Journal of Agriculture and Rural Development in the Tropics and Subtropics
Vol. 123 No. 1 (2022) 1–11

https://doi.org/10.17170/kobra-202201195568 ISSN: 2363-6033 (online); 1612-9830 (print) – website: www.jarts.info

The role of crop protection products of multinational brands for agricultural sustainability in the cotton-growing zone in Pakistan

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Abstract

Despite the use of Bt (*Bacillus thuringiensis*) cotton in Pakistan, the country is still far behind in farm harvest per unit compared to other cotton-producing countries such as China and Turkey. Cotton is a pest-sensitive crop, and inappropriate crop protection products contribute to lower agricultural sustainability. This issue attracts additional attention in developing countries such as Pakistan, where generic formulation/sub-standard crop protection products are easily and abundantly available. However, the impact of the application of crop protection products of multinational brands in contrast to generic formulation/sub-standard crop protection products on total farm revenue is explicitly not documented. We employ a stochastic frontier production framework using a survey of smallholder farming households in the cotton-growing zone in Pakistan (N=266). The estimates of stochastic frontier production models show a positive relationship between the use of crop protection products of multinational brands and total farm revenue. The estimates of technical inefficiency models show that specialisation and regional dummy, among others, emerge as the key to determining the smallholders' technical inefficiency. To get higher farm revenue and technical efficiency, we propose the agricultural policy makers of Pakistan to explicitly focus on the quality of crop protection products. Moreover, agricultural policy makers are advised to revisit the cropping system in the study area. This revisit may positively contribute to agricultural sustainability.

Keywords: agro-ecological zone, farm revenue, smallholder farming households, specialisation, technical efficiency

1 Introduction

Among Pakistan's major cash and staple food crops, cotton (*Gossypium* spp.) and wheat (*Triticum aestivum*) hold particular importance in contributing to GDP and consumption; cotton unaided contributes 0.8 % to GDP (The Government of Pakistan, 2019). Over the last decade, cotton production has faced a severe decline; presently, cotton production is 9,148 thousand tonnes, in contrast to 13,595 thousand tonnes in 2011 (PBS, 2021). More importantly, since the inception of Bt cotton (*Bacillus thuringiensis*) by the Punjab Seed Council of Pakistan (James, 2012), Pakistan is still far behind in the yield per unit as compared to other cotton-producing countries. The cotton yield gap between Pakistan (Cotton yield: 671 kg ha^{-1}) and China (Cotton yield: 1708 kg ha^{-1}) is wide in contrast to the area sown under cotton crop in Pakistan (2.50 Mha) compared to China (2.90 Mha) (Foreign Agriculture Service/USDA, 2019).

Weeds and pests pose a serious threat to actual yield losses, and they may reduce yield per ha by approximately 30 % for cotton worldwide (Popp *et al.*, 2013). Therefore, crop protection products (e.g., insecticides, fungicides, and herbicides) usage is inevitable (Alam *et al.*, 2016), and smallholder farming households potentially benefit from reducing the actual yield losses due to weeds and pests (Chao *et al.*, 2015). Looking back at the past four decades, the low yield per ha persists despite increased crop protection products in developing countries (Oerke, 2006). Pakistan is no more an exception; the use of crop protection products over the last decades has increased in Pakistan (Spielman *et al.*, 2017). In particular, there is evidence of usage of WHO hazardous category-I crop protection products (e.g.,

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Published online: 22 January 2022 – Received: 11 August 2021 – Accepted: 11 January 2022

carbamates, organophosphates, and pyrethroid) by smallholder farming households (Khan *et al.*, 2011). Additionally, the aggressive application of crop protection products may favour unsustainable pest control strategies, which is a severe threat to human health, farm habitat, and agricultural sustainability (Wilson & Tisdell, 2001; Khan *et al.*, 2010; Williamson *et al.*, 2008; Zhang *et al.*, 2015).

The increase in farm productivity and agricultural sustainability is associated with the judicious use of crop protection products (Oerke, 2006; Pretty & Bharucha, 2015). However, smallholder farming households of Pakistan are less aware of the unsustainable consequences of low-quality products usage, particularly the use of generic formulation crop protection products/sub-standard quality (Khan *et al.*, 2010). Existing literature on crop protection products suggests a prevalence of quality-based crop protection products in the agricultural heartland of Pakistan (Khan *et al.*, 2013). It varies from crop protection products of multinational brands to the abundance of generic formulation crop protection products/sub-standard (Bilal & Barkmann, 2019).

