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Impact of On-Farm Demonstrations on Technology Adoption, Yield, and Profitability Among Small Farmers of Wheat in Pakistan—An Experimental Study

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Abstract: Do the intensive demonstrations result in consistent technology adoption and yield enhancement? While extension methods show significant immediate effects of an intervention, their impact may fade over time. In a government-led natural experiment in Pakistan, a long-lasting adoption of certified seeds, fertilizers, and pesticides/herbicides in post-treatment years were observed by employing difference–indifferences with a fixed effect method on panel data. The intervention increased the technology adoption in terms of certified seeds by 34%, fertilizers by 15 kg/ha, and pesticides/herbicides by 0.22 L/ha among adopters for four years. Similarly, the wheat yield increased by 0.41 tons per hectare, and profit increased by 12% among the treatment group compared to the control group. In view of these findings, this study suggests continuing this supervised method of extension to other crops in Pakistan.

Keywords: on-farm demonstrations; certified seeds; technology adoption; FE-DID; long-lasting effect

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1. Introduction

1.1. Background

Enhancing crop yields has been extensively debated to improve income, livelihood, and poverty alleviation among small farmers of developing countries [1–3]. In this regard, the long-standing policies of subsidizing farm inputs have been considered ineffective in improving farm productivity [4] and agricultural development [5]. It is also assented that economic policies should discourage subsidized inputs whose overuse damages the environment [6], distorts the agricultural economy, and is not surely increasing the output to the appropriate scale [7]. In the same way, it is opined that instead of merely following the broad development theories, historical contexts should be considered while formulating development policies [8]. Within political economies of developing countries, the diverse socioeconomic contexts determine the suitability of a certain agricultural policy which might not be appropriate for others. With this in view, an understanding has been developed to reconsider and reshape policies when the desired results are not achieved. For instance, due to the ineffectiveness of agricultural subsidies, attention has recently been diverted to smart subsidies [9] with impact-based farm experimental designs [10]. The farm-based experimental outcomes made the researchers and policy makers agree that farmers require supervisory guidance instead of subsidized inputs in their fields to adopt modern technologies and increase yields [10,11]. While designing policies and theories, thoughtful consideration to historical and socioeconomic contexts [8] would transform not only agriculture but also pave the way to sustainable development in developing countries [12]. In this regard, the role of governments has been considered crucial in increasing agricultural productivity, crop yields, and profitability among small farmers through agricultural extension services [13].

The extension services in the agriculture field are meant to educate, support, and provide resources to farmers and publicize solutions for the challenges they face. The extension agents (EAs) promote technology adoption using certified seeds, fertilizers, pesticides, row planting, and farm machinery to increase per unit yield [14]. The mode of guidance includes field farm schools, curriculum-based material, farm gatherings, and on-farm demonstrations [15]. The existing literature has discussed different extension methods to increase technology adoption, farm productivity, and profitability. For example, farmers field schools increased agricultural productivity and reduced poverty [15–18]. In addition, the extension trainings to adopt certified seeds [16] and to follow row planting [19] caused a significant increase in wheat yield in Ethiopia. Similarly, video-based extensions services with a role model motivator showed enhanced technology adoption in India [20]. Many studies found out that technology adoption through field experiments and extension programs helped improve the agricultural output, livelihood, and income of small farmers [21–23].

Such extension methods and the varying outcomes they produce reflect the diverse agricultural contexts across regions. In Asia, for example, significant progress has been witnessed in increasing farmers' incomes and well-being through technological advancement. However, the pace of mechanization has been slower in South Asia compared to Southeast Asia. A study [24] by Otsuka and Fan argues that the majority of farmers in South Asia operate small farms, which limits their capacity to adopt technology and hinders intensive mechanized farming. Furthermore, many small farmers in the region are unable to afford new technologies. A few researchers in a study [25] highlighted the inadequacy of agricultural extension programs in South Asia, which fail to provide farmers with the knowledge needed for sustainable and efficient farming practices.

The limitations of extension programs are not confined to South Asia; similar challenges also exist in other regions, such as Africa. The literature [26] highlighted the effectiveness of extension programs in Africa but criticized their limited coverage. Additionally, a study [27] pointed out the inefficiencies of these programs, emphasizing that while applying experimental outcomes obtained from a research field, the real-world conditions are often overlooked by extension agents (EAs). As a result, these research outcomes do not always produce the desired results when implemented by farmers.

Amongst many extension methods, the on-farm demonstrations—the least researched method—delivered by the EAs have been found effective in enhancing crop yields. On-farm demonstrations aim to increase farmers' practical exposure to new technologies, such as farm inputs and machinery, to increase yields. A few farm level experiments [28–30] investigated the impact of demonstration trainings on crops' yield and technology adoption. Their studies discovered a significant increase in technological adoption and, consequently, higher farm yields during the treatment year. However, these studies did not examine the long-lasting effects of the interventions. It has been argued that extension services for technology adoption often fail to show a long-lasting treatment effect and income improvements among small farmers over time [31].

The discussion above reveals two key problems: (i) the limited coverage of field experiments or government programs, and (ii) inefficiencies in extension methods except the on-farm demonstrations. In the context of the impact assessment of experimental studies, only immediate post-treatment effects have been observed in the literature. To address these issues, this study evaluates the long-lasting impact of a large-scale publicly funded program in Pakistan that utilized the on-farm demonstration method of extension services to increase wheat yield. The intervention involved supervised methods of technical advice and the application of results from the experiment station to the farms in a monitored environment. The EAs conducted on-farm demonstrations on randomly selected farms and promoted technology adoption among small farmers.

The existing empirical literature concentrated on evaluating the immediate post treatment effect of the on-farm demonstration method of extension services on different outcome variables. Moreover, none of the existing studies have utilized panel data in this regard. Thus, this study contributes to the empirical literature by evaluating the long-lasting treatment effect for four years using panel data of a natural experiment which has not been assessed in such a type of field experiment previously. Though the impact of the intervention on yield has been examined extensively, diverse technology adoption variables, the cost of production, and profitability have been rarely evaluated. Moreover, this study will analyze a publicly funded agricultural program for the first time in Pakistan, determining the causal relationship employing a fixed effects difference-in-differences (FE-DID) estimation approach.

