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Agroforestry, Soil Conservation Technologies, and Agriculture Production in Pakistan

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Abstract: This study estimates the impacts of adopting agroforestry and other soil conservation technologies (SCTs) on agricultural production in Pakistan. Using the stratified random sampling technique, 428 farmers were interviewed through well-designed questionnaires. The treatment effects model is used to accommodate the self-selective nature of technology adoption. It is found that agroforestry and chemical fertilizer significantly increase land and total factor productivity (TFP). However, the average treatment effect on adopters of agroforestry technology is slightly negative due to the negative self-selection effect. It can be concluded that these SCTs can be characterized as preventive actions taken by the farmers facing adverse conditions. Using the same estimation technique, SCT's impacts were analyzed on land and labor productivity. Its results are comparable with those of TFP results, conforming that these SCTs primarily increase land productivity.

Keywords: Agroforestry, Agriculture Output, Treatment Effect Model

1. Introduction

Pakistan is an agricultural-based economy, with agriculture accounting for 21% of GDP and 43.7 percent of employment, and agricultural land makes for 47.03 percent of total land. Agriculture accounts for 25.6 percent of national growth and 42.02 percent of Pakistan's workforce. Agriculture supports around 9% of overall exports, indicating a good influence on economic growth. Meanwhile, the current state of affairs has been exacerbated by low quality, ineffective supply chain management techniques, and global market competition.. Pakistan's agriculture industry faces restraints from industrialized nations (Economics Survey, 2020). Pakistan is one of the majority of developing nations that rely on the agricultural industry. Pakistan has 79.6 million hectares, of which 21.17 million hectares (26.6%) are cultivated areas (G.O.P., 2014). 10% out of 26.6% of the cultivated area can easily be used to plant trees. Pakistan's government is also trying to minimize forest deficiency and successfully brought 2% of agricultural land under trees (Qureshi, 1998). FAO (Food and Agriculture Organization of the United Nations) reported that Pakistan had 3.1% area under forests now, which remained at 2.5% in the year 2010[1]. There is a need to increase the area under trees to meet material needs and ecological and environmental services provided by the forests. The FSMP (Forestry Sector Master Plan) reported that the annual growth rate of trees was 14.4 million m^3, of which 7.7 million m^3 were planted on farm land (Qureshi, 1998). Agroforestry acts as a double edge sword. On one side, it reduces pressure on existing forests. However, because agroforestry has a good effect on agriculture productivity, it also serves as a tool for soil protection. Agroforestry has manifold benefits, such as preservation of soil moisture, mitigation of soil erosion, alleviation of crop failure risks, and refilling soil fertility by providing organic fertilizers (Okoji and Moses, 1998; Young, 1989; Mathuva et al., 1998). Otsuki (2010) came to the conclusion that agroforestry and soil

[1] http://www.fao.org/forestry/fra/67090/en/pak/, page=8 (calculated from the given table, dated 18 April 2016)

conservation technologies (SCTs) should be important considerations for reducing pressure on deforestation and maintaining sustainability in food production SCTs. It is also generally found that agroforestry leads to an increased income level (Hussain, 2012; Anjum et al., 2011; Khaliq et al., 2003), providing food and fodder (Hussain, 2012; Irshad et al., 2011), providing timber for fuel and furniture (Dwivedi et al., 2007), controlling over pollution and providing shade for human and animals (Hussain, 2012; Nouman et al. 2006). Additionally, the benefits of this agroforestry include social, ecological, and environmental. (Leakey, 1996; Anthony young, 1988).

Small-scale agroforestry and livelihood resilience thinking are two strategies for fostering local economic development that are the subject of this research study. BTAP (Billion Tree Aforestration Project) emphasizes by providing ecosystem services such as flood control, soil erosion, wild population management, watershed management, and establishing small business units such as nurseries and creating jobs as forest cover increases, agroforestry can improve environmental sustainability and local economic development activities (Rauf et al., 2019). Working in nurseries, fuel woods, construction material supply, fodder, non-timber products, honey, beeswax, traditional cures, mushrooms, other edible fruits, ecotourism, and other small businesses can aid local households in increasing their income, claim Zada and Shah (Zada et al., 2019). Because local businesses purchase raw materials from other local businesses and because their employees spend their paychecks locally first, these local economic activities are amplified. They offer items to a vast market and contribute to the country's exports (Lv & Wu, 2021). Early regional development theories and growth, on the other hand, focus on in-migration after employment prospects are developed.

Many studies, especially in the case of Pakistan, have used simple comparison techniques like the net present value (NPV) approach (Khaliq et al., 2003; Khan et al., 2007; Anjum et al., 2011), benefit-cost ratio (Khaliq et al., 2003; Khan et al., 2007; Dwivedi et al., 2007), Gini coefficient (Lambert, 2011), a simple comparison of means and other descriptive statistics (Nouman et al., 2006; Irshad et al. 2011; Hussain, 2012; Hasan et al., 2014), and simple ordinary least square technique (OLS) (Lambert, 2011). The main aim of this study is to statistically analyze the impacts of adopting agroforestry and other soil conservation technologies SCTs on agriculture production in the study area. Both approaches, a Simple comparison of means of the outcomes and the OLS. Because SCT adoption is self-selective, estimates including a dummy variable for adoption status are unsuitable. These techniques work on the premise that adoptions occur at random, hence the results should be comparable. But unobserved responsible factors like the production and management skills of the peasant can increase the likelihood of both productivity and adoption. In this sense, to evaluate the effect of adoption, the outcome for both scenarios (i.e., adoption and non-adoption) for the same person should be compared. Since the counterfactual (the product for the circumstance which is not selected) cannot be observed, the methods mentioned above can't make a proper comparison, leading to inconsistent estimates of the treatment effect. The treatment effect model can compare the actual outcome with the counterfactual by incorporating the self-selective nature of agroforestry. Pattanayak and Mercer (2002) use the treatment effect model to estimate the effect of agroforestry on soil quality where inverse Mill's ratio is included as a regressor for correction of selection bias, followed by Heckman (1978).

Agroforestry comprises a land-use system that combines trees and shrubs with crops and farm animals in the same land management system (Nasir, 1993). All around, well-managed Agroforestry systems can lead to many advantages, for example, maximum production in each space and time, wildlife habitat and soil stabilization, etc. in the case of Pakistan, these practices are not new as here traditionally, people grow trees in their home quadrangles and on their farmlands for multiple purposes. Farmers often practice agroforestry systems on their agricultural land to reduce soil erosion, retain water, provide shade, generate income, and sustain agricultural production. In Punjab province, most found trees on their farmlands (Farooq et al. 2018).

In the last few decades, due to donor-funded project execution and awareness of the benefits from such practices motivated by governmental institutions, more prominent consideration and significance have been given to these agroforestry systems. Garland (1944), who worked in Sindh province, presented the conceptual and practical description of agroforestry in Pakistan as early as that year. "Forestry Planning and Development Project," Pakistan's first national agroforestry initiative, was introduced in 1985 (Dove 1992). Literature also shows that crop failure in semiarid areas of Pakistan could be minimized by implementing intercropping and livestock integration techniques (Mohammad and Salim, 1989). Nevertheless, agroforestry practices are not limited to degraded lands or fringe only. Trees can be planted on the farming ground and homesteads in large amounts as woodlots in groups within fields, pastures, or along field boundaries in shelterbelt rows; all these practices utilize many tree species. In Sindh province, large areas underpin forests; however, farmers implement agroforestry practices to reclaim degraded land.

