demonstrator selection for increasing technology adoption. *Review of Economics and Statistics*, *103*(4), 680-693.

EPA. (n.d.) Integrated Pest Management(IPM) Principles accessed on May 9, 2024. https://www.epa.gov/safepestcontrol/integrated-pest-management-ipm-principles

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of Technology Adoption. *Annual Review of Economics*, *2*(1), 395–424. https://doi.org/10.1146/annurev.economics.102308.124433

Genius, M., Koundouri, P., Nauges, C., & Tzouvelekas, V. (2014). Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *American Journal of Agricultural Economics*, *96*(1), 328-344.

Gupta, A., Kagin, J., Taylor, J. E., Filipski, M., Hlanze, L., & Foster, J. (2018). Is technology change good for cotton farmers? A local-economy analysis from the Tanzania Lake Zone. *European Review of Agricultural Economics*, *45*(1), 27-56.

Helfand, S. M., & Taylor, M. P. (2021). The inverse relationship between farm size and productivity: Refocusing the debate. *Food Policy*, 99, 101977.

Imai, K., & Ratkovic, M. (2014). Covariate balancing propensity score. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *76*(1), 243-263.

Iyenger, S. S., & Lepper, M. R. (2000). When Choice is Demotivating: Can One Desire Too Much of a Good Thing? Journal of Personality and Social Psychology, 79(6), 995-1006.

Jack, B. Kelsey. 2013. “Constraints on the adoption of agricultural technologies in developing countries.” Literature review, Agricultural Technology Adoption Initiative, J-PAL (MIT) and CEGA (UC Berkeley).

Uysal, S., Słoczyński, T., & Wooldridge, J. M. (2023). KAPPALATE: Stata module to estimate the local average treatment effect (LATE) using Abadie's kappa approach and other weighting estimators.

Khan, S., & Tamer, E. (2010). Irregular identification, support conditions, and inverse weight estimation. *Econometrica*, *78*(6), 2021-2042.

Khonje, M. G., Manda, J., Mkandawire, P., Tufa, A. H., & Alene, A. D. (2018). Adoption and welfare impacts of multiple agricultural technologies: evidence from eastern Zambia. *Agricultural Economics*, *49*(5), 599-609.

Magruder, J. R. (2018). An assessment of experimental evidence on agricultural technology adoption in developing countries. *Annual Review of Resource Economics*, *10*, 299-316.

Miah, M. A. M., & Mondal, M. R. I. (2017). Oilseeds sector of Bangladesh: challenges and opportunities. *SAARC Journal of Agriculture*, *15*(1), 161-172.

Mullen, J. D., Norton, G. W., & Reaves, D. W. (1997). Economic analysis of environmental benefits of integrated pest management. *Journal of Agricultural and Applied Economics*, *29*(2), 243-253.

Norton, G., Alwang, J., Kassie, M., & Muniappan, R. (2019). Economic impacts of integrated pest management practices in developing countries. *The Economics of Integrated Pest Management of Insects. CABI Publishing, Boston, MA*, 140-154.

Rada, N. E., & Fuglie, K. O. (2019). New perspectives on farm size and productivity. *Food Policy*, 84, 147-152.

Rahman, M. S., Norton, G. W., & Rashid, M. H. A. (2018). Economic impacts of integrated pest management on vegetables production in Bangladesh. *Crop Protection*, *113*, 6-14.

Rahman, M. S. (2022). Farmers' perceptions of integrated pest management (IPM) and determinants of adoption in vegetable production in Bangladesh. *International journal of pest management*, *68*(2), 158-166.

Rao, C. A., Rao, M. S., Naraiah, P., Malathi, B., & Reddy, Y. V. R. (2008). An economic analysis of adoption of integrated pest management in groundnut. *Indian Journal of Agricultural Economics*, *63*(1).

Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, *235*(2), 2218-2244.

Ruzzante, S., Labarta, R., & Bilton, A. (2021). Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Development*, 146, 105599.

Schewartz, B. (2004). The Paradox of Choice: Why More is Less. New York: Harper Perennial.

Słoczyński, T., Uysal, S. D., & Wooldridge, J. M. (2023). Covariate Balancing and the Equivalence of Weighting and Doubly Robust Estimators of Average Treatment Effects. *arXiv preprint arXiv:2310.18563*.

StataCorp. (2023). *Stata 18 Base Reference Manual*. College Station, TX: Stata Press.

Suraya, P., Chowdhury, A. R., Islam, M. M., Ahmed, M. B., & Rubayet, A. (2018). Present status and problem confrontation of oilseed cultivation in southwest region of Bangladesh. *Journal of the Bangladesh Agricultural University*, 16(2), 198-207.

Takahashi, K., Muraoka, R., & Otsuka, K. (2020). Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics*, *51*(1), 31-45.