1.2. Conceptual Framework

Agriculture is the primary sector of the economy where farmers prefer traditional methods of farming based on their indigenous knowledge. However, according to the conceptual ideologies of Schultz (1964), it is asserted that traditional factors of production alone cannot increase output, until the technological inputs are applied [32]. Farmers are considered the best profit maximizers by choosing a set of inputs for higher outputs; however, they need technical transformation in their farming methods for higher returns [32]. In the same way, it is also argued that merely increasing the fertilizer quantities, supplying certified seeds, and providing subsidies do not necessarily boost agricultural production; rather, their unchecked, excessive use harms the environment [9] and disequilibrates the agricultural economy [7]. Understanding these facts, many economists have shifted their focus to field experiments [21]. Various field experiments indicated that the proper application of farm inputs coupled with a supervisory approach encourage behavioral changes in farming decisions to adopt technology. If timely supply of inputs is ensured, the supervisory experiments significantly increase both production and farmers' return [11,21].

In this context, the relevant empirical literature highlights the importance of demonstrating farming practices under careful supervision and guidance to achieve better outcomes. For instance, in a farm experiment in Ethiopia aiming to increase teff yield, the EAs demonstrated farming practices in real world conditions [28]. The teff yield of demonstration plots was significantly increased compared with the farms managed by farmers. In another experiment based on a randomized controlled trial in Ethiopia [29], the demonstration trials and field days led by the extension agents caused the adoption of the new wheat varieties among the treated farmers. Similarly, in Tanzania [30], a demonstration program increased the adoption intensity of the rice production technologies among the participant farmers to promote sustainable farming practices. The studies discovered a significant increase in farm yield and technology adoption due to demonstrations, direct exposure to technology, and more communicative EAs.

In addition to the above, frontline demonstrations [33,34] and crop-check practices [35] also enhanced the yields of different crops in India and Australia. It is empirically emphasized that practical presentation of sustainable farming practices by the technical experts significantly increased the crop yields and profits. The role of extension agents, continuous monitoring, and communication with farmers are critical factors in enhancing the yield and profits of small farmers. Building on this, the current study postulates the following hypotheses:

- Hypothesis 1: the on-farm demonstration will increase the technology adoption (certified seeds, fertilizers, pesticides and herbicides, and mechanized farming), yield, and profit during the treatment year;
- Hypothesis 2: there will be a long-lasting treatment effect, observed through technological adoption of inputs and increased yield and profitability.

The first hypothesis deals with the immediate post-treatment effect, which is a common practice in empirical research, whereas the second hypothesis proposes to estimate average post-treatment effect for four years. Empirically, the long-lasting treatment effect has rarely been examined and claimed to fade out over time [31]. For that reason, the rationale for the second hypothesis is to witness the long-lasting treatment effect, whether the treated farmers continue the demonstrated practices or not in subsequent years. A schematic of the conceptual framework is presented in Figure 1 which shows the role of on-farm demonstrations in enhancing technology adoption, yield, and profitability for the 1st post-treatment year. The improved yield and profits in the first treatment year would encourage the farmers to continue demonstrating practices in subsequent years, leading to a long-lasting treatment effect.

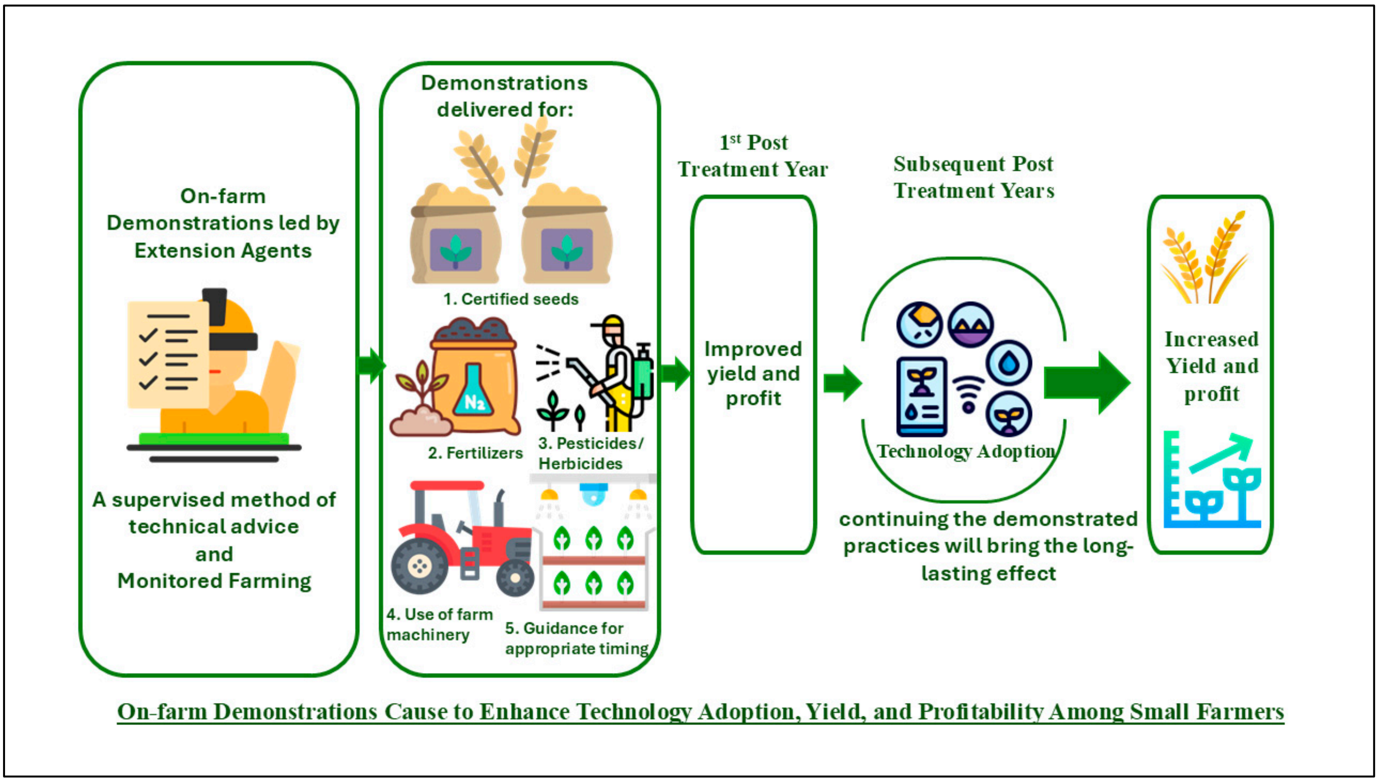

Figure 1. Conceptual framework: on-farm demonstrations cause enhanced technology adoption, yield, and profitability. Source: Authors' creation.

In this study, technology refers to the use of machinery, certified seeds, fertilizers, pesticides, and herbicides. It is hypothesized that small farmers will be motivated to adopt new technologies if the adoption in previous years led to higher yields, reduced costs, and increased profits [36,37]. In the subsequent post-treatment years, farmers' choice of input type and quantity will indicate whether farmers have maintained the practices they adopted during the treatment period.