According to the Department of Plant Protection, Ministry of National Food Security and Research, Pakistan, the diversity of crop protection products of varying quality goes from multinational brands to generic formulation crop protection products (The Government of Pakistan, 2018). A recent study by Bilal & Barkmann (2019) highlights the farmers' subjective opinions about the quality of adopted crop protection products. A substantive proportion of the total sample smallholder farming households (49 %) perceives the quality of generic formulation crop protection products from low to poor quality. Moreover, the generic formulation crop protection products/sub-standard quality may include outdated ingredients or low-quality formulations, insufficient declarations, safety, and usage information (Khan *et al.*, 2013; Hashmi, 2016). In contrast, the adoption of branded products attracts consumers due to genuine products labelling, products specification, products information, and packaging attributes (Lewis *et al.*, 2016). However, the higher price of crop protection products of multinational brands tempted smallholder farming households to adopt generic crop protection products (Khooharo *et al.*, 2008). A substantial number of studies indicate a positive contribution of innovative technology to farm revenue/harvest and farmers' technical efficiency (Chen *et al.*, 2009; Battese *et al.*, 2017). However, the impact of innovative technological products, particularly crop protection products of multinational brands, on farmers' technical efficiency and contribution to farm revenue/harvest is not explicitly documented.

We see a few cross-continental and regional studies that attempt to quantify the farm revenue/harvest effect of crop protection products—relying on the farmers' quantitative use of crop protection products in terms of active ingredients at plot level. For instance, the work of Hossard *et al.* (2014) highlights the impact of crop protection products on-farm harvest at a reduced rate of the use of crop protection products. They report a significant shortfall in farm harvest (5 % to 13 %) for French wheat farmers when crop protection products are reduced by 50 %. Chao *et al.* (2015) use survey data of Chinese farmers and show that the optimal level of crop protection products affects productivity positively. Such productivity and efficiency analysis may be ambiguous in contrast to developing countries. Such as Pakistan, wherein the crop protection products of multinational brands and generic formulation crop protection products/sub-standard quality are available in the rural agricultural market.

Few contextual studies exist regarding crop protection products in Pakistan. For instance, Abedullah *et al.* (2015) highlight that the Bt cotton farm harvest is positively associated with less crop protection products. They report a quantitative aspect of the given crop protection products by considering active ingredients used at the plot level. But the origin and brand of the applied crop protection products remain unaddressed. Also, Battese *et al.* (2017) observe the quantity of the given herbicides (in mls) on improved wheat varieties at the plot level. Such synergy may be misleading because the origin and qualitative aspects of the applied crop protection products also remain unaddressed. In a more recent study, Wei *et al.* (2020) estimate the efficiency of cotton growers in Pakistan and employ data envelopment analysis. However, the origin and qualitative aspects of prime input for cotton production, i.e., crop protection products, are not discussed. In addition, the importance of agro-ecological zone to improve farmers' efficiency remain unaddressed. Therefore, physically solid evidence about the availability and the use of crop protection products of varying qualities by the Pakistani farmers requires robust evidence for productivity and efficiency. Hence, Popp *et al.* (2013) suggest that innovations in crop protection products may aid agricultural sustainability and deliver significant rural livelihood benefits. Likewise, Pretty (2008) and Pretty & Bharucha (2015) highlight the quality and awareness of agricultural technology products among stakeholders having the potential to attain sustainability in agriculture.

We improve the existing literature and explicitly address the qualitative aspect of crop protection products. Thus, we conducted a reconnaissance vis-à-vis prospects of crop protection products of multinational brands towards farm revenue/harvest and technical efficiency. We use smallholder farming households' data collected in the cotton-growing agro-ecological zone of Punjab, Pakistan.

We employ a stochastic production frontier approach and develop different regression models to understand the proper functional form better. Farm revenue is used as the dependent variable. The variables which may explain the impact on the dependent variable are the adoption of crop protection products of multinational brands, quality of cottonseed, and as a proxy for the degree of specialisation the Herfindahl Hirschman Index (HHI), including classical explanatory variables of production frontier. Moreover, we use HHI: specialisation, regional dummy, and other observed farm and farming capital variables to determine the technical inefficiency. Mainly, this study aims to estimate the impact of crop protection products of multinational brands on the farm revenue and the technical efficiency, which may capture the nuance of agricultural sustainability for smallholder farming households. Therefore, we are mainly interested in responding to the following research questions:

- Does the adoption of crop protection products of multinational brands affect farm revenue?
- Does HHI: specialisation influence the technical inefficiency of smallholder farming households from cotton-growing agro-ecological zone?

2 Materials and methods

2.1 Study site and sampling methodology

We conducted the final survey in December 2017 after piloting the households' survey instrument in January 2017. We purposively selected the cotton-growing agro-ecological zone of Punjab province, Pakistan. According to the Punjab development statistics, out of the total area of Punjab sown under cotton crop, 70 % comprised the studied site (The Government of Punjab, 2017). The selection of the study site also depends on the availability and accessibility of crop protection products of multinational brands to generic formulation/sub-standard quality crop protection products.