Babul (Acacia nilotica), locally called 'hurries', is planted as woodlots by farmers in lower Sindh. Khyber Pakhtunkhwa (KPK) the province situated in the northern part of the country is very famous/entire for/of natural forests. Due to the higher altitude of KPK province, high-quality fruit trees are planted and intercropped in the farming system as agroforestry practice. In a vast area of the section, Populus spp. has also been produced. In Mastung valley of Balochistan Province, Eucalyptus species are planted in enormous areas for income generation, woodfuel supplies and vegetation enhancement. The Punjab Province comprises various irrigated, rainfed, dry, and desert regions that produce multiple crops and tree species. It is also known as the 'food and fruit basket' for the whole country. Numerous agroforestry systems can be implemented in this province as they have a very high potency to support various practices. Zizyphus Muritiana (Ber) and A. nilotica[2] are occasionally intercropped for timber, shade, fodder and fuelwood in the Pothwar Plateau of the Punjab province. Similar to this, Dalbergia sissoo (Shisham) is planted in the region's irrigation system for the same reason. These trees are employed as shelterbelts or windbreaks by growing on the edge of agricultural fields, according to Baig et al. (1999). Agroforestry systems are applied in farming in all the provinces of the country. Different kinds of eucalyptus are able to grow quickly and thrive in dry environments.are planted in regions having average rainfall of less than 300 mm (Baig et al. 1999).

In the case of Pakistan, agroforestry techniques can produce a number of benefits.. As in several countries with the same climate and soil conditions, agroforestry comes up with different products and services. These benefits include regulating soil erosion, mitigating climate change effects, providing forestry products and increasing cultural services. According to Essa et al. (2011) and Ahmad et al. (2013), agroforestry systems may provide higher agricultural revenue and, boost land productivity by assisting food production, enhancing wood production, mitigating climate change’s adverse effects, and combating land degradation. In the same plot, agroforestry systems can produce higher output than monoculture production systems by enlarging the capture of solar radiation, water and nutrients by all crops. It improves the quality of water, light and nutrient use. The agroforestry system also provides other marketable food products. Research in Africa (Mbow et al. 2014) and South-East Asia (Roshetko and Bertomeu 2015) shows that the successful practices of agroforestry systems lead to sustaining agricultural production and food with the help of tree crops output. Agroforestry systems like crop sheltering and wind-breaking shield croplands from hot and desiccating winds (Abbas et al. 2017). Additionally, it offers food for humans, wood for fuel, pollen for honeybees, fodder for cattle, and wood for construction projects. In the same way, Pakistani farmers adopt appropriate agroforestry practices to achieve sustainable production and enhance their incomes (Essa 2004; Essa et al. 2011; Magsi et al. 2014; Ahmad et al. 2017).

According to the 2019 Global Climate Risk Index, among the ten most vulnerable nations to climate change (Eckstein et al. 2018). W.W.F.’s (2012) report predicted a 4^{o}C rise by 2100, faster than most other countries. According to Salam (2018), Pakistan faces severe drought and floods, menacing agriculture, health and water supplies. Like other regional countries, Pakistani farmers should adapt to climate change. Rainfall has different affects; estimates for the near future show a decrease in rainfall in the Lower Indus Basin and an increase in rainfall in the Upper Indus Basin (A.D.B. 2017). Agroforestry can alter climate change by sheltering understory crops from high temperatures while reducing wind speeds, crop transpiration, and soil evaporation. Therefore, the Govt. of Pakistan has initiated a plan to plant 100 million trees in 5 years to alleviate climate change effects (Pakistan Economics Survey 2018). Globally one of the critical targets is to reduce the release of greenhouse gases and minimize deforestation. Trees play a significant role in above-ground carbon sequestration increment, and it also increases the carbon level of cultivated land (Abbas et al., 2017). Agroforestry also minimizes emissions resulting from forest degradation or harvest with the help of form timber and fuelwood (Minang et al., 2011; Madalcho and Tefera, 2016; Abbas et al., 2017). Agroforestry has considerable capability to sequester atmospheric carbon into the soil and in above and below-ground biomass (Abbas et al. 2017). According to Asif et al. (2018), using agroforestry systems increases tree cover outside forested lands. These systems provide more employment, increase income for farmers, and take environmental benefits.

Rahim and Hasanain (2010) describe that 72% of timber and 90% of fuelwood in Pakistan are obtained from agroforestry systems rather than their state forests. Despite that, the estimated 330 million trees on 19.3 Mha are still not enough to fulfill the national demand, which necessitates import. Gilgit Baltistan, having an area of approximately 28,000 sq Miles, is located in Northern Pakistan sharing borders with Afghanistan, China, and India. This province has vast natural forests due to its high altitudes and cool climate. Here local people yield forests for grazing, woodfuel, and timber. In order to ease strain on the remaining natural forests, the government was making several attempts to persuade locals to adopt agroforestry by planting poplar trees on their properties and in their fields. But due to the lack of agroforestry adaptation in a large area, it was still not viable to fulfill their fuelwood needs (Khan et al. 2017).

According to Jamilu et al. (2014), agroforestry can increase plant cover and decrease soil erosion, and it can lay out a path to the rehabilitation of barren land in Pakistan. W.R.I. (2019) states that land which has lost its natural productivity up to some degree caused by human processes is known as degraded land. It contains negative changes in the soil's biological, chemical, and physical properties and vegetative degradation. Agroforestry is an economical approach to reversing land degradation by increasing soil vegetative cover (Tolunay et al., 2007; Glover, 2010).

2. Materials and Methods (Data and Methods)

Khyber Pakhtunkhwa, which was also known as N.W.F.P. from 1901 to 2010, was purposely selected from Pakistan for this study. It consists of 25 districts. District Nowshera, which is one of the most fertile, peaceful, and strategically located central districts

[2] A. nilotica is a pioneer plant that grows rather quickly in dry environments. It is a significant riverine tree in Senegal, Sudan, and India, where it is grown for timber.

of Khyber Pakhtunkhwa Province of the Islamic Republic of Pakistan, is purposely selected for this study. It is also one of the province's largest cities and lies on the G.T. road 27 miles due east of Peshawar at $34^0 0'55N\ 71^0 58'29E$. Five other communities and F.R. area surround this district, Namely Peshawar, Charsadda, Mardan, Swabi, Attock and FR Kohot. It is a big city with an area of 1748 km^2, having 874,373 (approx.) inhabitants. It has one tehsil and 47 union councils. The population density is approximately 500 persons per square kilometer with an annual growth rate of 2.90 at the district level, and the population of rural dwellers was 74% (census 1998). The total agriculture area of District Nowshera is 52,540 hectares. And the primary source of income of district Nowshera is the agriculture sector. Until 1988 district Nowshera was a tehsil (subdivision) of Peshawar, while in 1988, it became a district. The climate of this area is extreme; the temperature in July and August is recorded at about 48^0 C and falls to almost 2^0 C in December and January, July to August and December to January are rainy seasons. Major agricultural crops produced in District Nowshera are Wheat, Maize, Tobacco, Sugarcane, and Potatoes.