2. Materials and Methods

2.1. Experiment Design—Wheat Productivity Enhancement Program (WPEP)

In Pakistan, the small farmers were barely benefitted through extension services due to the biased designs and approach of programs towards large farmers owning more than 5 ha of land [38]. It resulted in low technology adoption and wheat yield among the small farmers. According to Agriculture Census 2010, the land distribution in Pakistan is categorized into various farm ownership groups. The small farmers group (90% of the total farmers) owning up to 5 ha of land holds 58% of total cultivated land in Punjab [39]. Within these small farmers, a subgroup with land ownership less than 2 ha are very poor, are engaged in subsistence farming, and are facilitated by the government either in social safety nets or targeted farm inputs subsidies.

The government of Pakistan, following the rationale of a direct relationship between land size and productivity [40] and considering its own socioeconomic historic context [8], designed WPEP for the small farmers owning land between 2 to 5 ha. They represent 41% of total farmers holding 28% of the total cultivated land in Faisalabad [39]. In addition to this misrepresentation of small farmers in policies, the other major challenges faced by them are inaccessibility to bank loans, lack of value chains, inaccessibility to markets, interrupted water for irrigation, lack of storage facilities, minimal awareness about climate and climate change and cropping trends, high input prices, and low returns [41–43]. Hence, to address some of these challenges, WPEP was implemented in Punjab, Pakistan, in 2019 so that technology adoption, wheat yield, and profits of small farmers could be enhanced. The target for enhancing wheat yield was set up to 0.69 (t/ha) by the government. The program also revamped the extension services' delivery in the shape of on-farm demonstrations. The contents of the demonstrations are shown in Table 1.

Table 1. Brief contents of on-farm demonstrations.

S.No.	Type of Input	Demonstrations and Instructions
1.	Application of certified seeds	Supervised purchase/selection of certified seeds from a designated supplier nominated by the government Demonstrated seed sowing on a pre-decided date depending upon the seed brand and nature of soil 100–125 kg/ha Sowing from 15th October to 30th November Row planting, with average row spacing of 25–30 cm
2.	Application of fertilizers	Supervised application of fertilizer to each farm according to the need of land. The quantities according to land type are as follows: Fertile: DAP 155 kg/ha, urea 185 kg/ha, and potash 61 kg/ha Medium fertile: DAP 185 kg/ha, urea 216 kg/ha, and potash 61 kg/ha Less fertile: DAP 247 kg/ha, urea 247 kg/ha, and potash 61 kg/ha The recommended time for application of fertilizers: DAP and potash at sowing time Urea and nitrogen at the 1st and 2nd irrigation time points
3.	Application of pesticides and herbicides	Crop is checked by the extension agent (EA), if required; quantity is recommended by the EA 1 L/ha on average
4.	Use of machinery	Supervised seed drills, such as guidance on zero tillage drill, dry sowing drill, use of wheat bed planter, slasher, and mechanical sowing Guided use of thresher and harvester

The presence of EAs was mandatory at each step from the application of inputs until harvesting. Overall, the growth of crops was closely monitored until harvesting, i.e., end of April.

2.2. Study Site

We selected Faisalabad purposively as a study site due to being (i) the second largest district in wheat production in Punjab, (ii) canal-irrigated, and (iii) less prone to weather changes.

The total area of Faisalabad district is 5856 square kilometers. The treatment area was spread between longitude 73° and 72° east and latitude 30° and 31.9° north. The location of each treated farm was recorded by the extension department during treatment, whereas the control group was recorded by the survey team during data collection, as shown in Figure 2. The farmers in both groups do not share the borders of their farmlands as they were located very far apart from one another. The shortest distance between the two closest points (of control and treatment) was 2 km. There was less of a chance of a spillover effect during the treatment due to the anonymity of the treatment as well as the unfamiliarity of farmers with each other, each being from a different village.

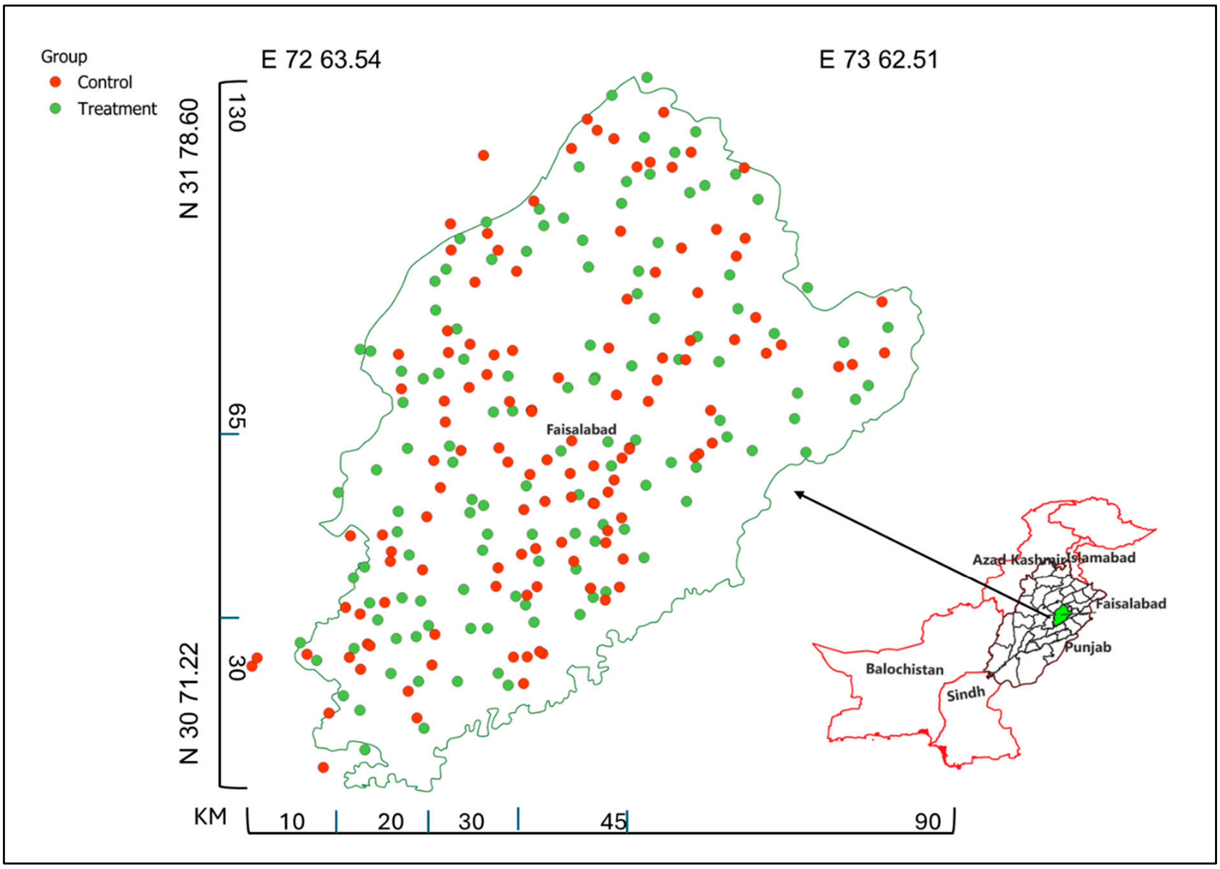

Figure 2. The study site—Faisalabad Map (authors' creation).