Wooldridge, J. M. (2021). Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators. *Available at SSRN 3906345*.

Tables and Figures

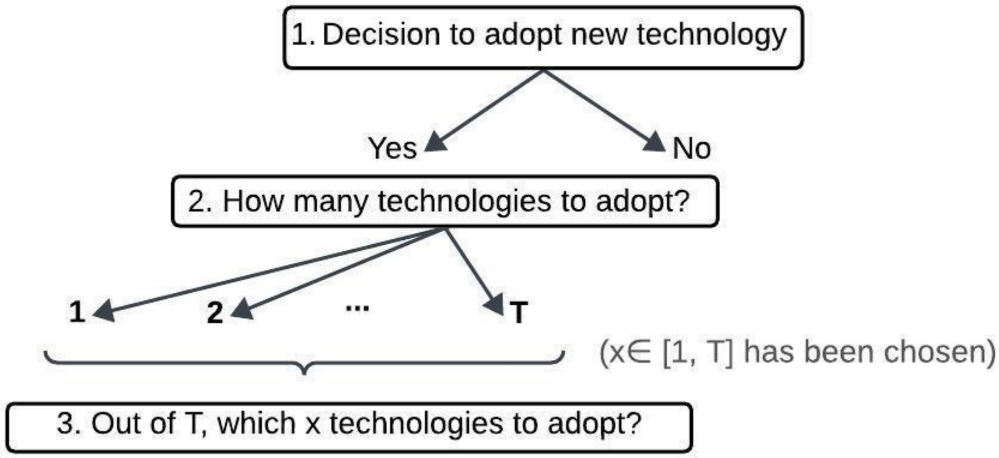

Figure-1: Representative farmer's adoption decision process

Table 1: Sampling Design with Sample Sizes

Survey round	Assigned to Treatment		Control		Total
	Treatment group *(4 wards in Char Madras)*	Non-compliers *(4 wards in Char Madras)*	Control 1 *(4 wards in Osmanganj)*	Control 2 *(8 wards in Tazumuddin Upazila)*	
Baseline *(Dec 11-21, 2022)*	150	132	112	127	521
Follow-up *(Jul 8-18, 2023)*	148	132	112	127	519

Notes: The 4 wards in the non-complier group are the same as the treatment wards.

Table 2: Two-sample t-tests of Baseline Balance in Demographic Variables

Demographic Variables	Treatment (T)	Non-compliers (NC)	Control (C)	Difference (T – NC)	Difference (T – C)
HH Head Age	47.30	45.80	51.57	1.50	-4.27***
	(12.10)	*(11.79)*	*(13.52)*	*(1.43)*	*(1.35)*
HH Head Female	0.04	0.06	0.05	-0.02	-.01
	(0.20)	*(0.24)*	*(0.21)*	*(0.03)*	*(0.02)*
HH Head years of Education	4.59	4.22	4.62	0.37	-.04
	(4.33)	*(4.09)*	*(4.31)*	*(0.50)*	*(0.45)*
HH Size	5.05	5.29	5.41	-0.24	-.36
	(1.73)	*(1.64)*	*(2.16)*	*(0.24)*	*(0.22)*
N	150	132	239		

Notes: The two-tailed t-tests are between the treatment and non-complier groups and between the treatment and pure control groups. The standard deviations are in parentheses in columns for T, NC, and C. Standard errors from t-tests appear in parentheses for the columns (T-S) and (T-C). p * < 0.1, **<0.05, ***<0.01.

Table 3: Baseline Balance in Groundnut Cultivation Characteristics

Characteristics with groundnut cultivation	T	NC	C	T-NC	T-C
Experience (in years) of main decision maker in groundnut cultivation	16.37	15.68	17.24	0.69	-0.87
	(8.08)	*(8.89)*	*(9.35)*	*(1.01)*	*(0.93)*
Experience (in years) of the HH in groundnut cultivation	28.54	30.52	25.23	-1.99	3.31**
	(11.90)	*(12.85)*	*(14.49)*	*(1.49)*	*(1.42)*
Groundnut is the main source of income	0.35	0.20	0.23	0.16***	0.12**
	(0.48)	*(0.40)*	*(0.42)*	*(0.05)*	*(0.05)*
Total number of own plots	4.99	4.50	7.18	0.49	-2.19***
	(4.35)	*(2.34)*	*(8.06)*	*(0.43)*	*(0.72)*
Number of plots in groundnut cultivation	2.55	2.11	1.80	0.44***	0.75***
	(1.40)	*(1.15)*	*(0.91)*	*(0.15)*	*(0.12)*
Plot size (in acres)	3.02	2.66	2.00	0.36	1.02***
	(1.76)	*(1.86)*	*(1.18)*	*(0.22)*	*(0.15)*
Own land holding (in acres)	4.12	3.57	5.63	0.55	-1.52**
	(6.34)	*(6.02)*	*(7.52)*	*(0.74)*	*(0.74)*
Area for groundnut cultivation (in acres)	6.51	4.74	3.09	1.77***	3.42***
	(3.57)	*(2.89)*	*(1.57)*	*(0.39)*	*(0.27)*
Own land area in groundnut cultivation (in acre)	1.64	1.41	1.44	0.23	0.20
	(2.48)	*(2.28)*	*(1.70)*	*(0.29)*	*(0.21)*
Share of farmers who leased in land	0.76	0.73	0.56	0.03	0.20***
	(0.43)	*(0.44)*	*(0.50)*	*(0.05)*	*(0.05)*
Yield of GN (kg per acre)	75.98	85.40	116.65	-9.42	-40.67***
	(60.64)	*(64.47)*	*(66.10)*	*(8.20)*	*(7.10)*
N	150	132	239		