2.1 Sample Size and Sampling Method

This study is based on primary data as the objective of this study is to estimate the impacts of agroforestry, chemical fertilizers, and manure adoption on agricultural production in District Nowshera, Pakistan. A well-designed pretested questionnaire is formed for data collection. There are 47 union councils in District Nowshera in which more than 30 union councils have cultivated land (source: district account office). We have chosen 22 union councils using the Stratified Random Sampling technique. Twenty respondents are selected in each union council through a simple random sample technique for data collection. It comprises a total of 440 samples which is large enough.

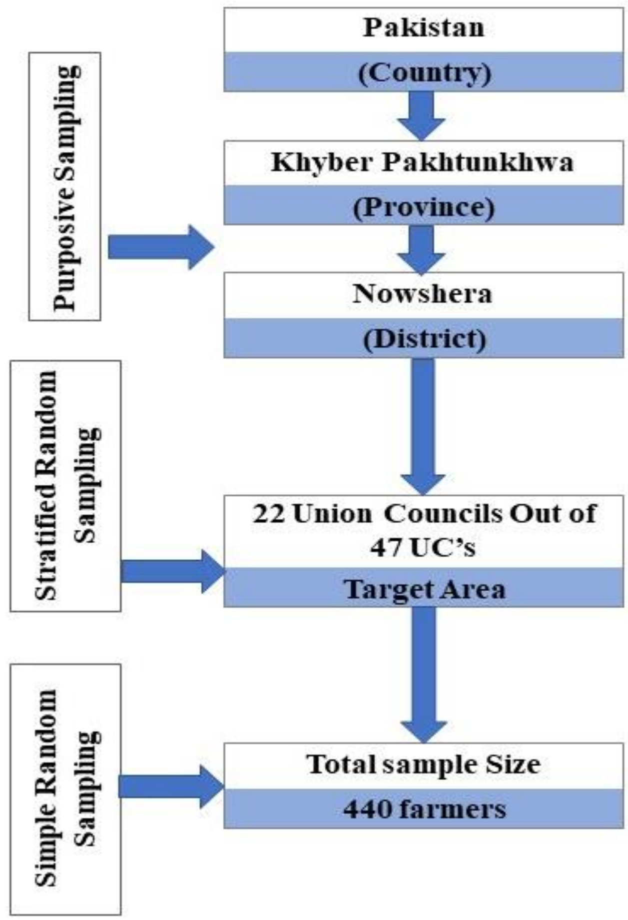

Figure 1. Sampling.

2.2 Econometric Model (Treatment effects model)

The main aim of this study is to statistically analyze the impacts of adopting agroforestry and other soil conservation technologies SCTs on agriculture production in the study area. Both approaches, a Simple comparison of means of the outcomes and the OLS estimates with a dummy variable representing adoption status, are inappropriate because the Adoption of SCTs is self-selective. These methods assume that an Adoption is a random event, and therefore outcomes would be comparable. But unobserved responsible factors like the production and management skills of the peasant can increase the likelihood of both productivity and adoption. In this sense, to evaluate the effect of adoption, the outcome for both scenarios (i.e., adoption and non-adoption) for the same person should be compared. Since the counterfactual (the product for the circumstance which is not selected) cannot be observed, the methods mentioned above can't make a proper comparison, leading to inconsistent estimates of the treatment effect.

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The standard treatment effects model can be writing as

$$Y_i = X_i\beta + \delta I_i + V_i \tag{1}$$

Here, Y_i is the regressed variable representing total outcome, and i= 1, 2, 3… N, vector X_i represents exogenous variables. B is a vector of coefficients parameters associated with X_i; I_i is a binary treatment variable that shows adoption status, while δ is a coefficient estimator for I_i, interpreted as a treatment effect. V_i is a white noise error term. The individual's adoption is based on different determinants Z_i is specified as:

$$I_i^* = Z_i\gamma + U_i \tag{2}$$

I_i^* is a latent variable, γ is a vector of its coefficient parameters, and U_i is the error term. The latent variable (I_i^*) is unobservable and is related to I_i according to the following rules:

$$I_i = 1 \text{ if } I_i^* > 0, \tag{3}$$

I_i= 0 otherwise

If the unobserved factors in eq (2) are correlated with V_i, then the correlation between $U_i$and $V_i$will be nonzero and is denoted by ρ. Thus OLS. estimator will be inconsistent (Greene, 2008). The expected outcomes, by following normal distribution, for participants for *I* becomes

$$E[Y_i|I_i = 1, X_i , Z_i] = X_i\beta + \delta + E[V_i|I_i = 1, X_i, Z_i]$$
$$= X_i\beta + \delta + \rho\sigma_v[\emptyset(Z_i\gamma)/ \Phi(Z_i\gamma)] \quad (4)$$

Here, $\rho\sigma_v$represent covariance between V_i *and* U_i, $\emptyset(Z_i\gamma)$ is the marginal probability density of standard normal at $(Z_i\gamma)$, and $\Phi(Z_i\gamma)$ is the cumulative probability of everyday normal at$(Z_i\gamma)$. The last term includes the inverse mill's ratio to control for a possible sample selection bias, denoted by $\lambda_i = \emptyset(Z_i\gamma)/ \Phi(Z_i\gamma)$, and $\beta_\lambda \equiv \rho\sigma_v$this will be the λ_i coefficient parameters. And for the non-participant, the expected outcomes will become as follows:

$$E[Y_i|I_i = 0, X_i , Z_i] = X_i\beta + \rho\sigma_v[-\emptyset(Z_i\gamma)/ 1 - \Phi(Z_i\gamma)] \quad (5)$$

In this equation, the inverse mill's ratio is $\lambda_i = -\emptyset(Z_i\gamma)/ 1 - \Phi(Z_i\gamma)$. Then the difference between participants' and non-participants expected outcomes becomes

$$E[Y_i|I_i = 1, X_i , Z_i] - E[Y_i|I_i = 0, X_i , Z_i] = \delta + selection\ term \quad (6)$$

In equation (6), a positive sign of the selected terms suggests that OLS overestimates δ and vice versa, and the selection term sign depends on the sign of the ρ. Maddala (1983) and Greene (2008) proposed a maximum-likelihood estimation technique that produces consistent estimators. Maddala (1983) also offered another two-step estimation technique that gives consistent estimators; first equation (3) will be estimated by using the probit model, and then in the second stage, before estimating eq (1), the predicted values of selectivity correction of the first model will be included in eq (1) as a new regressor. Many studies use this technique to evaluate the SCTs effects. But we will use the maximum-likelihood method as it jointly estimates the productivity equations and adoption equations and allows us to test the significance of cross-equations correlation ρ. If in case of maximum-likelihood convergence is not achieved, then we will use two-stage estimation techniques.