2.3. Randomization of Farms

In view of several challenges faced by the small farmers, the Extension and Adaptive Research Department, Punjab, advertised the program in the newspapers and on the official website [44] by setting an eligibility criteria to screen out the population of interest [45]. A random sample from the population of interest was selected for participation in the program who met the following criteria: (i) land ownership from 2 to 5 hectares, (ii) demonstration land near to a bricked road, (iii) land irrigated by a canal, and (iv) farmers registered with the agricultural extension department. There are 13,120 small farmers registered within the category of 2–5 ha land ownership in Faisalabad district. Only 253 small farmers met the criteria and stood eligible to participate who were divided into treatment and control groups.

The selection process was completely random after scrutiny of all applications. The agriculture extension department conducted an electronic lottery through which 123 farmers were assigned to the treatment group and the remaining 130 were considered as the control group. In this way, this intervention complied with all assumptions of randomization and data collection from an eligible population to treatment assignment as described in the randomization toolkit [45]. The external validity was ensured at an initial level when people applied for the program, and internal validity was ensured through random assignment. The randomly selected farmers were informed on their mobile device through text messages. These on-farm demonstrations imparted on the randomly selected farms are a first trial of its kind in Pakistan.

2.4. Data

This study has used both primary and secondary data sources. The baseline data for the whole sample were acquired from the extension department which included a list of participants with their village's addresses, age, land size, seed type, input quantities, sowing and harvesting dates, and yield of all demonstrated farms. For the treatment group, in addition to the baseline data the two years post-treatment observational secondary data were also acquired from the department. For the later years it was recorded on the request of the researchers).

For data recollection from the treatment group for the two post-treatment years and from the control group for four years, a survey team was hired from the Pakistan *Pak. J* Statistics (PBS), Government of Pakistan. The authors along with the survey team conducted interviews to collect data based on the recall method, a common practice in development economic research [46,47]. Though ref. [48,49] emphasized that recall data for more than ten years must not be used for research or descriptive analysis the face-to-face surveys with different options/prompts increase the precision in data collection. In addition, ref. [23] has used recall data for two years in a similar study. Keeping in view these considerations, our survey team has effectively collected data from the control group for all variables. The small farmers owning land totaling more than 3 ha maintained an accounting ledger to record income and expenses. These data were triangulated with information obtained through the interview. The revenue and profit were computed for both groups considering the costs of inputs (the revenue is the total amount received by the farmers after selling their produce. Profit is obtained by subtracting the total cost of production from the revenue. The total cost of production includes all imputed and paid out costs (for inputs and machinery)). In doing so, we tried to avoid respondents' bias in self-reporting the cost and quantities data to the maximum extent by matching them with the wholesale rates of the nearest markets [50]. We noticed during interviews that none of the participants showed any hesitation in giving information due to their trust in the PBS survey team. Many farmers owning land totaling less than 3 ha were content with the support and supervision of extension agents as it was the first time for them to be approached by the EAs individually.

2.5. Balance Check of Baseline Data

In Pakistan, agriculture is predominantly a male-dominated profession, with women primarily involved in traditional and manual tasks such as making dung-pads, cleaning animal sheds, preparing rice nurseries, and producing pulses. The most significant contribution of women in wheat production is their helping hand in harvesting, which is now increasingly being replaced using harvesters and threshers [51–53]. All participants in this WPEP program are male farmers.

Table 2 demonstrates the balance checks of the household characteristics, farm inputs, yield, and other financial variables at the baseline between the treatment and control groups using a *t*-test.

Table 2. The balance check before treatment.

Variables	Mean		Difference	t-Stats.
	Treated (N = 123)	Controlled (N = 130)	T-C	
Household Characteristics				
Age (No. of Years)	47.334	47.485	−0.151 (1.064)	−0.15
Family size (No.)	5.675	5.508	0.167 (0.226)	0.75
Farmers' education (years of schooling)	7.87	7.692	0.177 (0.387)	0.45
Family education (years of schooling)	12.268	12.207	0.06 (0.231)	0.25
Land size (Hectare)	4.41	4.35	0.05 (0.094)	0.60
Distance of farm from road (km)	1.877	1.808	0.071 (0.097)	0.75
Type of irrigation (canal = 1, tubewell and canal = 2)	1.805	1.777	0.028 (0.052)	0.55
Own a tractor (if yes = 1)	0.553	0.577	−0.024 (0.062)	−0.4
Labor (No. per hectare)	1.065	1.062	0.003 (0.03)	0.1
Use of website/FB (If yes = 1)	0.708	0.684	0.022 (0.058)	0.4
Quantity of Yield and Farm inputs				
Yield (t/ha)	4.61	4.59	0.02 (0.07)	0.35
Use of certified seeds (if yes = 1)	0.39	0.45	−0.05 (0.062)	−0.9
Fertilizers (Kg/ha)	240.87	239.97	0.90 (5.04)	0.2
Pesticides/herbicides (L/ha)	2.27	2.318	−0.04 (0.059)	−0.7
Seed quantity (Kg/ha)	120.38	119.22	1.16 (2.002)	0.6
Cost of inputs				
Seeds cost (Rs./ha)	6655.9	7072.7	−416.80 (388.8)	−1.05
Pesticide/herbicide cost (Rs./ha)	2047.28	2076.70	−29.412 (53.12)	−0.55
Machinery cost (Rs./ha)	27,300.5	26,552.5	748.02 (696.2)	1.05
Fertilizers cost (Rs./ha)	14,108.118	13,953.600	154.51 (314.32)	0.5

Table 2. *Cont.*

Variables	Mean		Difference	t-Stats.
	Treated (N = 123)	Controlled (N = 130)	T-C	
Cost of Prod. (Rs./ha)	57,021.8	56,914.5	107.3 (602.9)	0.2
Revenue (Rs./ha)	149,925	149,188.0	736.98 (2251)	0.35
Profit (Rs./ha)	92,903.12	92,273.50	629.62 (1880.6)	0.35
No. of observations	123	130	-	-

Note: there is no statistically significant difference in covariates of treatment and control groups. Standard errors are in parenthesis.

