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# Contract Farming and Technical Efficiency: A Case of Export-Oriented Organic Rice Farmers in Pakistan

**Rabia Mazhar [1], Bi Xuehao [1], Thomas Dogot [2], Rytis Skominas [3], Vjekoslav Tanaskovik [4], Hossein Azadi [2] and Zou Wei [1,*]**

[1] College of Public Administration, Nanjing Agricultural University, Nanjing 210095, China
[2] Department of Economics and Rural Development, Gembloux Agro-Bio Tech, University of Liège, 5030 Gembloux, Belgium
[3] Bioeconomy Research Institute, Vytautas Magnus University, LT-44248 Kaunas, Lithuania
[4] Faculty of Agricultural Sciences and Food-Skopje, Ss. Cyril and Methodius University in Skopje, 1000 Skopje, North Macedonia
* Correspondence: zw@njau.edu.cn

**Abstract:** Although organic rice is a niche market in Pakistan, it has exhibited enormous potential for growth in export-oriented production. Since contract farming is the leading promoter of export-oriented organic rice production in Punjab, Pakistan, improving the technical efficiency of smallholder rice farmers through contract farming holds sufficient potential. This work examines the influence of contract farming participation on smallholder rice farmers' technical efficiency using a cross-sectional data set of 650 respondents. We applied a stochastic frontier analysis (SFA) to examine the production frontier and inefficiency estimates. Further, propensity score matching (PSM) was used to control endogeneity and self-selection bias in technical efficiency estimates. The results reveal that the technical efficiency score of organic rice farmers in Punjab, Pakistan, is 89.7%, which can still be improved by 10.3% at the current sociodemographic characters and input levels. Likewise, land size, seed, and machine expenditures are the key inputs of the production frontier. Results show a positive and significant connection between contract farming participation and technical efficiency. The study extends the literature on technical efficiency, export-oriented production, contract farming, and the well-being of smallholder farmers. Moreover, the study's findings provide cues for policies and practices.

**Keywords:** contract farming; technical efficiency; export-oriented production; organic rice; smallholders' well-being; food policies

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## 1. Introduction

Organic rice is receiving rapid recognition as a possible means to ensure a healthier food grain supply vis-à-vis reducing environmental footprints attached to traditional agriculture production systems [1]. Currently, organic rice is fetching premium prices due to its massive demand in the market worldwide and could be a tool to eradicate smallholder farmers' poverty [2]. Therefore, under these prospects, expanding organic rice productivity, increasing technical efficiency (TE) and grain quality, and upgrading smallholder organic rice farmers' positions in modern value chains are crucial [3]. Improving TE has significant potential to be a boom for smallholder organic rice farmers' income [2,4]; knowledge gaps remain on whether (and how) contract farming manifests TE among export-oriented organic rice growers.

Existing literature about contract farming is inconclusive regarding its potential role in smallholder farmers' upgradation. Many studies reported that contract farming is an institutional arrangement used to improve smallholder farmers' market access by providing agricultural raw materials to improve TE [5–8]. Research studies note that smallholder farmers participate in contract farming to reduce the risk associated with production to processors and put the subject cost burden—i.e., seed, pesticides, and fertilizer—on the processor and/or exporters [9,10]. According to recent studies [5–8], contract farming offers farmers higher productivity and increases their market access. Likewise, Mishra et al. [11] reported that contract farming might be a plausible solution to improve TE and help remove constraints along with production and marketing and ensure the supply of crop inputs, information, and capital to farmers. Even though contract farming improves the possibility of crop success, at some point, the unavailability of appropriate crop varieties, organic amendments, and weed-control measures will pose critical challenges for contract farmers [1]. Further, in developing countries, such as Pakistan, weaker vertical integration exists between the farmers and contractors (e.g., processors, exports), which threatens the sustainability of organic rice production and export [12]. In parallel, little is known regarding the deployment and development of organic rice varieties and related services being provided to the contract farmers to help reduce the risk of crop failure.