Notes: The baseline values of groundnut cultivation are based on respondents' self-reported values for the 2021-22 *Dhulot* season. The two-tailed t-tests are between the treatment and non-complier groups and between the treatment and pure control groups. The standard deviations are in parentheses in columns T, NC, and C. Standard errors from t-tests appear in parentheses for the columns (T-NC) and (T-C). p * < 0.1, **<0.05, ***<0.01.

Table 4: Baseline Balance in Groundnut Agricultural Characteristics and Practices

Input Use	T	NC	C	T-NC	T-C
Quantity of groundnut seed (in kg) per acre	5.03	5.41	5.38	-0.38***	-0.34***
	(1.01)	*(1.24)*	*(1.31)*	*(0.14)*	*(0.13)*
Treated groundnut seed before sowing	0.67	0.62	0.61	0.05	0.06
	(0.47)	*(0.47)*	*(0.49)*	*(0.06)*	*(0.05)*
Perceived degree of soil salinity (on a scale of 1-3)	2.00	2.02	1.67	-0.02	0.33***
	(0.72)	*(0.07)*	*(0.75)*	*(0.09)*	*(0.08)*
Farmer has good drainage system	0.63	0.72	0.70	-0.09	-0.07
	(0.48)	*(0.45)*	*(0.46)*	*(0.06)*	*(0.05)*
Made channels between rows for better drainage	0.66	0.73	0.62	-0.07	0.04
	(0.48)	*(0.44)*	*(0.49)*	*(0.05)*	*(0.05)*
Used Power tiller	1.00	0.99	0.98	0.01	0.02
	(0.00)	*(0.09)*	*(0.13)*	*(0.01)*	*(0.01)*
Space between saplings (in inches)	6.32	6.36	6.16	-0.04	0.16
	(1.27)	*(1.46)*	*(0.98)*	*(0.16)*	*(0.11)*
Cleaned dead plants	0.67	0.62	0.49	0.05	0.18***
	(0.47)	(0.49)	(0.50)	(0.06)	(0.05)
N	148	132	239		

Notes: The baseline values of groundnut agricultural characteristics and practices are based on respondents' self-reported values for 2021-22 *Dhulot* season. The two-tailed t-tests are between the treatment and non-complier groups and between the treatment and pure control groups. The standard deviations are in parentheses in columns T, S, and C. Standard errors from t-tests appear in parentheses for the columns (T-NC) and (T-C). p * < 0.1, **<0.05, ***<0.01.

Table 5: Baseline Input Usage Amounts (in kg/acre)

Inputs	T	NC	C	Recommendations
Urea	3.02	3.55	4.00	Increase
	(3.06)	*(4.49)*	*(2.66)*	
TSP	7.55	8.52	9.56	Increase
	(3.18)	*(7.79)*	*(12.54)*	
SOP/MOP	3.56	3.76	3.64	Same
	(1.96)	*(3.49)*	*(1.89)*	
Zinc	0.35	0.35	0.29	Same
	(0.37)	*(0.42)*	*(0.46)*	
Gypsum	2.42	2.97	2.92	Increase
	(2.32)	*(2.58)*	*(2.10)*	
N	150	132	239	

Note: This table shows the mean usage amount of the commonly used inputs in the baseline. The standard deviations are given in parentheses. The recommendation column indicates whether the farmers were asked to increase or decrease the usage amounts.