We employed a multi-stage random sampling methodology. We randomly selected three districts in the first stage: Pakpattan, Rahimyar Khan, and Vehari. In the second stage, we randomly selected one tehsil[1] from each district. After that, we randomly selected 18 villages from three randomly selected tehsils and in the last step, we interviewed N=275 randomly selected smallholder farming households.

According to the government of Punjab (2017) farmers owning agricultural land ≤ 2.02 ha fall under the category of small farmers. The survey seeked information about socio-demographics, farm-specific aspects (e.g., land, family labour, hired labour, seasonal labour, and farm machinery), and adoption status of crop protection products from smallholder farming households. Despite a favourable agro-ecological zone for cotton and wheat crops (Ahmad *et al.*, 2016), farmers cultivate other staple-food crops as well (e.g., maise and rice). As this study was confined to the cotton-growing zone, a total of nine observations were dropped from the total sample because of the cultivation of sugarcane as it is known as a perennial crop with a long maturity period (i.e., 12-18 months). Hence, we used a sample size of N=266.

[1]Tehsil or sub-district is a sub-division of the district.

2.2 Empirical and theoretical framework

We have employed stochastic frontier analysis (SFA) to estimate the technical inefficiency of smallholder farming households. We mainly focused on the total farm revenue that could be reached for the crop protection products of multinational brands. The distinguishing feature of the production frontier is to produce maximum output producible with the set of inputs and a given technology. Producers are technically efficient when producing on their production frontier, and those producing below their production frontier are termed as technically inefficient (Kumbhakar & Lovell, 2000). The stochastic frontier production function is given below in Eq. (1).

$$\begin{aligned} y_i &= f(x_i;\beta)exp(-\mu_i) \quad (\mu_i \geq 0) \\ y_i &= f(x_i;\beta)exp(v_i).exp(-\mu_i) \quad (v_i \leq 0) \; and \; \mu_i \geq 0) \\ y_i &= f(x_i;\beta)exp(v_i - \mu_i) \end{aligned} \tag{1}$$

There are two error components in Eq. (1) The error component v_i a noise effect on the model output by exogenous shocks not under farmers' control (e.g., fluctuations in weather, disease outbreaks if any) and assumed independently and identically distributed as $N(0, \sigma^2_{v_i})$. The error component μ_i is the non-negative technical inefficiency part of Eq. (1) and is assumed to be distributed independently of v_i and to satisfy $\mu_i \geq 0$. Also, the non-negative technical inefficiency component is the attributes related to smallholder farming households and assumed as the truncation at zero (half-normal distribution) of the $N(|0, \sigma^2_{\mu_i}|)$ (Aigner *et al.*, 1977).

We deal with the parametric frontier model. In the present case, we preferred the translog functional form over the Cobb-Douglas frontier model based on the specification test (Table 3). As such, we assumed the translog functional form to describe the production function of the farmers, and it includes the determinants of technical inefficiency in the same model. The variables included a single output measured as total farm revenue and a set of explanatory variables including crop protection products and determinants of technical inefficiency. Having cross-sectional data, we specified the translog functional form and expressed it as:

$$lnY_i = \beta_0 + \sum_{j=1}^{6}\beta_j lnX_{ji} + 0.5\sum_{j=1}^{6}\sum_{k=1}^{6}\beta_{jk} lnX_{ji} lnX_{ki} + \sum_{j=1}^{5}\beta_{0j} D_{ji} + \nu_i - \mu_i \tag{2}$$

Where Y = total farm revenue in PKR[2] and X's = land, total labour hours (family and permanently hired), seasonal labour employed (both male and female), capital[3], fertiliser quantity in kg ha^{-1}, crop protection products cost ha^{-1}, seed quality, adoption of crop protection products, and HHI: specialisation.

We estimated stochastic frontier analysis following a one-step procedure and employ the model for technical inefficiency proposed by Wang & Schmidt (2002) given in Eq. (3).

$$\sigma^2_{\mu_i} = exp\{Z_i\delta_j\} \tag{3}$$

Where term $\sigma^2_{\mu_i}$ is the variance of inefficiency for the ith smallholder and Z_i is a vector (M×1) of explanatory variables (access to credit, adoption status in neighbourhood farm, and duration of the adoption crop protection products of multinational brands, HHI: specialisation, and a regional dummy if farm located in the Southern-Punjab) that could influence the technical inefficiency of smallholders and δ_j is a (1×M) vector of parameters have to estimate that captures the influence of potential explanatory variables associated with technical inefficiency and μ_i is non-negative such that $\mu_i(Z_i\delta_j) \geq 0$. The framework we estimated by the maximum-likelihood method. In this way, we investigated the role of crop protection products of multinational brands towards agricultural sustainability. More succinctly, we estimated the effect on the farm revenue and the technical inefficiency of farming households of the sample area. Hence, we can specify the model as:

$$Y_i = f(X_{i'}s) + \nu_i - \mu_i(Z_i\delta_j) \qquad (\mu_i(Z_i\delta_j) \geq 0) \tag{4}$$

[2]Pak Rupee (PKR): 1 USD = 110.45 PKR at the time of data collection, presently (January 2022) 1 USD = 177 PKR.