2.3 Productivity estimation.

To measure individual farmers' performance and land productivity, we will focus on TFP, while most studies focus on per acre yield of land productivity. We will focus on TFP because, at given inputs and product prices, an increase in TFP leads to an increase in on-farm income, while an increase in land productivity doesn't mean a rise in on-farm income level as the quantity of input labour and other factors may change simultaneously. If Soil Conservation Technology involves extensive use of additional labor and other inputs, on-form net income may decrease.

In the standard description, TFP is defined as $TFP = y_i / F(X_i)$, where y_i is the actual output, $F(X_i)$ is the production function, and X_i represents the input vector. We include Labor (L) and land (H) as inputs as they both are the primary inputs in the study area. Labour is constructed from a total number of men for production's all activities, including land preparation, plantation, weeding and harvesting. And the total area which is cultivated is used only as a land variable.

We will use the stochastic frontier model due to its merits in separating random noise from the productivity component (kumbhakar and Lovell, 2000). The stochastic frontier model for the Cobb-Douglas production function is:

$$\ln y_i = \alpha_0 + \alpha_L L_i + \alpha_H H_i + \in_i - u_i \quad (7)$$

Where α's are coefficients parameters and intercept, and $\in_i$ is white noise error term representing other components of outputs like weather etc. The term u_i is the inefficiency term that will be transformed into a technical efficiency score by simple transformation (Kumbhakar and Lovell, 2000). In a single time in cross-sectional data, the technical efficiency indicates TFP This model will also be estimated through the maximum-likelihood method by assuming half-normal distribution on the inefficiency term.

2.4 Stochastic frontier model.

Aigner et al. (1977) and Meeusen & Broeck (1977) were the first who developed stochastic frontier models, which assume that the output of a firm is a function of a set of inputs, inefficiency, and random error where inefficiency is identified with a disturbance term in the functional equation (Greene, 1993a). A general stochastic production function with a single dependent variable can be written as:

$$Y_i = f(x_i; \beta). \exp(\varepsilon_i) \quad (8)$$
$$\varepsilon_i = v_i - u_i$$

Where Y_i represents output, β is a set of parameters, x_i represents a set of inputs and subscript *i* represents producers, v_i means random errors, which are also known as "statistical noise", u_i is a non-negative random variable, accounts for technical inefficiency, and ε_i is a composed error term which consists of two elements (v_i and u_i)

2.5 Variables used in the study for empirical analysis.

In Table 1, variables are grouped into SCTs, plot-related attributes, and farmer-related attributes. SCTs variables show the state of adoption and non-adoption of soil conservation technologies, a binary variable taking values 1 for adoption and 0 for non-adoption. And the plot and farmer specific variables will be used as explanatory variables either in stage one of adoption regression or stage two of productivity regression. Those variables that affect both the adoption and productivity like soil fertility, slope, farm size, soil type, and education will be used in both the equations.

Table 1. The variables used for the empirical analysis.

Soil conservation technologies	
Agroforestry Chemical fertilizers Manure	Dummy of adoption of SCTs: 1=adoption, 0=non-adoption
Plot-specific attributes	
Soil type	1=Mostly sand, 2=Sandy-clay, 3=Clay, 4=Rocky
Slope	The gradient of land: 1=Flat, 2=Slight slope, 3=Gently slope, 4=Steep slope
Environmental Degradation	Perceived environmental degradation: 1=very serious, 2=serious, 3=moderate, 4=negligible, 5=none
Soil fertility	Soil fertility: 1=poor, 2=fair, 3=good, 4=very good
Plot size	The total area of cultivated land in acre
Total output value	The monetary value of total output
Distance to output market	in kilometre
Distance to the input market	in kilometre
Farmer-specific attributes	
Family size	number of family members
Credit	Application to loan: 1=applying, 0=not applying
Income	total income of the household
Cattle	1=owned, 0=not owned
Household education	Categorical variable taking values ranging from 1 to 10
Farmer education	Categorical variable taking values ranging from 1 to 10
Labourer	Total number of men for production activities

2.6 Empirical Specification

The following equations of the stochastic frontier model and treatment effect model are estimated.

2.6.1 Stochastic frontier model.

$$\ln y_i = \alpha_0 + \alpha_L L_i + \alpha_H H_i + \in_i - u_i \quad (9)$$

The stochastic frontier model for the Cobb-Douglas production function is estimated to isolate random noise from the productivity component.

The total output value ($\ln y_i$) is the natural log of the monetary value of the total output of individual farmers.

Labor (L_i) is the natural log of the total number of men for production's all activities, including land preparation, weeding, harvesting, and plantation.

Land (H_i) is the natural log of the total area in acres under cultivation.

White noise error term ($\in_i$) is a white noise error term representing other components of outputs like weather etc.

The inefficiency term (u_i) is the inefficiency term that will be converted into a technical efficiency score by simple transformation through this formula (Kumbhakar and Lovell, 2000).

$$TE_i = E(\exp(-u_i) \mid \varepsilon_i) = \left[\frac{1-F(\sigma_* - \mu_{*i}/\sigma_*)}{1-F(-\mu_*/\sigma_*)}\right] . exp\left\{-\mu_{*i} + \frac{1}{2}\sigma_*^2\right\} \quad (10)$$

2.6.2 Treatment effect model.

The standard treatment effects model can be written as

$$Y_i = a_0 + a_1 sfer + a_2 slope + a_3 stype + a_4 psa + a_5 fedu + a_6 credit + a_7 dim + a_8 dom + \delta I_i \quad (11)$$

Technical efficiency (Y_i) is the technical efficiency for all individual farmers ranging from 0 to 1. "0" shows perfectly inefficiency while "1" perfectly shows efficiency.

The independent variables are as follows:

Soil fertility (sfer): it is a categorical variable representing the nature of soil fertility by assigning different values ranging from 1 to 4.

Slope (slope): it is a categorical variable measuring the gradient of the surface by assigning different values ranging from 1 to 4.

Soil type (stype): soil type represents different kinds of soil like clay, sandy, and/or sandy clay. It is a categorical variable that assigns different values ranging from 1 to 4.

Plot size in acres (P.S.A.) shows the total length of cultivated land.

Farmer education level (fedu): this is a categorical variable showing the education level of the farmers by assigning different values ranging from 1 to 10.
Credit (credit): this is a dummy variable if the individual farmer takes a loan (credit=1) or not (credit=0).
Distance to input market (dim): this variable shows the distance from input markets to farms in kilometers (approx.).
Distance to output market (dom): this variable shows the distance from farms to output markets in kilometers (approx.).
Adoption status (I_i): it represents the adoption status of individual farmers depending on some factors; it has the following equation.

$$I_i^*(1,0) = a_0 + a_1 sfer + a_2 slope + a_3 stype + a_4 edeg + a_5 psa + a_6 lnhinc + a_7 fedu + a_8 fsize + a_9 cattle \quad (12)$$

The latent variable (I_i^*) is unobservable and is related to I_i according to following rules:

I_i= 1 if I_i^*>0,
I_i= 0 otherwise.