Pakistan is one of the major rice-producing countries in the world and is famous for 'Basmati' rice, characterized by its long grain size, unique aroma, fine texture, and delicious taste [13]. Likewise, in the country, there are nine specialized–geographically indicated rice grower districts that have distinct specialties in producing aromatic Basmati rice with an average grain length of more than 7.40 mm [14]. In recent years, an increasing number of rice farmers have started organic rice farming; they perform traditional cultivation practices throughout the production stages. To capture the huge demand, premium prices (almost 42% higher than conventional rice), and emerging market opportunities, this cluster of farmers has significantly transformed into commercial organic rice producers (Data were obtained from Pakistan Organic Farms (Available Online: https://pakof.com/ (accessed on 15 August 2022)), and the Rice Exporters Association (Available Online: https://reap.com.pk/ (accessed on 15 August 2022))) [15]. Thus, a wider uptake of contract farming for promoting organic rice production might help increase farmers' income and export earnings for the country. Organic rice mostly comes from developing and emerging economies, such as Pakistan. However, a few research studies have explored the impact of contract farming on the TE and export-oriented production of organic rice [16–18], particularly among smallholder farmers in developing countries such as Pakistan. Due to poor crop input use, shortage of information, and technical assistance, farmers are far from achieving potential rice yield [19,20]. Therefore, it is a matter of core interest to study the role of contract farming in improving smallholder export-oriented rice farmers' technical efficiencies and incomes. This study contributes to the literature on contract farming and TE by developing a conclusive understanding of the smallholders' contract farming participation. It bridges the literature gap on socioeconomic characteristics of smallholder contract farming participating characteristics. Further, it specifies a stochastic frontier analysis (SFA) and propensity score matching (PSM) to analyze farm-level primary data of export-oriented rice farmers in Punjab, Pakistan. Based on the findings, the study has coherent policy implications for realizing a broader trajectory in contract farming and export-oriented rice production. It also suggests policy options for farmers, agriculture entrepreneurs, and stakeholders linked with agri-food supply chains to increase organic rice production and stakeholders' income.

The remainder of this paper is structured as follows. Section 2 presents data, and research methodology, followed by results and discussion. Finally, in the last section, major findings, conclusions, policy implications, and research limitations for future studies are acknowledged.

## 2. Data and Research Method

### *2.1. Sample and Data Collection*

This study was conducted in Punjab, Pakistan. The data were collected in six of nine Punjab province rice-growing districts (see Figure 1). The final field survey was conducted in January–March of 2021. The farmers in the nine districts were the key population target, called the "kalar track", a specialized geographically indicated region for basmati rice production and export. In the region, the farmers hold livestock, and smallholder farmers produce wheat and vegetable, yet rice is the leading market crop.

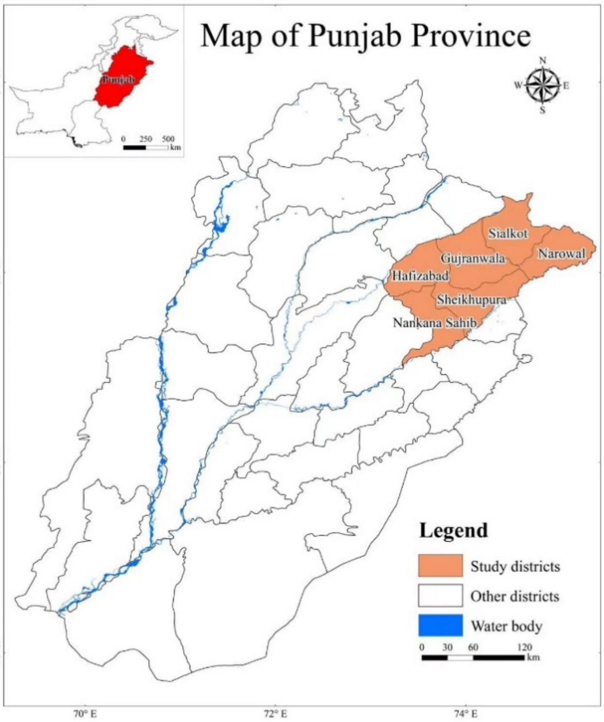


**Figure 1.** Map of the selected districts.

Apart from farming, smallholder farmers also engage in other off-farm activities to increase their incomes. For data collection, we used a two-step process. In the first stage, we conducted focus group discussions and 50 face-to-face interviews with organic rice farmers. Based on the pre-testing results, we incorporated the changes in the questionnaire to make it comprehensive regarding farmers, contact, crop, and market characteristics. Further, we considered crop homogeneity in the selected districts. Finally, we used a well-structured questionnaire to collect data from 750 smallholder organic rice growers using random selection. To ensure the comparability of contact and non-contract farmers, we conducted surveys in areas where most farmers were engaged in contract farming. Altogether, we obtained the lists of seven key organizations/contractors to access the contract farmers in their villages and conducted face-to-face interviews with 407 contract farmers and 343 non-contract farmers. Meanwhile, after removing the questionnaires with missing entries, the final data set consisted of 650 respondents.