[3]We included two additional dummy variables following Battese (1997), see section 3.2

We estimated the technical efficiency (TE) as follows:

$$\begin{aligned} TE_i &= \frac{Y_i}{f(X_i;\beta).exp(\nu_i)} \\ &= \frac{f(X_i;\beta).exp(\nu_i).exp(-\mu_i)}{f(X_i;\beta).exp(\nu_i)} \end{aligned} \tag{5}$$

$$TE_i = exp(-\mu_i)$$

3 Results

3.1 Crop revenue proportions concerning types of crops

The crop revenue percentage of all crops grown annually on available land units among adopters (exclusive crop protection products of multinational brands users) and non-adopters (generic formulation crop protection users/otherwise) is presented in Table 1. It is evident from Table 1 that a substantial share of the total farm revenue came from cotton and wheat crops. The full sample yields 81 % of total farm revenue from cotton and wheat, which is an affirmative characteristic and highlights the prominence of the respective agro-ecological zone of the Punjab province, Pakistan.

Table 1: *Crop revenue percentage among adopters and non-adopters.*

Crop	*Adopters N=138*	*Non-Adopters N=128*	*Full sample N=266*
Cotton	57 %	37 %	47 %
Wheat	30 %	38 %	34 %
Maize	6 %	14 %	10 %
Rice	7 %	11 %	9 %
Total	*100 %*	*100 %*	*100 %*

Notes: We calculated the percentage as an individual revenue share of the crop in Pakistani rupees out of the total revenue of all crops grown at the farm at full sample and adoption levels.

3.2 Description of output and input variables

The descriptive statistics of variables used for the stochastic frontier analysis are presented in Table 2. The output variable is the aggregate of the revenue measured as Pak rupee (PKR), which is the share of all crops sown in the area under operations. The land was measured as the total cultivated farm area. It included the aggregate of land ownership by the smallholder farming households and the rented-in land. Labour was calculated as the sum of a total number of labour hours of the given year, including family, permanently hired, and seasonal labours[4] employed solely for agricultural farming. Capital was measured as the actual value in PKR of all kinds that farm machinery respondents own. Most notably, more than half of all farms adopted crop protection products of multinational brands (52 %). To construct the input variables, especially for factor endowments such as seasonal labour and capital input variable, we followed Battese (1997). When dealing with smallholder farming households mostly low farm mechanisation and high employment of households' members in the farming activities is encountered (Foster & Rosenzweig, 2010). Therefore, most smallholder farming households did not own farm machinery and seasonal labour. We constructed two additional dummy variables for capital and seasonal labour to overcome biased parameters' estimates, following Battese (1997). The intermediate inputs measured as fertiliser applied in kg ha^{-1} and crop protection in cost ha^{-1}. We also included a few dummy variables as shifter inputs (adoption of crop protection products of multinational brands, adoption status of Bt cotton, and HHI: specialisation). We constructed the HHI: specialisation as measured by the revenue share of each crop following the HHI. The index is widely applied and accepted as a valid representation of crop diversification/specialisation in previous studies dealing with productivity and efficiency analysis (Brümmer *et al.*, 2006; Nguyen, 2014). The HHI ranges from 0 to 1, the value closer to 0 shows diversification, and a value closer to 1 shows specialisation (Brümmer, 2001; Ogundari, 2013).

For the determinants of inefficiency, we considered access to credit, duration since the adoption of crop protection products of multinational brands, adoption in neighbouring farms, and HHI: specialisation. We initially found that the time since the inception of crop protection products of multinational brands and neighbourhood adopters of crop protection products of multinational brands may have captured the effect of agricultural extension services because of a strong positive correlation[5]. Therefore, extension service visits dropped from the final specification to reduce the risk of multicollinearity. Furthermore, we included a regional dummy. It takes a value of one of the farms located in the southern region of the cotton-growing zone to test the hypothesis of higher technical efficiency for farms located in the central region of the cotton-growing agro-ecological zone.

[4]Temporarily hired basically on daily wages to perform different farm operations particularly, cotton picking and wheat harvesting etc.