Differences of all demographic characteristics such as age, education, family size, family's education, land size, farming asset (tractor), type of irrigation and distance from road of both groups are statistically insignificant before treatment. The insignificant differences between covariates, quantities, and costs of farm inputs ensure a similar distribution of all characteristics in the population which eliminates the potential influence of confounding variables on the results.

Another important concern that natural experiments face is attrition which we have not found in this study. The farmers of both groups have been living in the same place for generations, and the extension department does have their residential and farm addresses. Further, the department assured us that there was barely any chance of a spillover effect as the people belonging to both groups were spread across the district, because they were randomly chosen with a lottery and live in different villages.

2.6. Estimation Model

In view of our panel data collection and the implementation of randomization to the maximum extent, we used a fixed effects with differences-in-differences (FE-DiD) model to examine the long-lasting effect of treatment. We expect that FE-DiD would potentially reduce unobserved heterogeneity in the sample [54] by using the following equation:

$$Y_{it} = \alpha_i + \lambda_t + \rho T_{it} + X_{it}\beta + \epsilon_{it} \quad (1)$$

where Y_{it} is the dependent variable, i.e., yield, technology inputs, and profit, α_i represents the fixed time-invariant characteristics of farmers (capacity or individual characteristics), λ_t represents the time-specific fixed effects (unobserved time-specific factors, weather, etc.) for each year t, ρ is the treatment effect, T_{it} is the treatment status of each farmer, X_{it} are the covariates (age, education, family size, etc.), and ϵ_{it} is the error term. In [55], it is argued that the literature has supported using the DiD wherever one pre-treatment data point is available.

2.7. Robustness Check

While taking advantage of panel data, we used Analysis of Covariance (ANCOVA) for a robustness check to observe the potential effects of covariates or unobserved confounders on the outcome variables. ANCOVA has the statistical power and precision to adjust nuisance/variability within the group and can eliminate confounder bias between the groups [56]. Hence, we used the OLS ANCOVA model of [57], which is specified as follows:

$$Y_{it} = \alpha_i + \beta T_{it} + \delta ln Y_{it-1} + u_{it} \quad (2)$$

where the outcome and treatment coefficients are the same as in Equation (1) except for δ which is the coefficient of the outcome variable taken for the previous yield in this study.

3. Results

3.1. Main Results

Table 3 presents the FE-DID estimation results of the treatment on technology inputs, i.e., certified seeds, fertilizers, pesticides/herbicides, and machinery usage. Column 1 presents the immediate treatment effect and column 2 presents the average of 2020–2023. All treated farmers used certified seeds in the first treatment year, reflecting an increase of 61% from the baseline, whereas the average usage was found to be increased by 34% during 2020–2023. Similarly, the quantities of fertilizer and pesticides/herbicides increased by 14.7 kg/ha and 0.22 L/ha, respectively, in the treatment group in 2020. The treatment effect remained consistent and significant during 2020–2023 on both inputs. However, the usage of machinery in terms of cost was significant in 2020 at the 5% significance level and was later found to be insignificant, depicting an equal use of machinery by both groups.

Table 3. Impact of treatment on technology adoption (FE-DID).

	Certified Seeds (%)		**Fertilizers (kg/ha)**		**Pesticides/Herb (L/ha)**		**Machinery (Rs./ha)**	
	2020 (1)	**2020–2023 (2)**	**2020 (1)**	**2020–2023 (2)**	**2020 (1)**	**2020–2023 (2)**	**2020 (1)**	**2020–2023 (2)**
D-training	0.61 ***	0.34 ***	14.7 ***	15.2 ***	0.22 ***	0.22 ***	1913.7 **	762.5
	(0.088)	(0.069)	(2.39)	(2.32)	(0.051)	(0.048)	(1107.6)	(795.2)
Constant	0.42 ***	0.51 ***	241.4 ***	245.4 ***	2.31 ***	2.35 ***	30,497.7 ***	45,503.9 ***
	(0.021)	(0.027)	(0.58)	(0.90)	(0.012)	(0.019)	(269.2)	(309.3)
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	506	1265	506	1265	506	1265	506	1265
R-Sqd.	0.49	0.28	0.94	0.86	0.79	0.70	0.73	0.90

Note: the variable 'D-training' is a treatment dummy that takes the value of 1 if an individual has received the D-training. Against each outcome variable, column 1 presents the effect of treatment for 2020 and column 2 for four years, 2020–2023, using the fixed effects difference-in-differences specification. In the regression model, year and individual fixed effects have been used. Standard errors, shown in parentheses, are clustered at the individual level. p-values testing a zero-treatment effect are shown as ** $p < 0.05$ and *** $p < 0.001$.

Table 4 presents the FE-DID estimation results of the treatment on wheat yield, the cost of production, and profit with 'year' and 'households' fixed effects for each variable in each year. For the year 2020 in column 1, the treatment effect is statistically significant at the 1% significance level for yield, cost of production, and profit. The treatment effect for all variables remained consistent during the next four years as shown in column 2. The treatment has caused an increase in the yield by 0.37 t/ha among treated farmers, making it 4.99 t/ha in 2020. Similarly, the average yield for four years was estimated at 5.09 t/ha among the treated farmers, i.e., 0.41 t/ha higher than the control group.

During the treatment year, the higher use of inputs caused an increase in the cost of production as well as generated higher revenues due to increased yield. The consistently higher yields and revenues coupled with the declining cost of production for four years kept the profits higher among the treatment group.

Table 4. Impact of treatment on yield, cost of production, and profit (FE-DID).

	Yield (t/ha)		CoP (Rs./ha)		Profit (Rs./ha)	
	2020 (1)	**2020–2023 (2)**	**2020 (1)**	**2020–2023 (2)**	**2020 (1)**	**2020–2023 (2)**
D-training	0.37 ***	0.41 ***	8698.7 ***	6193.9 ***	4325.4 ***	18,743.4 ***
	(0.017)	(0.019)	(805.0)	(771.8)	(820.7)	(1750.7)
Constant	4.62 ***	4.68 ***	62,642.9 ***	98,700.3 ***	93,319.7 ***	149,940.5 ***
	(0.0042)	(0.0075)	(195.7)	(300.2)	(199.5)	(680.9)
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	506	1265	506	1265	506	1265
R-Squared	0.99	0.98	0.90	0.98	0.96	0.97

Note: the variable 'D-training' is a treatment dummy that takes the value of 1 if an individual has received the D-training. Against each outcome variable, column 1 presents the effect of treatment for 2020 and column 2 for four years, 2020–2023, using the difference-in-differences specification. In the regression model, year and individual fixed effects have been used. Standard errors, shown in parentheses, are clustered at the individual level. *p*-values testing a zero-treatment effect are shown as *** $p < 0.001$.