The remaining independent variables are as follows:
Environmental degradation (edge): this variable categorically represents environmental degradation perceived by farmers. It takes values ranging from 1 to 5.
Household income (lnhinc) is the natural log of total household income either from farming or non-farming sources.
Family size (fsize): it shows the size of household family members.
Cattle head (cattle): it shows the number of cattle heads owned by the household regardless of sex or age.
The remaining variables in the adoption equation have already been discussed in the productivity equation specification.

3. Results

3.1 Soil conservation technologies in the study area.

A farmer who practices one type of soil conservation technology (SCT) may also be practicing a different kind of soil conservation technology. Agroforestry is usually combined with other SCTs like manure and chemical fertilizers in the target area. Table 2 reports of the incidence of agroforestry and other SCTs is presented in counts and probabilities. It shows that both technologies are jointly adopted with agroforestry.

Table 2. Combination patterns between agroforestry, chemical fertilizers and manure by the number of sample observations.

			Chemical Fertilizers			Manure		
			No	Yes	Total	No	Yes	Total
Agro Forestry	No	Count	47	133	180	67	113	180
		% of Total	(7.7%)	(21.9%)	(29.6%)	(11.0%)	(18.6%)	(29.6%0
	Yes	Count	71	357	428	108	320	428
		% of Total	(11.7%)	(58.7%)	(70.4%)	(17.8%)	(52.6%)	(70.4%)
	Total	Count	118	490	608	175	433	608
		% of Total	(19.4%)	(80.6%)	(100.0%)	(28.8%)	(71.2%)	(100.0%)

Source: Author's estimation based on survey data for District Nowshera K.P.K., Pakistan (2015).

The conditional probability of Adopting chemical fertilizers and manure is much higher for agroforestry adopters than for non-adopters. Intercrop trees generate organic fertilizers, but they can't contain sufficient phosphorus. Therefore, it is adequate to combine agroforestry with chemical fertilizers (Amadalo et al., 2003).

3.2 Total factor productivity.

To estimate TFP for individual farmers, we must estimate the coefficients of the Cobb-Douglas production function in equation 6. The results are given in Table 3.

By using the maximum likelihood method, the coefficients of the production function in eq. 6, i.e., a_L and a_H, are estimated to be 0.315 and 0.685, respectively. They both, as well as intercept, are significant at the 1 percent level of significance. It shows a constant return to scale in the target area as the sum of both the parameters is equal to one, i.e., 0.315+0.685=1. For each sample, technical efficiency scores are calculated once the inefficiency term u_i is adjusted such that it will not take the values beyond the range (0, 1). The descriptive statistics of technical efficiency measures are the mean being 0.649, the standard deviation 0.111, the minimum 0.099, and the maximum 0.908.

Table 3. Stata Output for Stochastic Frontier Model.

Stochastic frontier half-normal model				Number of observations		= 608
				Wald chi2 (2)		= 673.68
Log likelihood = -619.871				Prob > chi 2		= 0.0000
ln (total value)	Coefficients	Std. Err.	Z	P> |z|	[95% Conf.	Interval]
ln (culti area) (acre)	0.6848067	0.0460205	14.88	0.000	0.5946081	0.7750053
ln (total labor)	0.3151147	0.0410741	7.67	0.000	0.234611	0.3956184
Constant	10.20454	0.1450873	70.33	0.000	9.920176	10.48891
/lnsig2v ($ln\sigma_v^2$)	-1.171199	0.1172141	-9.99	0.000	-1.400935	-0.9414641
/lnsig2u ($ln\sigma_u^2$)	-0.9351959	0.2527429	-3.70	0.000	-1.430563	-0.4398289
sigma_v (σ_v)	0.5567718	0.0326308			0.4963532	0.6245449
sigma_u (σ_u)	0.6265054	0.0791724			0.4890545	0.8025874
sigma2 ($\sigma_s^2 = \sigma_u^2 + \sigma_v^2$)	0.7025039	0.0766326			0.5523066	0.8527011
Lambda ($\lambda = \sigma_u/\sigma_v$)	1.125246	0.1054692			0.9185303	1.331962
Summary Statistics of Total Factor Productivity (Technical Efficiency)						
ariable	**Observations**	**Mean**	**St. Dev.**	**Min**	**Max**	
Technical Efficiency	608	0.6489	0.1112	0.0990	0.9084	

Source: Author's estimation based on survey data for District Nowshera K.P.K., Pakistan (2015).

3.3 The effect of Adoption of agroforestry and other SCTs.

To examine the impact of agroforestry adoption on productivity, we have specified the productivity equation by setting a productivity index as Y_i, exogenous factors X_i to influence Y_i, and the dummy of agroforestry adoption as I_i in Equation (1). The Adoption equation is specified by setting the independent variables of agroforestry adoption as Z_i in Equation (2). We also consider alternative SCTs as chemical fertilizers and manure for the productivity equation.

The results of both the adoption and productivity equations are given in Table 4, where the technical efficiency scores are used as the productivity measure. The table shows the standard error of each variable, the coefficient estimate, the inverse Mill's ratio λ, and the estimate of coefficient parameter ρ for the productivity and adoption equations. The table also shows the chi-squared statistics for the Wald test for model predictability. In all the three models, the *p*-values for the Wald test suggest the joint significance of coefficient parameters at less than one per cent significance, implying good model predictability.

The adoption equation results denote that perceived environmental degradation, Farm size, Soil type, income level, and Soil fertility are essential variables for agroforestry or other SCTs adoption, conforming results of the previous studies. Across the treatment types of significant coefficient, parameters are different. Generally, it can be said that it is the land's adverse condition that induces peasants to adopt SCTs. Ajayi (2007) used survey data from Zambian farmers and pointed out that those farmers who are more concerned about soil fertility conditions have a higher potential to adopt soil conservation technologies.

The productivity equation results denote that agroforestry and chemical fertilizers adoption increase total factor productivity. In contrast, manure decreases TFP Agroforestry adopters and chemical fertilizer adopters enjoy high production, on average, and therefore high on-form income. Combining these findings with the first stage results that farmer having sloping land, more income, common soil type, perceived environmental degradation, and large farm size tend to adopt agroforestry and chemical fertilizer technology, minimization of possible productivity loss resulting from soil erosion act as a motivator to agroforestry adoption. The negative coefficient parameter for manure may be due to the unavailability of a sufficient quantity of manure as an SCT required for a specific plot size.

The estimated coefficients for the adoption dummy give the difference in TFP between adopters and non-adopters. It is most excellent for agroforestry showing the effectiveness of this technology. Combining the first stage adoption regression finding, agroforestry is likely used by farmers having large farm sizes, perceived environmental degradation, and low soil type. Agroforestry adopters are not only successful in averting soil erosion but also in increasing production.

4. Discussions

Some of the estimated parameters in Table 4 require explanation.