[5]The correlation matrix results are not reported here but can be made available on request.

3.3 Tests of the null hypothesis of translog SFA production function

Table 3 reports a few pertain tests of the null hypothesis. The first row of table 3 presented the null hypothesis of using Cobb-Douglas functional form as a valid representation to estimate the productivity and inefficiency to yield unbiased estimates of included parameters. We rejected it at a 10 % level of significance. This rejection translated that second-order coefficients of the translog SFA production function model were statistically different than zero. Therefore, translog yields better, flexible, and unbiased estimates. The second row of Table 3 presents the null hypothesis of the coefficients of the HHI: specialisation is zero in the translog SFA production function model and rejected at a 5 % level of significance. This inclusion means that the unrestricted model with HHI: specialisation in the translog SFA production function model was significantly relevant for the productivity of smallholder farming households.

The third row of Table 3 reports also that the null hypothesis of the coefficients of the HHI: specialisation is zero in the production function and inefficiency model and strongly rejected at a 1 % level of significance. Hence, the unrestricted model with HHI: specialisation in the production function and inefficiency model has significant importance for the productivity and inefficiency of smallholder farming households.

The fourth row of Table 3 presents the null hypothesis that inefficiency effects are absent from the model at every stage and strongly rejected at a 1 % significance level. We accepted the alternative hypothesis about inefficiency effects in the selected model. Also, it is essential to highlight here the observed value of the gamma parameter. We can estimate the value of γ-parameter by single-step estimation as proposed by Battese & Corra (1977) in terms of the parameterisation: $\gamma = \sigma^2_{\mu_i}/\sigma^2$. The value of the γ-parameter lies between 0 and 1. A value of $\gamma = 1$ indicates that the deviances from the frontier are due to technical inefficiency. The random effect on a production system is zero, and a value of $\gamma = 0$ shows that the deviances from the frontier are due to noise effects means perfect efficiency in a production system. Therefore, the observed value of the γ-parameter was 0.92, indicating the strong influence of technical inefficiency effects.

The second last row of Table 3 presents the null hypothesis that smallholder farming households' socio-economic and farming characteristics have no effects on inefficiency. We firmly rejected the null hypothesis at a 1 % level of significance. Therefore, the inefficiency determinants were relevant to explain the productivity and inefficiency of smallholder farming households adopting crop protection products of

Table 2: *Descriptive summary of the production frontier and inefficiency models variables.*

	Unit	*Mean*	*Min*	*Max*	*Std. Dev*
Variables in the frontier models (N=266)					
Total farm revenue	PKR	402456	25000	1442450	261528
Land	ha	1.29	0.40	2.02	0.55
Land own	ha	1.19	0	2.02	0.61
Land rented	ha	0.10	0	2.02	0.33
Labour	Hours	2574	24	12288	2051
Seasonal labour male	Number	2.80	0	15	2.75
Seasonal labour female	Number	3.75	0	15	3.14
Total seasonal labour	Number	6.55	0	25	5
Seasonal labour (Yes = 1; No=0)	Dummy	0.19	0	1	0.39
Capital	PKR	132114	0	1991000	322353
Capital (Yes = 1; No = 0)	Dummy	0.77	0	1	0.42
Fertiliser	kg ha^{-1}	931.5	123.6	2718.0	492.72
Crop protection cost (PKR)	cost ha^{-1}	11263	900	93000	8482.8
Adoption of crop protection products of multinational brands (Yes = 1; No=0)	Dummy	0.52	0	1	0.5
Variables in the inefficiency models					
Access to credit (Yes = 1; No = 0)	Dummy	0.42	0	1	0.50
Duration of adoption of crop protection products of multinational brands	Years	3.80	0	25	4.46
HHI: specialisation	Score	0.52	0.25	1	0.18
Neighbourhood adopters	Number	2.48	0	12	2.35
Region	Dummy	0.38	0	1	0.49

Table 3: *Tests of the null hypothesis of translog SFA production function.*

Null hypothesis	*Log likelihood (H0)*	*Test statistics*	*C.V.*	*d.f.*	*Decision*
H0: Cobb – Douglas	-98.04	30.64*	29.61	21	Rejected
H0: No HHI: specialisation effects	-86.73	8.02***	6.63	1	Rejected
H0: No simultaneous effects of HHI	-72.19	6.02**	5.99	2	Rejected
H0: Inefficiency effects absent	-82.72	30.38***	5.41^{a}	1	Rejected
H0: No effects of determinants of inefficiencies	-82.72	27.09***	14.32^{b}	5	Rejected
H0: Linear homogeneity at the sample mean		0.68	3.84		Not rejected
Full Model	-69.18				

Notes: The C.V. is a critical value for the appropriate X^2 distribution for the given degrees of freedom (d.f.), except for the ^{a,b} C.V. (obtained from Kodde & Palm (1986)). The level of significance is $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

multinational brands versus sub-standard/generic formulation crop protection products.