Figure 3 presents the treatment effect over the four years on yield. In Figure 2, we tested the treatment effect at the 95% significance level and found positive and significant changes in coefficients for all subsequent years. The year-on-year treatment effect was highest at 0.15 t/ha from 2022 to 2023. On average, it depicts a long-lasting post treatment effect over the period of four years.

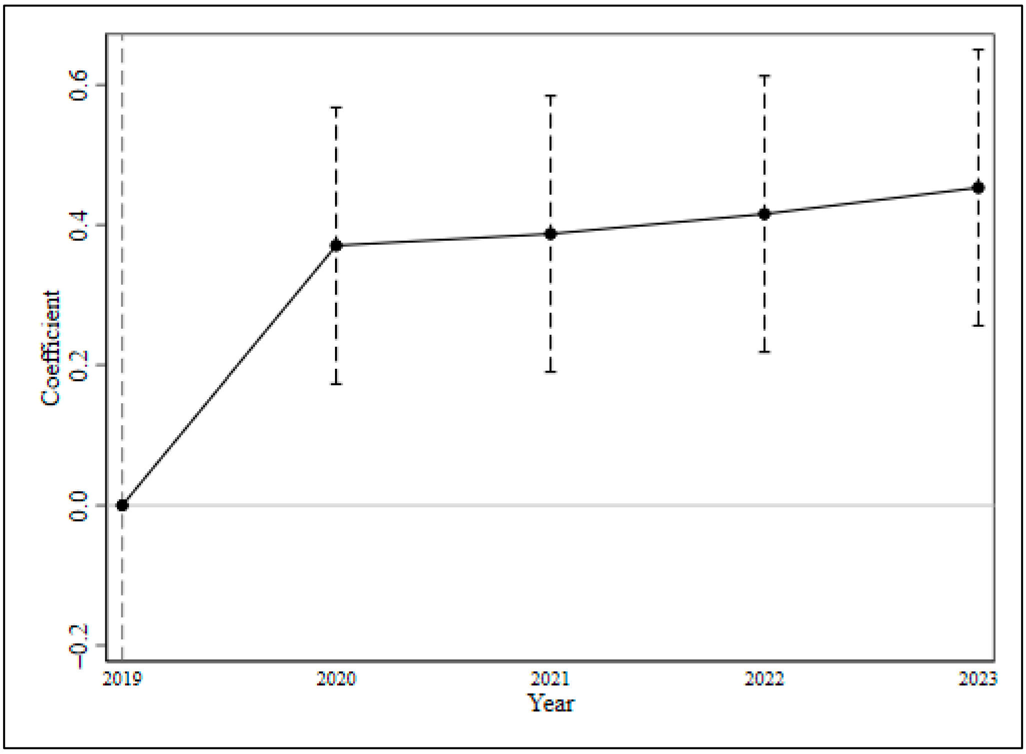

Figure 3. Event study of yield—four year treatment effect.

3.2. Robustness Check Results

ANCOVA was used for robustness and sensitivity analysis by taking the lag of dependent variables such as lag yield as an added covariate in addition to the treatment variable (Tables 5 and 6). For instance, the previous year's yield has the highest correlation with the outcome variable (the following year's yield). The coefficients of certified seeds, fertilizers, pesticides/herbicides, and yield in the ANCOVA are similar to the FE-DID models, showing a robust outcome of the treatment. The impact of D-training faded in the following years, but the constant showed an improved coefficient as shown in column 2 of Table 5. The coefficients and behavior of financial coefficients are also found to be similar to our main results for the immediate post-treatment year. However, for long-lasting impact, the literature does not recommend ANCOVA to be used for panel or follow-up data [58,59]. A fixed effects model was recommended by most researchers for panel data [55,60,61]. Therefore, we report only the results for the first post treatment year using ANCOVA for the cost of production and profit which are similar to our main results as shown in Table 6. The negative intercepts in Table 6 show the strength of the treatment as in its absence there would be less yield and monetary loss based on the previous year's yield.

Table 5. Impact of treatment on technology adoption (ANCOVA).

	Certified Seeds (%)		**Fertilizers (kg/ha)**		**Pesticides/Herb (L/ha)**		**Machinery (Rs./ha)**	
	2020 (1)	**2020–2023 (2)**	**2020 (1)**	**2020–2023 (2)**	**2020 (1)**	**2020–2023 (2)**	**2020 (1)**	**2020–2023 (2)**
D-training	0.54 ***	0.33 ***	14.9 ***	5.54 ***	0.20 ***	0.11 ***	2299.3 **	216.3
	(0.042)	(0.028)	(2.14)	(0.98)	(0.04)	(0.017)	(1062.7)	(363.5)
Constant	0.57 ***	0.66 ***	50.9 ***	57.2 ***	1.25 ***	1.03 ***	20,847.3 ***	6435.6 ***
	(0.021)	(0.024)	(8.83)	(5.30)	(0.018)	(0.12)	(3295.7)	(930.0)
N	253	1012	253	1012	253	1012	253	1012
R-Sqd.	0.46	0.14	0.79	0.71	0.37	0.47	0.11	0.43

Note: the variable 'D-training' is a treatment dummy that takes the value of 1 if an individual has received the D-training. Against each outcome variable, column 1 presents the effect of treatment for 2020 and column 2 shows the overall effect that consist of years between 2020 and 2023 using ANCOVA model specifications considering the effect of the lag of outcome variable on the current year's value. Standard errors, shown in parentheses, are clustered at the individual level, and p-values testing a zero-treatment effect are shown as ** $p < 0.05$ and *** $p < 0.001$.

Table 6. Impact of treatment on yield, cost of production, and profit (ANCOVA).