First, ρ is the estimated rho in the variance-covariance matrix showing a correlation between the error V_i of the regression equation (1) and the error U_i of the selection equation (2). Here, in the case of agroforestry, $\hat{\rho} = -0.6692$. Stata estimates it through inverse hyperbolic tangent of ρ. It is an intermediate step through which Stata estimate ρ. The sigma value is the estimated σ_v in the variance-covariance matrix; it is the variance of the regression error term in equation (1). Here, in the case of agroforestry $\hat{\sigma}_v = 0.1174$, Stata estimates it through $(ln\sigma_v)$. The statistic "*lambda"* is the non-selection hazards, or the inverse mills ratio, which is the product of the two terms (i.e., $\hat{\lambda} = \hat{\rho}\hat{\sigma}_v = (-0.6692)(0.1174) = (-0.0786)$). It is the required statistic Heckman used it in two-step estimators (i.e. $\lambda_i = \emptyset(Z_i\gamma)/\,\Phi(Z_i\gamma)$) in equation (4) to obtain a consistent estimation of the first step equation.

Table 4. Regression results on productivity (dependent variable=total factor productivity).

	Model 1	Model 2	Model 3
Soil conservation technology	Agroforestry	Fertilizers	Manure
Productivity equation			
Soil conservation technology	0.1407*** [a]	0.1054***	-0.0579*
	(0.0192) [b]	-0.0258	-0.0306
Soil fertility	0.0168**	0.0225***	0.0225***
	-0.0076	-0.0071	-0.0075
Slope	-0.0169**	-0.0084	-0.0088
	-0.0079	-0.0073	-0.0073
Soil type	-0.0222***	-0.0093	-0.0021
	-0.0078	-0.0069	-0.0069
Farm size (acre)	0.0019	0.0005	0.0025
	-0.0016	-0.0017	-0.0016
Education status	-0.0051**	-0.0051**	-0.0055***
	-0.0024	-0.0023	-0.0023
Distance to input markets (km)	-0.0023	-0.0022	-0.0021
	-0.0016	-0.0016	-0.0016
Distance to output markets (km)	0.0077***	0.0079***	0.0076***
	-0.0009	-0.0009	-0.0009
Credit	0.0124	0.0136	0.0136
	-0.0086	-0.0087	-0.0088
Constant	0.5499***	0.5073***	0.6126***
	-0.0272	-0.033	-0.0254
λ (Lambda)	-0.0786**	-0.0563***	0.0383
	-0.0108	-0.0151	-0.0177
Adoption equation			
Soil fertility	-0.1274	-0.3769***	0.3461***
	-0.0876	-0.1062	-0.0914
Slope	0.1485*	-0.1148	0.1016
	-0.0897	-0.1079	-0.0924
Soil type	0.3754***	0.1933*	0.1511*
	-0.0839	-0.1017	-0.0844
Farm size (acre)	0.0443**	0.4218***	-0.0746***
	-0.0211	-0.0668	-0.0184
Education status	-0.0102	-0.0264	0.037
	-0.0279	-0.0337	-0.0303
Ln of income	0.0042	0.2606*	0.1208
	-0.1074	-0.1409	-0.136
Degradation	0.2063***	0.1909***	-0.1538***
	-0.0462	-0.0579	-0.0615
Family size	-0.0266	-0.023	0.0457
	-0.0367	-0.0471	-0.0437
Cattle	-0.0166	-0.2623	0.2519*
	-0.1358	-0.1733	-0.1501
Constant	-0.8356	-1.9736	-1.9680**
	-0.9946	-1.3254	-1.3249
Estimation method	**ML**	**ML**	**ML**
ρ (P-value)	-0.67 (0.00)***	-0.52 (0.00)***	0.36 (0.125)
Model χ^2 (P-value)	150.10 (0.00)***	110.0 (0.00)***	100.3 (0.00)***
Log-likelihood	176.04	283.97	187.25
N	608	608	608

Source: Author's estimation based on survey data for District Nowshera K.P.K., Pakistan (2015).
Note: [a] The symbols "***", "**", and "*" means a 1, 5, and 10 percent significance level, respectively.
[b] Inside the parentheses are Standard Errors. A command "etregress" of Stata 14 is used for the estimation.

Second, the treatment effect model assumes that the correlation between the regression and selection equation error terms is nonzero because violation of this assumption leads to estimation bias. Stata also produces results of a likelihood ratio test against "$H_0: \rho = 0$" at the bottom of the output. It compares the joint likelihood of an independent probit model for the selection equation and a regression model on the observed data against the treatment effect model likelihood. Here, in the case of agroforestry, chemical fertilizer, and manure, it is $\chi^2 = 13.62, 7.79\ and\ 2.35$ with (p < 0.01, 0.01 and 0.125), respectively. We can reject the null hypothesis at a statistically significant level (1%) for the first two technologies and conclude that $\rho \neq 0$. These results suggest that applying the treatment effect model is appropriate.

Third, the interpretation of the estimated coefficients of the regression equation (i.e., the top panel of Table 4) is just like the simple linear regression model. The sign and magnitude of the regression parameters show the change in the dependent variable due to one unit change in the independent variable. However, the interpretation of the estimated coefficients of the regression of the selection equation is somewhat complicated because the observed I variable takes only two values (0 vs 1). At the same time, the estimation process uses the probability of I=1. Nevertheless, the sign of the regression coefficient is always meaningful, and the significance of the coefficient is vital. For example, using the variable slope (whether a farmer's plot is flat or flat=1, having slight slope=2 etc.) as its coefficient is positive (i.e., Slope=0.1485), we know that the treatment is positively related to slope status. That is, farmers having sloping land are more likely to adopt soil conservation technologies, and this relationship is statistically significant. Thus, coefficients with p values less than 0.05 indicate variables that contribute to the adoption of soil conservation technologies. Even though we can calculate the marginal effect of the probit model by simple transformation after manual calculation of the model or by using the "mfx" command in Stata, in our case, we only need to know about the relationship between different SCTs and its covariates.

Forth, this study analyzes the impacts of SCT's Adoption on agriculture production by taking the TFP of significant crops as a dependent variable because persistent high TFP ensures steady long-run economic development in the agriculture sector. A positive effect of SCTs on TFP would imply that more output can be produced for a given number of inputs or that forgiven output level land and other inputs can be conserved. Empirical studies on agroforestry and other soil conservation technologies SCTs have focused on agriculture revenue or income in their effect. However, since land size or other inputs are correlated with these unnormalized outcome variables, the estimated impact of adoption is more likely to be biased if adoption is not independent of input size. Land productivity is a normalized variable (Lee et al., 2006), but as it shows partial productivity only, it fails to reflect substitution with other inputs, like capital and labor; thus, an increase in land productivity doesn't ensure a boost in agriculture revenue. If the positive effect of agroforestry adoption on TFP alone is found, then the existence of other benefits makes it even more profitable. Moreover, the outcome dependent variable TFP is a continuous variable ranging from 0 to 1.