Before an interview, farmers could only be part of this study if they met three prescribed inclusion criteria. First, (s)he should be an export-oriented rice farmer and not grow organic rice just for auto-consumption. Second, farmers must engage in organic rice production for the last three years. Third, apart from participation decisions, a farmer must know about the contract farming and contracting organization, contract terms and conditions, input, market and advisory services, and benefits. Most of the surveyed organic rice growers bought rice inputs from contractors and contracting organizations at the start of the sowing season and, therefore, subjected costs were deducted from the final payments after harvesting. The contractor's agriculture advisory wing visits farmers' crops once or twice a month, provides advisory services, and collects the final product from farmgate at harvesting. In case of lower prices due to glut supply in the harvesting season, a farmer may store the rice harvest at the farm or in the contractor's store for up to 50 days. However, farmers need to pay storage charges to the contractor warehouses. In two cases, contracting organizations provided credit instead of crop inputs and let farmers choose and apply input of their choices, yet organic rice varieties must be taken from their recommended list.

### 2.2. Model Specification

To study the impact of contract farming on TE, we used the approach Knox Lovell (1996) developed on efficiency measurement with the lowest cost of inputs. Recently, many studies have applied SFA to agricultural production efficiency and factor productivity [21–23]. Since SFA is quite effective in evaluating the influence of contract farming on TE, we applied SFA to examine the posited relationship herein. Further, SFA is quite robust in controlling primary data noises and errors [24]; thus, it is a suitable selection for this study.

In this study, we adopted a conceptual framework from the studies of [25], and [17], which present how various crop inputs and socioeconomic characteristics impact output and export-oriented production among organic rice growers. Likewise, we compared the agriculture production frontiers of contract participants and non-participants to examine the TE level and the determinants of technical inefficiency among organic rice farmers. Since we posited that contract farming, being an institutional arrangement, offers a higher production frontier and TE, we used contract farming as a dummy variable. Hence, a frontier approach is essential to avoid endogeneity and self-selection bias in the treatment variable. Further, following Coelli and Battese's [16] work on the determinants of technical efficiency among Indian farmers, we used maximum likelihood and assumed that all organic rice growers used similar agriculture practices except participation in contract farming, which might influence their TE. Moreover, we accounted for farmers' characteristics, which could affect the technical inefficiency [26]. Given this, we included farmers' education, organic rice cultivation experience, credit access, off-farm income, contract participation status, and agriculture advisory access as the possible TE factors.

Therefore, *TE* was measured by dividing $Y^*$ ($TE = Y_a/Y^*$), where $Y$ denotes farmers' observed current output (without contract participation) and $Y^*$ indicates the optimal output (maximum) level that can be achieved [26]. The following equation gives the expression of the stochastic frontier model:

$$y_i = f(x_i; \alpha) \exp(\varepsilon_i) \quad (1)$$

where $y_i$ represents the farmers $i$ scalar output export quantity; $x_i$ is a vector of inputs used; $\alpha$ indicates unknown parameters, and $\varepsilon_i$ is a noise vector, which includes two independent components $\varepsilon_i = v_i - u_i$. The term $v_i$ is a two-sided stochastic term; it is expected to be independent and normally distributed as $N$ (0, $\sigma_v{}^2$) indicates missing variables, measurement error, and statistical interference. The term $u_i$ values are the one-sided random variable half-normally distributed with zero modes ($u_i$ ~ $N$ + (0, $\sigma_u$) with variance parameter $\sigma$. The $u_i$ vector is a function of non-negative unobservable variables related to the technical inefficiency of production [27]. The stochastic terms $v_i$ and $u_i$ are assumed to be uncorrelated in this model. The variation of $u_i$ is specified by Equation (2).

$$VAR(u_i) = \frac{\pi - 2}{\pi}\sigma_u^2 = \frac{VAR(u_i)}{VAR(u_i) + \sigma_v^2} \quad (2)$$