	Yield (t/ha)		**CoP (Rs./ha)**	**Profit (Rs./ha)**
	2020 (1)	**2020–2023 (2)**	**2020 (1)**	**2020 (1)**
D-training	0.37 ***	0.13 ***	8745.4 ***	4296.4 **
	(0.017)	(0.0082)	(763.5)	(812.9)
Constant	−0.052 ***	0.34 ***	36,111.9 ***	−2772.4
	(0.097)	(0.024)	(4652.2)	(3173.6)
N	253	1012	253	253
R-Sqd.	0.95	0.92	0.42	0.86

Note: the variable 'D-training' is a treatment dummy that takes the value of 1 if an individual has received the D-training. Against each outcome variable, column 1 presents the effect of treatment for 2020, and column 2 shows the overall effect for yield only for 2020–2023 using ANCOVA model specifications considering the effect of lag yield on the current year's yield. Standard errors, shown in parentheses, are clustered at the individual level, and p-values testing a zero-treatment effect are shown as ** $p < 0.05$ and *** $p < 0.001$.

4. Discussion

From the above findings, we observed that the on-farm demonstrations have been effective at increasing technology adoption, enhancing yield, and earning profits among the treatment group. In the context of demonstration extension methods, our results are in line with the relevant studies conducted in Africa [28–30], India [33,34] and Australia [35] where the demonstration interventions have caused technology adoption and increased the yield of teff, wheat, and potato. The significant factors in making the demonstration method successful include the timely delivery of inputs, accessibility to information via extension agents [28], communicative EAs, targeting the non-model farmers [29], and demonstrating the multiple technologies to farmers [30]. In this regard, at first, the EAs of our experimental study ensured the prior availability of all farm inputs before the demonstration to be carried at each step, such as at certified seeds at sowing time, time management for the combined application of fertilizers with irrigation, pesticides application after observing the crop health, and so on. Secondly, this program involved a random group of farmers across the district of approx. 6000 square kilometers, which was larger than the areas of earlier studies. Thirdly, the convincing role of EAs led the farmers to use only the recommended types of inputs which delivered compelling results in yield enhancement, increased technology adoption, and profitability. In contrast, despite the EAs being trained prior to the demonstration experiment in [29], it could not increase the crop's yield significantly but did increase the multiple technologies' adoption. This contrasting fact signified the field expertise of EAs and the novelty of the program design in delivering impactful results. Further elaboration of each section is given below.

4.1. Technology Adoption

Depending upon the experimental designs [62] combined with advanced extension services, the treatment resulted in a higher technology adoption [63,64]. In our study, the certified seeds' adoption was mandatory on demonstration plots. The EAs verified the authenticity of the certified seeds before demonstrating their application in the field. For that reason, both factors, being inseparable, played a significant role in the 100% adoption of certified seeds in 2020. The adoption during 2020–2023 was found to be 84% which showed an encouraging and long-lasting treatment effect in view of better result demonstrability. A slight decline in the use of certified seeds on average during 2020–2023 can be attributed to the regulatory policy (Ministry of National Food Security and Research, 2021) announced to discourage the use of informal/conventional seeds. It created excess demand and caused a shortage of certified seeds. In this regard, it is inferred that the certified seeds' adoption requires more attention in the country as also highlighted by [65]. This study has found that the adoption of certified seeds remained 34% higher in the treatment group compared with the control group in the overall four years' effect, indicating a promising trend in technology adoption through on-farm demonstration.

The use of fertilizers and pesticides/herbicides remained higher and consistent in all years among the treated group showing a long-lasting treatment effect. According to the Food and Agriculture Organization (FAO), the recommended quantity of fertilizer for wheat in irrigated areas of Pakistan is 195–330 kg/ha. As discussed earlier in a time series analysis [65], the current fertilizer offtake in the country was encouraging in positively contributing to the wheat crop which was lower previously. In this study, the average fertilizer usage by the treatment group is 260 kg/ha which is aligned with the FAO recommendations. The difference between the quantities of fertilizers used by both groups is not very wide; however, the impact is significant for the treatment group. It reflected the efficiency and effectiveness of demonstrations imparted by the EAs in terms of suitable timings, quantities, and methods to apply fertilizers. The fertilizer use at baseline was 240 kg/ha which kept on increasing over the years. Though the upper bound of fertilizer offtake is still within the recommended range, it is advisable that EAs must educate the small farmers about the harmful effects of excess fertilizer use for soil fertility, biodiversity, and water and air quality [66]. Presently, the balanced and supervised use of farm inputs is necessary not only for sustainable production but also for sustainable development given scarce natural resources [12].

Moreover, a study [67] in Pakistan recommended 1.2 L/ha of pesticides for the wheat crop, whereas, in terms of efficiency, 1.0 L/ha of herbicides was recommended [68] for wheat crops. Hence, the combined quantity of pesticides and herbicides (sprays) used by the treated farmers is within the recommended dosage. The difference between the quantity used by the treated farmers and the control group is 0.22 L/ha. The significant impact of sprays was obtained due to the close monitoring of the crops and the right timing of the application of sprays by the EAs among treated farmers. Hence, the same quantity of the sprays was used by the small farmers over the four years, showing a significant and long-lasting treatment effect.

Regarding machinery usage, it is asserted that mechanized farming has been significantly increased in Pakistan since 2014 [69]. The use of harvesters and threshers has become very common since the last decade, and a majority of farmers have used them as a replacement for labor. Our study has witnessed that the treatment effect for machinery usage was significant in the first treatment year at the 5% significance level due to the use of few extra machines, but later, the difference became insignificant between both groups. The literature acknowledged the wide use of farm machinery in Punjab in the context of higher net incomes [70], time efficiency and less grain-loss [71], and increased productivity [72]. In this context, our study also depicts the positive outlook of technology adoption in Pakistan.

4.2. Yield Enhancement

Proper land preparation, the pertinent choice of certified seeds, in-time application of fertilizers, chemicals and sprays, and holistic farming practices ensure a higher yield of crops and income [73]. Though the small farmers are experienced and have indigenous knowledge of farming, they need proper guidance in the right selection of the type and quantities of inputs in this dynamic market system [11]. Understanding this fact, the full package of farming instructions through demonstrations and guidance by the EAs has significantly increased the yield of treated farmers up to 4.99 t/ha in 2020 and 5.09 t/ha during 2020–2023. On the other hand, the per-year change in yield during 2021 and 2022 was not significantly different than the control group due to the shortage of certified seeds in 2022 as depicted in Figure 2 (event study). Although, it kept up pace in 2023, yet follow-up of the treatment is always advised for a steady and consistent treatment effect [74].

Regarding the yield in 2023, Faisalabad district recorded an average yield of 5.4 t/ha [75] which is higher than the national average of 3.5 t/ha for the same year. It used remote sensing technology which has become an essential tool in monitoring and recording crop production, offering reliable and accurate data for agricultural management [76]. It evidences that our results are not different from [75]. However, our study reinforces the role of human-based monitoring through EAs. Their interaction proved to be more impactful by demonstrating practices, minimizing farmers' apprehension for technology adoption, and offering guidance as required by the small farmers, which helped in achieving higher yields.