Recently, many studies in conservation science and social science have demonstrated agroforestry and other SCTs effect on soil conservation (Okoji and Moses, 1998). Studies to evaluate the economic benefits of these technologies are rather scarce (otsuki, 2010). This study is an attempt to quantify the economic benefit of these technologies. The results showed that SCTs like agroforestry, chemical fertilizers, and other factors, i.e., soil fertility, slope, soil type, and distance to output market, contribute to TFP Most factors' results are significant and vary across the models and by expected signs already reported by past literature.

Agroforestry and chemical fertilizers are the main factors responsible for increasing TFP in the target area. Results show that they both are with their expected signs and statistically significant at a 1% level. The estimated coefficient for agroforestry (0.1407), meaning that other things being equal, farmers who have adopted agroforestry practice had a mean TFP that was 0.14 units (or 14%) greater than farmers who did not adopt this technology. And the farmers who use chemical fertilizers for soil conservation have 0.10 units (or 10%) more output than those who did not use chemical fertilizers. Agroforestry adopters and chemical fertilizers adopters, on average, enjoy higher productivity and, therefore, higher form income. Many past studies report the same results (Nakano et al., 2014; Lema et al., 2013; Otsuki, 2010; Lambert, 2011). The estimated parameter for manure is with a negative (unexpected) sign and statistically significant with a 10% level. This result is contradicted by past literature (Kato et al., 2011; Buriro et al., 2014). It may be due to the unavailability of a sufficient quantity of manure/acre required for per acre crops cultivation.

Soil fertility is positively related to TFP and statistically significant at a 5% level in all three models conforming to the previous studies' results (Kato et al., 2011; Outsuki, 2010; Saba et al., 2013). The estimated coefficient for model 2 is (0.0225), indicating that other things being equal, a farmer who has fertile land with poor quality may enjoy 0.0225 units (0r 2.25%) more TFP (i.e., TFP is a continuous variable and ranging from 0 to 1). Soil fertility is an ordinal variable having a nominal scale. It shows that as soil fertility increases, TFP will also increase. Combining these results with first stage results, farmers with common soil type, perceived environmental degradation, and large farm size will tend to adopt this technology. Mitigating possible productivity loss due to low soil fertility seems to motivate this technology's adoption. The same logic is valid for model 1.

The slope is negatively related to TFP in all three models and statistically significant at a 5% level. It is also an ordinal variable with a nominal scale having categories flat, slight slope, gentle slope and steep slope ranging from 1 to 4. In the case of model 1, agroforestry, the estimated coefficient (-0.0169) shows that a farmer having sloping land will lose 0.016 units (or 1.6%) of TFP Combining these results with the first stage results that farmers have sloping land, common soil type, large farm size, and perceived environmental degradation will tend to adopt agroforestry. Its estimated parameter is more extensive than the slope coefficient, so it will vanish its negative impacts. These results contradict previous findings (Otsuki 2010). The same reason holds for the other two models.

Soil type is also negatively related to TFP in all three models but statistically significant only for model 1, agroforestry, at a 1% level. The estimated parameter (-0.0222) shows that farmers adopting agroforestry will lose 0.022 units (or 2.2%) of TFP Combining these results with first stage results, those farmers having low soil type, large farm size, and perceived environmental degradation will tend to adopt this technology. Due to its superior impacts on TFP, which vanish its negative effects.

Farm size is with its expected sign in all three models, but it is statistically insignificant for all three models, even at a 10% significance level. And its estimated coefficients (0.0019, 0.0005, and 0.0025, respectively) for all three models are very small, having little impacts. This result is consistent with previous studies (Norris et al., 1987; Rahm et al., 1984; Irshad et al., 2011)

Education status is with an unexpected sign, negatively related to TFP, and statistically significant for all three models at a 5% level. It is also an ordinal variable with a nominal scale ranging from 1 to 10. For model 2, chemical fertilizer, the estimated coefficient is (-0.0051), which shows that farmers having some education and adopting this technology will lose 0.005 units (or 0.5%) of TFP In all the three models, the impacts of education on TFP are very low (nominal), as shown in Table 4. Combining this with the first stage results in farmers with low soil fertility, low soil type, large farm size, and perceived environmental degradation will tend to adopt this technology, which will vanish its negative impacts. Weir and Knight (2000) reported that there are many types of chemical fertilizers (and agroforestry practices) best known by highly educated farmers only. It requires more non-farm income to purchase and use them. But in the case of the target area, as many farmers have a meager average income, therefore besides having some education, they can't adopt all of them, and its relationship with TFP seems to be negative.

Distance to input markets (Km) is with a negative (expected) sign and insignificant for all the three models. It shows that as the distance to the input market increases, the TFP will tend to decrease because it requires more transportation costs. The estimated coefficients for all three models are very low, having a negligible impact on TFP This implies that farmers prefer near input markets to enjoy more agricultural output (Otsuki 2010).

Distance to output markets (Km) is positively correlated to TFP and significant in all three models. In the case of model 1, agroforestry, the estimated parameter is (0.0077), showing that an output market with, say, 10 Km (10*0.0077=0.077) will tend to increase TFP by 0.077 units (or 7.7%). They combine these results with first stage results that farmers with sloping land and perceived environmental degradation will tend to adopt this technology and boost their total factor productivity. The same explanation holds for the remaining two models, as their coefficients are very similar to this. This result is also consistent with previous findings (Otsuki 2010).

Credit is positively correlated to TFP, although statistically insignificant in all three models. It suggests that some institutions should provide credit to farmers with easy conditions as most farmers can't use better soil conservation technology due to a lack of non-farm income. The estimated coefficient for model 2, chemical fertilizer, is (0.0136), indicating that a farmer can increase their TFP by 0.0136 units (or 1.36%) through loans. The same logic holds for the other two models.

Estimated rho values for all three models (agroforestry, chemical fertilizer, and manure) are $\hat{\rho} = -0.67,\ -0.52,\ and\ 0.36,$ respectively. It is statistically significant at a 1% level for the first two models, while for the third model, it is insignificant. It shows a correlation between the two error terms of regression and selection equations. This implies that the sample selection bias is present regarding SCTs adoption. The negative selection bias suggests a negative correlation between the two error terms. Therefore, it is appropriate to apply the treatment effect model. These results for the first two models differ from our original expectation that a more active adopter of these technologies is likely to have a higher return to SCTs adoption. A probable explanation is that those farmers tend to adopt SCTswho meet with unobserved adverse factors of their land. There appear to be some other negative factors than low soil fertility, low soil type, and sloping ground, such as lack of good quality seeds, limited access to water, and lack of holding land title etc. therefore, these negative factors may have dominated the positive aspects such as production and management skills.

4.1 Comparison between different approaches.

Using the same estimation technique as for TFP, we examine SCTs impacts on land and labor productivity, as shown in Table 5. Here the value of output per acre is used as the land productivity index, and the value of the production per worker is used as the

Table 5. Regression results on land and labour productivity.

Dependent variable = land productivity			
Treatment type	Agroforestry	Chemical fertilizer	Manure
Treatment	0.6599*** [a]	0.3557*	-0.5658***
	(0.1617)[b]	(0.1971)	(0.1464)
Dependent variable = labor productivity			
Treatment	0.7421***	0.4424**	-0.6692**
	(0.2248)	(0.1778)	(0.2725)

Source: Author's estimation based on survey data for District Nowshera K.P.K., Pakistan (2015).