3.4 *Estimates of the inefficiency model*

The determinants of technical inefficiency described in Eq. (3) are presented in Table 4. The signs of estimated coefficients are vital to extracting the actual effect. All determinants of technical inefficiency have exhibited the expected signs.

3.5 *Individual technical efficiency estimates of smallholder farming households*

Fig. 1 shows the distribution of smallholder farming households based on individual technical efficiency estimates; 72 % of smallholder farming households have an individual technical efficiency greater than 70 %. We found that the remaining 28 % of small farmer households have less than 70 % individual technical efficiency. That means that most farmers can enhance their technical efficiency by 30 % through the judicious use of crop protection products, HHI:

Table 4: *Estimates of the inefficiency model.*

Variables	*Coefficients*	*Standard error*
Access to credit	−0.23	0.29
HHI: specialisation	-6.54^{***}	2.10
Duration of adoption	-0.14^{**}	0.06
Neighbourhood adopters	-0.20^{**}	0.09
Region	1.35^{***}	0.35

Notes: The level of significance is $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

specialisation, access to credit, adoption status in neighbourhood farms, and a regional dummy if farms are located in Southern-Punjab.

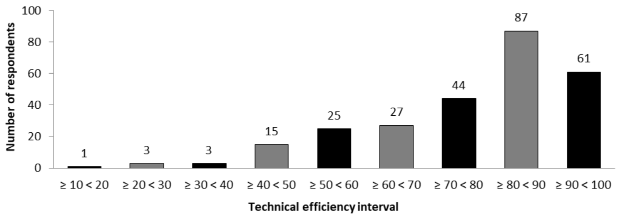

Fig. 1: *Frequency distribution (%) of smallholder farming household's estimated technical efficiency interval.*

3.6 Estimates of the translog SFA production function model

This sub-section describes the translog SFA production function model estimates estimated by the maximum-likelihood method. The estimates of the translog SFA production function model estimated by a maximum-likelihood method with robust standard errors generated from STATA version 15 is presented in Table 5.

4 Discussion

The sum of partial production elasticities at the sample mean equals 1.08. Hence, we failed to reject the null hypothesis of constant return to scale for smallholder farming households of the cotton-growing zone. Similarly, Battese & Hassan (1999) could not reject the null hypothesis of constant return to scale for cotton-growing farmers of Punjab in Pakistan. There is substantial retrospective empirical evidence based on the irrefutable hypothesis of constant return to scale (Brümmer 2001; Felipe & Adams, 2005; Chen *et al.*, 2009; Makombe *et al.*, 2017).

This study's variable of prime interest was crop protection products of multinational brands. It depicted positive and statistically significant partial production elasticities at the sample mean for farm revenue. Furthermore, concerning the adoption of branded products, quality and awareness of crop protection products, revisiting the suggestions from Popp *et al.* (2013), Pretty & Bharucha (2015), and Lewis *et al.* (2016) can aid in placing our results – and thus have the potential to deliver significant rural livelihood benefits – in perspective. However, the higher price of crop protection products of multinational brands tempts smallholder farming households to adopt generic crop protection products (Khooharo *et al.*, 2008). In particular, the existing literature indicates that sub-standard crop protection products include outdated ingredients or low-quality formulations, insufficient declarations, safety, and usage information. Therefore, adopting crop protection products of sub-standard quality may lead to unthoughtful consequences on agricultural sustainability and hamper farm harvest (Khan *et al.*, 2013; Hashmi, 2016).

Interestingly, we found a substitution effect between crop protection products of multinational brands and labour. This effect indicated that smallholder farming households apply lesser crop protection products of multinational brands with each additional labour input. The extra unit of labour input performs different cultural practices (e.g., hoeing, weeding, pruning) in a conventional way to reduce the use of crop protection products of multinational brands and vice versa. Conversely, we found a complementary effect between crop protection products of multinational brands and farm machinery. This effect indicated that when smallholder farming households adopt the crop protection products of multinational brands to utilise them efficiently, they also require farm machinery (e.g., spray machine, tractor) to perform farm operations.