While comparing regional averages of wheat yield from 2019 to 2024, India and Bangladesh recorded 3.5 t/ha whereas Pakistan recorded 2.9 t/ha [77]. Achieving 5.09 t/ha yield in Faisalabad for four years due to this treatment shows the success of the program. It also implies that the self-sufficiency in wheat production would lead the small farmers to adopt other crops. In this regard, the role of extension services and private agricultural organizations was found to be positive in educating farmers about crop diversity and adoption of the latest farming technology in the country [78–80]. Moreover, the market forces have also been observed to be effective in adopting new crops and technology when certified seeds, chemicals, and other farm inputs were made available in the market [81]. Hence, there seems to be a great potential for crop diversification if the information is disseminated properly.

4.3. Profitability and Cost of Production

In developing countries, small farmers are more likely to invest in new agricultural technologies, anticipating better yield, income, and profit [82]. Sometimes they bear extra costs to obtain better and stable yield [83], as we also observed in our study. The treatment group recorded higher profits resulting from higher yields though they incurred a higher cost of production due to technology adoption as compared with the control group in all years. It shows a consistent treatment effect. It is pertinent to note that none of the demonstration-related studies examined the income or profit of the small farmers. The significance of our study lies in the fact that we computed the profitability of small farmers as the financial values better measure the worth of produce and are what small farmers are looking for. The selling price of the produce in a competitive market determined the net benefit, which depicted the improved or deteriorated well-being of the farmers. In our study, the treated farmers remained profitable in all years, which reflected their improved well-being.

In view of the above, we accept our null hypothesis as follows:

- Hypothesis 1: the on-farm demonstration has encouraged technology adoption (certified seeds, fertilizers, pesticides/herbicides and mechanized farming) and increased the yield and profit in the first post-treatment year;
- Hypothesis 2: a long-lasting treatment effect in technology adoption was observed for certified seeds, fertilizers, and pesticides/herbicides but not in machinery usage. The wheat yield and profit also showed a long-lasting treatment effect.

Precisely, this study contributes to the literature by displaying a cogent program design which targeted random small farmers and engaged them by demonstrating the appropriate farming practices at each step. The on-farm demonstrations encouraged the adoption of certified seeds, fertilizers, pesticides/herbicides, and farm machinery. Moreover, this experimental study estimated the long-lasting treatment effect for four years which has been overlooked in the literature. Ultimately, the success of this intervention emphasizes the significance of involving a wider range of small farmers in the natural experiment and the ability of well-supported EAs to drive meaningful agricultural improvements.

4.4. Theoretical Implications

This study emphasizes that the interactive, convincing, and supervisory role of EAs influences the farmers' behavior which leads to a long-lasting technology adoption and treatment effect. This is contrary to the viewpoint [31] that treatment effects fade out in long-term evaluation. On the other hand, the results of this study are an addition to the existing understanding that the small farmers have a positive learning attitude and motivation for technology adoption [21,78–80] due to individual attention [28–30], which was exemplified by their consistent usage of technology inputs in the post-treatment period. It highlights the importance of farmers' direct engagement in building trust in EAs and facilitating technology transfer. This study will be helpful in designing agricultural and rural development policies involving extensions services that can improve small farmers' well-being.

4.5. Managerial, Practical, and Policy Implications

The managerial strength of this program makes this study more credible as compared with [28–30] which utilized a limited number of field agents. This program engaged many agriculturalists who provided individual attention to each demonstrated farm. There is a central agriculture extension office supported by 6–7 union councils. Each council has six villages and 5–7 field agents, enabling one-to-one field agent supervision for each village. There were 123 demonstrated farms, one from each village. The fully dedicated staff made this supervisory program successful. To replicate this program, the unobserved dedication of EAs in addition to their field-specific skills must be considered before engaging them. The uninterrupted supply of farms' input, specifically certified seeds, should be ensured beforehand.

Practically, the outcomes of natural experiments are often not generalized given the varied human behavior, socioeconomic contexts, and climatic conditions. Therefore, the scaling up of such a program must consider geographic, human, and institutional characteristics.

4.6. Study Limitations and Future Directions

The program was designed by the government department. Thus, the eligibility criteria and initial farmers categorization was not in the control of researchers. However, the sample from the population of interest was drawn randomly so the researchers tried to comply with the randomization assumptions. Considering the encouraging results in terms of profitability, the researchers anticipate examining the utilization of profits by the small farmers in future studies. In the case of increased income, whether they prioritize reinvestment in agricultural activities or in improving human capital, such as education, can be explored in the future work.

5. Conclusions

The existing literature primarily focuses on the short-term effects of on-farm demonstrations on yield and technology adoption, without addressing income or profitability impacts for small farmers. This study fills that gap by analyzing a public program taking on-farm demonstrations as the treatment by assessing both immediate and long-lasting effects on small farmers of Faisalabad. This study is the first to assess the causal impact of a public agricultural intervention in Pakistan, using a fixed effects difference-in-differences (FE-DID) estimation approach. The results show that on-farm demonstrations had a significant and long-lasting impact on three key outcomes: technology adoption, wheat yields, and farmer profits. Notably, treated farmers consistently displayed higher technology use compared to the control group, resulting in increased wheat yields and long-term profitability.

These findings make several contributions to the existing literature. First, they provide robust evidence of the effectiveness of on-farm demonstrations in improving agricultural outcomes, an area of study with limited empirical research, particularly in the context of developing countries. Second, they highlight the potential of scaling up such interventions to other crops in Pakistan and similar regions worldwide, addressing the broader challenge of enhancing agricultural productivity in resource-constrained settings. Based on the results, we recommend conducting a province-wide causal impact assessment of this program, encompassing all districts in Punjab. Such an analysis would account for demographic variations and heterogeneous resource constraints, providing insights into differential impacts across districts. This evidence could inform more targeted and effective agricultural policies. Secondly, while conducting extension programs, the farmers should be educated about the minimum and maximum use of seeds, fertilizers, and pesticides/ herbicides for better output, environmental preservation, and cost effectiveness. Thirdly, the supply of certified seeds and fertilizers should also be ensured at the input-application time. A comprehensive package of demonstrations of expertise and input supplies will generate impactful outcomes of the extension program.

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Abbreviations

The following abbreviations are used in this manuscript:

PBS	Pakistan Bureau of Statistics
WPEP	Wheat Productivity Enhancement Project

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