Note: [a] The symbols "***", "**", and "*" means a 1, 5, and 10 percent significance level, respectively.

[b] Inside the parentheses are Standard Errors. A command "etregress" of Stata 14 is used for the estimation.

labor productivity index. These indices are normalized by taking the natural log of them. The results of both land and labor productivity are entirely comparable with those of TFP In both cases (i.e., TFP and land/labor productivity), agroforestry and chemical fertilizer are positive. In contrast, manure hurts agriculture, showing that these technologies increase total agricultural production.

For comparison, we have demonstrated in Table 6 the difference between the least square estimation, a simple comparison of the means and the treatment effect model with a focus on TFP. The ordinary least square estimation for agroforestry yields a downwardly biased estimator for the treatment effect (0.013), ignoring the selectivity correction. In addition, comparing simple means of TFP. between adopters and non-adopters for agroforestry demonstrates that the TFP. of the adopters is higher than that of non-adopters, confirming the results of past studies (Place et al. 2005). The mean of TFP. of adopters is 0.460, and that of the non-adopters is 0.188. The difference is 0.272 and 144.68 % higher than the non-adopters average. It is also higher than the estimates from the treatment effect model. The same logic holds for chemical fertilizer technology. In manure, the OLS. estimation yields an upwardly biased estimator for the treatment effect (0.005) due to ignoring the selectivity correction.

Table 6. OLS., Difference between the mean of TFP. between adopters and non-adopters and Treatment effect model Results.

Dependent variable = Technical Efficiency (Treatment effect model)			
Treatment type	Agroforestry	Chemical fertilizer	Manure
Treatment	0.1407*** [a]	0.1054***	-0.0579*
	(0.0192) [b]	(0.0258)	(0.0306)
Dependent variable = Technical Efficiency (Ordinary least square estimation)			
Treatment	0.0133	0.0188*	0.0054
	(0.0095)	(0.0111)	(0.0098)
Simple comparison of the means of TFP. between adopters and non-adopters			
I=1 (adopters)	0.4601	0.5275	0.4641
I=0 (non-adopters)	0.1888	0.1215	0.1849
Difference	0.2713	0.4060	0.2792

Source: Author's estimation based on survey data for District Nowshera K.P.K., Pakistan (2015).

Note: a The symbols "***", "**", and "*" means a 1, 5, and 10 percent significance level, respectively. b Inside the parentheses are Standard Errors.

4.2 Average treatment effect on treated (ATET)

The average treatment effect (ATE) on adopters can be estimated by taking the difference between the conditional mean outcomes of the Adoption (*I*=1) and counterfactual (*I*=0). Because this model allows us to investigate the outcomes under both scenarios, "adopt" and "don't adopt", for each sample. The ATET is identical to ATE in Table 4 because when there is no interaction term(s) between treatment variable and outcome covariates, Stata 14 command "etregress" directly estimates the ATE and ATET. Here, we allow the variable "plot size in acre" to interact with SCTs and then estimate ATE and ATET. In this case, ATE and ATET may differ because of interaction terms, which vary over outcome covariate values.

Table 7. Allowing interaction between treatment and outcome covariate, ATET.

Dependent variable = Technical Efficiency			
Treatment type	ATET	ATE	Difference
Agroforestry	0.1405*** [a]	0.1411***	-0.0006
	(0.0245) [b]	(0.0246)	
Chemical fertilizer	0.1174***	0.1155***	0.0019
	(0.0432)	(0.0413)	
Manure	-0.0560	-0.0566	0.0006
	(0.0343)	(0.0343)	

Source: Author's estimation based on survey data for District Nowshera K.P.K., Pakistan (2015).

Note: [a] The symbols "***", "**", and "*" means a 1, 5, and 10 percent significance level, respectively.

[b] Inside the parentheses are Standard Errors. A command "etregress", "margins r.treat" and margins r.treat subpop(treat)" of Stata 14 is used for the estimation.

Table 7 illustrates that ATET and ATE are very close, showing that the average predicted outcome for adopters is like the average predicted outcome for the whole sample population. The table shows that the difference value (-0.0006) for agroforestry is negative, although very small. According to the standard interpretation of ATE, "a particular farmer who adopts agroforestry would have had lower productivity, had he not adopted agroforestry". But it doesn't suggest that adoption makes a farmer worse off than he does not adopt; it implies that farmers with potentially low production tend to adopt agroforestry. Adopters are conscious of their land's low ability against soil erosion mitigation due to more significant disadvantages than average producers, motivating them to adopt countervailing measures (otsuki, 2010).

For chemical fertilizer, the difference value (0.0019) is positive. However, it is tiny, indicating that a farmer who adopts this technology would have had (0.19%) higher productivity had he not adopted it. While in the case of manure, both ATE and ATET are negative but in absolute form. It is lower for adopters than non-adopters, indicating that manure adopters would have had 0.06% less loss than the average predicted value for the whole sample population

5. Conclusions

Soil fertility, slope, soil type, farm size, and perceived environmental degradation are responsible factors for SCTs Adoption. Adopting agroforestry and chemical fertilizer increases total factor productivity (TFP) by 14 percent and 10 percent, respectively. The average treatment effect on adopters of agroforestry technology is slightly negative due to the negative self-selection effect. SCTs can be characterized as defensive actions taken by farmers facing adverse conditions. They often depend on the least square estimation and the simple comparison of means that could blur the actual benefit. Using the same estimation technique as for TFP, SCTs impacts were analyzed on land and labor productivity by taking the value of output per acre as land productivity index and the production per worker as labor productivity index. Both the variables have positive impacts on agroforestry and chemical fertilizer and negative effects on manure.

Government should make some institutions provide loans and agriculture inputs at easy terms and conditions for farmers. Most farmers are very poor and can't adopt many types of these SCTs. And only 37% of farmers receive credit from relatives/traders. It has been concluded that labor-intensive technology is used for agriculture production in the target area, which leads to low productivity. Table 1 shows that 48.38 laborers are used per acre plot, and Table 3 shows that the Government should launch an easy installment scheme for modern farming equipment. Farmers lack technical know-how about the implementation of different types of SCT. As education status shows a negative correlation with TFP., it may be argued that optimal use of different kinds of chemical fertilizers requires high education/training in understanding types of fertilizers for different crops. If the Government provides good seeds and special fertilizer to farmers holding such a large share of land, it will maximize their total agricultural output. There is a lack of roads and proper channels in the backward area of district Nowshera. It is also depicted by estimated parameters of distance to inputs markets, showing a negative correlation with TFP. Because farmers bear transportation and time cost to get required quality fertilizers/tree species. There should be a brief government policy regarding environment and soil conservation measures, an expert from the Indian Institute of Environment, Food and Agriculture (IEFA) has said. The estimated rho values show some unobserved adverse factors other than low soil fertility, low soil type, and slope, which dominate the positive impacts of production and management skills. These factors may be limited access to water, lack of land title, etc.

Conflicts of Interest: The authors declare no conflict of interest.

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