The only negative sign of partial production elasticities was fertiliser application, but the estimated fertiliser coefficient was not significantly different from zero. More importantly, the square term of fertiliser application was negative and significant, indicating that farm revenue-increasing effect decreases with increasing fertiliser application. Table 2 presented an apparent difference among the sample farmers' trends towards fertiliser application (on an average of $931.5\,\text{kg ha}^{-1}$, with a minimum of $123.6\,\text{kg ha}^{-1}$ and maximum standing at $2718.1\,\text{kg ha}^{-1}$). The possible intuitions behind the negative elasticities of fertiliser application may be due to the over usage/imbalanced use of fertiliser and crop diversification effect (Chao *et al.*, 2015). A substantive share of smallholder farming households (Table 1) cultivated multiple staple-food crops (e.g., maise, rice, and wheat) for dietary needs. Despite favourable agro-ecology for cotton and wheat crops, the cultivation of multiple staple food crops may have increased fertiliser usage as the agro-ecological

Table 5: *Estimates of the translog (TL) stochastic frontier analysis (SFA) production function model.*

Frontier	*Coef. TL[c]*		*Coef. TL[a]*		*Coef. TL[b]*		*Coef. CD[†]*	
Ln land	0.79***	(0.06)	0.74***	(0.06)	0.75***	(0.06)	0.79***	(0.04)
Ln labour	0.02	(0.03)	0.02	(0.03)	0.01	(0.04)	0.02	(0.02)
Ln seasonal labour	0.19***	(0.06)	0.23***	(0.05)	0.22***	(0.05)	0.18***	(0.04)
Ln capital	0.05	(0.03)	0.03	(0.03)	0.04	(0.03)	0.05***	(0.01)
Ln fertiliser	−0.07	(0.07)	−0.02	(0.06)	0.06	(0.05)	−0.03	(0.06)
Ln crop protection	0.09*	(0.05)	0.11**	(0.06)	0.11*	(0.06)	0.21***	(0.04)
Seasonal labour dummy	0.03	(0.05)	0.05	(0.06)	0.06	(0.06)	0.07	(0.06)
Capital dummy	0.05	(0.09)	0.00	(0.07)	0.00	(0.08)	−0.04	(0.05)
Multinational brands	0.15***	(0.05)	0.25***	(0.06)	0.23***	(0.05)	0.23***	(0.05)
Seed quality	0.20***	(0.05)	0.17***	(0.04)	0.16***	(0.04)	0.17***	(0.04)
HHI: specialisation	−0.92 ***	(0.18)	−0.49 ***	(0.15)			−0.63 ***	(0.14)
0.5*ln land sq	−0.24	(0.18)	−0.50 ***	(0.16)	−0.51 ***	(0.17)		
0.5*ln labour sq	−0.01	(0.03)	−0.02	(0.03)	−0.01	(0.04)		
0.5*ln seas labour sq	−0.06	(0.13)	−0.11	(0.10)	−0.11	(0.11)		
0.5*ln capital sq	0.01	(0.03)	0.01	(0.02)	0.01	(0.02)		
0.5*ln fertiliser sq	−0.27 **	(0.14)	−0.24 *	(0.13)	−0.31 **	(0.14)		
0.5*ln crop protection sq	−0.07	(0.06)	−0.12	(0.08)	−0.15 *	(0.08)		
Ln land*ln labour	0.02	(0.06)	0.05	(0.06)	0.05	(0.06)		
Ln land*ln seas labour	0.10	(0.10)	0.12*	(0.09)	0.13*	(0.07)		
Ln land*ln capital	−0.09	(0.07)	0.04	(0.07)	0.07	(0.07)		
Ln land*ln fertiliser	−0.05	(0.12)	0.02	(0.13)	0.03	(0.12)		
Ln land*ln crop protection	0.02	(0.07)	0.06	(0.07)	0.07	(0.07)		
Ln labour*ln seas labour	0.09	(0.06)	0.09*	(0.07)	0.09	(0.05)		
Ln labour*ln capital	0.03	(0.03)	0.02	(0.03)	0.02	(0.03)		
Ln labour*ln fertiliser	0.02	(0.06)	0.04	(0.07)	0.05	(0.08)		
Ln labour*ln crop protection	−0.06 *	(0.03)	−0.07 *	(0.04)	−0.10 **	(0.04)		
Ln seas labour*ln capital	0.00	(0.05)	−0.04	(0.05)	−0.06	(0.06)		
Ln seas labour*ln fertiliser	0.17	(0.10)	0.04	(0.10)	0.03	(0.11)		
Lnseaslabour*lncropprotection	−0.10	(0.07)	0.01	(0.08)	0.04	(0.08)		
Ln capital*ln fertiliser	0.09	(0.06)	0.14***	(0.06)	0.14***	(0.05)		
Ln capital*ln crop protection	0.08*	(0.04)	0.01	(0.04)	0.02	(0.05)		
Ln fertiliser*ln crop protection	0.00	(0.07)	0.03	(0.08)	0.06	(0.09)		
Constant	0.46***	(0.16)	0.37***	(0.13)	0.15	(0.10)	0.44***	(0.09)
Log likelihood	-69.183		-82.720		-86.730		-98.040	
Gamma	0.936		0.929		0.924		0.926	
Mean technical efficiency	0.77		0.70		0.68		0.67	