Table – 6: Descriptive statistics of change in agricultural behavior of treated farmers (compliers) as per recommendations

Treatment farmers	Baseline	Follow-up
IPM inputs (Number of treated farmers using the input)		
Trichocompost	0	8
Dynamic	0	16
Lycomax	0	4
Other IPM practices	0	11
Biofertilizer	8	20
Good Agricultural Practices		
Space between saplings (in inches)	6.32	6.79
	(1.27)	*(1.72)*
Space between rows (in inches)	9.16	8.30
	(1.77)	*(2.05)*
Channels between rows (1 for yes, 0 for no)	0.66	0.80
	(0.48)	*(0.40)*
Clean dead plants (1 for yes, 0 for no)	0.67	0.57
	(0.47)	*(0.50)*
Quantities of agronomical inputs (in kg/acre)		
Urea	3.08	3.59
	(3.07)	*(4.03)*
TSP	7.52	8.76
	(3.19)	*(8.04)*
SOP/MOP	3.55	4.13
	(1.99)	*(4.45)*
Zinc	0.33	0.60
	(0.32)	*(0.60)*
Gypsum	2.42	0.75
	(1.60)	*(2.18)*
N	150	148

Notes: Standard deviations are in parentheses

Table 7: Average Price of agronomical inputs for treated farmers in baseline and follow-up

Treatment (148 farmers)	Baseline	Follow-up
Average Prices of agronomical inputs (in BDT/kg)		
Urea	20.99	24.34
	(5.07)	*(6.04)*
TSP	30.80	29.68
	(19.05)	*(7.30)*
SOP/MOP	22.72	24.18
	(12.68)	*(6.59)*
Zinc	193.69	205.98
	(58.00)	*(56.27)*
Gypsum	53.53	37.54
	(51.11)	*(25.50)*

Notes: Standard deviations are in parentheses

Table 8: Treatment Effects on Quantity of Input Use from Difference-in-Difference Estimation

Input Usage (kilograms per acre)	Urea	TSP	MOP	Zinc	Gypsum
ATET					
Time × Treatment Dummy (1 vs 0)					
Coefficient (without controls)	0.83*	3.23***	0.40	6.65	0.01
Robust Standard Error	*(0.48)*	*(1.18)*	*(0.47)*	*(6.50)*	*(0.26)*
p-value	0.09	0.01	0.39	0.31	0.96
Coefficient (with controls)					
Robust Standard Error					
p-value					
N	387	386	386	386	385

Note: ATET estimate adjusted for panel effects and time effects. p * < 0.1, **<0.05, ***<0.01.

Table 9.1: Treatment Effects on Yield from Difference-in-Difference Estimation

Groundnut output (kilograms per acre)	(1) Without controls	(2) With HH characteristics	(3) With HH + Cultivation + General Agricultural characteristics	(4) With HH + Cultivation + General Agricultural characteristics + first principal component of shocks
ATET *Time × Treatment Dummy* (1 vs 0)				
Coefficient	18.03*	12.15	10.68	9.42
Robust Standard Error	*(10.16)*	*(11.39)*	*(11.90)*	*(12.13)*
p-value	0.08	0.29	0.37	0.44
N	376	373	369	369

Note: ATET estimate adjusted for panel effects and time effects. p * < 0.1, **<0.05, ***<0.01. In specification (1), there are no controls. In specification (2), we control for HH head age, HH head female, HH Head years of education, and HH size. In specification (3), we add the controls own land holding, the total number of plots owned, average plot size, if treated seed, soil salinity, drain channel, if used power tiller, space between saplings, and clean dead plants. In (4), we add the first principal component of all the general shocks like climate disasters, loss of a family member, serious illness, etc.

Table 9.2: Heterogenous Treatment Effects on Yield

Groundnut output (kilograms per acre)	(1) RA	(2) IPW	(3) AIPW
ATET			
Coefficient	3.57	18.03*	3.57
Robust Standard Error	*(19.49)*	*(10.14)*	*(19.49)*
p-value	0.86	0.08	0.86
N	322	351	322

Note: ATET computed using covariates: HH head age, HH head female, HH Head years of education, and HH size, land holding, the total number of plots, plot size, if treated seed, soil salinity, drain channel, if used power tiller, space between saplings, and clean dead plants farmer's experience in GN cultivation, the farmer's HH experience in GN farming, if the farmer considers GN to be their primary crop, GN cultivated area, how much of the GN area is owned by the farmer, and if the farmer has leased in land for GN. p * < 0.1, **<0.05, ***<0.01.

Table 9.3: Propensity Score Matching (PSM) and Nearest Neighbor (NN)

Groundnut output (kilograms per acre)	(1) PSM	(2) NN
ATET		
Coefficient	16.54	7.30
Robust Standard Error	*(12.86)*	*(12.94)*
p-value	0.20	0.57
N	349	270

Note: Some variables had to be dropped for collinearity. The rest of the covariates: HH head age, HH head female, HH Head years of education, and HH size, if treated seed, soil salinity, drain channel, if used power tiller, space between saplings, and clean dead plants farmer's experience in GN cultivation, the farmer's HH experience in GN farming, if the farmer considers GN to be their primary crop, GN cultivated area, how much of the GN area is owned by the farmer, and if the farmer has leased in land for GN. p * < 0.1, **<0.05, ***<0.01.