[†] CD: Cobb-Douglas; Notes: TL^a was preferred over Cobb-Douglas and TL^b (restricted model, control for HHI: specialisation). The TL^c final model estimates simultaneous production function and inefficiency variables. Robust standard errors are in parenthesis. The level of significance is $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

zone is particularly suitable for cotton and wheat. In addition to the mentioned plausible explanations, in the recent literature, we see considerable precedents of an inverse relationship between fertiliser application and farm harvest in the context of China and other developing countries (Chen *et al.*, 2009; Ogundari, 2013; Owusu, 2016).

We observed a mean value of technical efficiency of 77 %. Hussain *et al.* (1999) celebrate a somewhat closer mean value of technical efficiency (83 %) in the cotton-growing zone in Pakistan. As far as the variables in the technical inefficiency models, we first shed light on the variables of prime interest (e.g., the duration of the adoption of crop protection products of multinational brands and adoption status of crop protection products of multinational brands in the immediate neighbourhood). Consonant with the theory of diffusion of adoption, early adopters are the sources of proven experience. In the present case, the increase in the time since the adoption of crop protection products of multinational brands resulted in an increase in the technical efficiency of smallholder farming households.

Likewise, the adoption of crop protection products of multinational brands in the neighbourhood was positively associated with technical efficiency. Primarily, farms in the central region positively influenced the technical efficiency compared to those in the southern region of the cotton-growing zone of Punjab, Pakistan.

An interesting finding concerning the policy implications we got from HHI: specialisation. The growing issues of shrinking the cotton area and setting up new sugar mills in the cotton-growing zone resulting in a severe decline in the overall cotton production have been challenging for policy makers since the last few years (Mahmood, 2017; Dilawar, 2019). The point to ponder is that as the study area was confined to the cotton-growing zone and because of favourable agro-ecology, farmers turned technically efficient if they grew crops considering their agro-ecological zone. Here, the negative sign of the coefficient illustrated that HHI: specialisation decreases technical inefficiency or more succinctly, we could say that specialisation enhances the technical efficiency of smallholder farming households. Unlike most previous studies (Brümmer, 2001; Ogundari, 2013; Nguyen, 2014) that discuss the positive effect of diversification on technical efficiency, we found the negative effect of HHI: specialisation on technical inefficiency (Brümmer, 2006; Baten *et al.*, 2010). Moreover, the full sample attains 81 % of total farm revenue from cotton and wheat, which is an affirmative characteristic and highlights the prominence of these crops for the respective agro-ecological zone of the study site (Table 1, section 3.1).

Likewise, we found the negative relationship of HHI: specialisation with farm revenue, as given in Table 5. Therefore, we calculated the marginal effects of HHI: specialisation and employed the approach proposed by Wang (2002). The marginal effect estimates also showed the aggregative negative sign on the unconditional mean of inefficiency E(u) and variance of inefficiency V(u). The negative marginal effects of HHI: specialisation illustrate that specialisation increases smallholder farming households' technical efficiency and farm revenue. The average marginal effect of HHI: specialisation on E(u) is -0.028. More succinctly, the level of technical inefficiency is reduced, on average, by 2.8 percentage for each one per cent increase in specialisation.

There is a big room for improvement of technically inefficient farmers. They may enhance their technical efficiency by e.g. incorporating crop protection products of multinational brands into their production systems. Additionally, farmers may contribute to attaining agricultural sustainability by considering the importance of their agro-ecological zone for the cropping system implemented.

5 Conclusion

This paper examines the role of crop protection products of multinational brands for agricultural sustainability – farm revenue, technical inefficiency, and cropping system vis-à-vis the specific agro-ecological zone of Pakistan's smallholder farming households.

The stochastic frontier production model estimates show a significant and positive relationship between crop protection products of multinational brands and total farm revenue. The estimates of technical inefficiency models reveal a significant extent of inefficiency (such as HHI: specialisation, among others). Therefore, promoting crops other than cotton and wheat in such an agro-ecological zone may lead to unthoughtful consequences on the farm revenue and may impede agricultural sustainability.

Acknowledgements

We gratefully thank the financial support of the *fiat panis* Foundation (project no:29/2017) and the HEC/DAAD scholarship (reference:91591599). Essential comments for improving the initial version of this paper by three anonymous reviewers and the editor-in-chief of this journal are also gratefully acknowledged.

Conflict of interest

The authors declare that they have no conflict of interest.

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