Following [27], the organic rice grower's technical inefficiency is the ratio of the observed output and their stochastic frontier output. Given this, the *TE* of organic rice grower $i$ can be estimated as:

$$TE_i = \exp(-u_i) = \frac{q_i}{\exp(x_i{}'\beta + v_i)} = \frac{\exp(x_i{}' + v_i - u_i)}{\exp(x_i{}' + v_i)} \quad (3)$$

where $TE_i$ is the scalar vector of $TE$ of organic rice farmer $i$. To estimate the posited relationship between y and in Equation (1), we computed a trans-log model as follows:

$$y = \exp\left(\beta_0 + \sum_{n=1}^{N} \beta_n lnx_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} lnx_n lnx_m\right) \quad (4)$$

About the trans-log model for the parameter $\beta_n$, both side logarithms of Equation (3) are calculated as given in Equation (5).

$$Lny = \beta_0 + \sum_{n=1}^{N} \beta_n lnx_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} lnx_n lnx_m + v_i - u_i \quad (5)$$

The key disadvantage of the trans-log model is that it entails estimating several parameters. The calculated variance ($\gamma$) shows the variation in organic rice production [16] as follows:

$$\gamma = \frac{\sigma_u^2}{\sigma^2} \quad \text{With } \sigma^2 = \sigma_u^2 + \sigma_v^2 \quad (6)$$

The term $\gamma$ value must lie between zero and one; it indicates deviations from the frontier due to noise, and values of 1 refer to technical inefficiencies [28].

*2.3. Stochastic Frontier Approach and Propensity Score Matching*

Most of the prior studies about the TE have neglected sample selection bias while examining the influence of technology adoption on production frontiers [29]. This study assumes that all sampled organic rice growers are homogenous in technology adoption and access to join contract farming. Using the SFA, it was assumed that the noise term ($\gamma$) in the selection model correlated with unobserved variables

The SFA also assumed that all of the unobserved variables in the selection equation were correlated with the noise ($\gamma$) (see Equation (6)). Regarding the contract farming participation, for the observed variables, since some organic rice farmers could have higher TE before participating in the contract, it might increase the possibility of self-selection bias. Given this, the contract farming participation decision could be modeled as the propensity that depends on the farmers' observed sociodemographic factors specified as follows:

$$\partial_i = w_i\alpha + e_i \quad (7)$$

where the $\alpha$ vector indicates the parameters used and $e_i$ is a random error term. If any of the contract farming participation determinants, $w_i$, directly influence organic rice production but is not included in Equation (1), then the contract farming participation variable correlates with the error term $\varepsilon_i$. Under this situation, $\beta_n$ estimation in Equation (5) overlooks the potential endogeneity problem and, therefore, contract farming participation would be biased. For the observed variables, PSM was used to control self-selection bias and endogeneity, providing appropriate estimates for $TE$ and productivity analysis [30]. The PSM entails a three-step procedure to examine the influence of contract farming participation of $TE$. First, the probit model was used to test the contract farming participation probability and calculated each observation propensity score as being a contract farming participant rather than a non-participant. It can be estimated as the average treatment effect on the treated ($ATT$) value:

$$ATT = E(\Delta|Z, D = 1) = E\left(Y^1|Z, D = 1\right) - E\left(Y^0|Z, D = 1\right) \quad (8)$$

where $Y^1$ represents contract farmers' $TE$ score ($D$ = 1), and $Y^0$ represents the non-contract farmer's $TE$ score ($D$ = 0). The term $Z$ indicates conditioning variables, including any $x_i$ production input variables (see Equation (1)) and other sociodemographic characteristics related to observed variables and/or technical inefficiency determinants (see Equation (7)). The mean value $E\left(Y^1|Z, D = 1\right)$ can be found through the contract farmers' data. Yet, for identifying the counterfactual mean $E\left(Y^0|Z, D = 1\right)$, the assumption should be met about the *TE* of contract farmers had they not adopted contract farming. Hence, the differences in outcomes of self-selected non-contract participation $E\left(Y^0|Z, D=1\right)$ and approximate $E\left(Y^0|Z, D=1\right)$ indicates the selection bias. The selection bias results are presented as follows:

$$B(Z) = E\left(Y^0|Z, D=1\right) - E\left(Y^0|Z, D=0\right) \tag{9}$$

Second, each contract farmer was matched to a non-contract farmer having a similar propensity score. We used the nearest-neighbor matching approach by following Mayen et al. (2010) [26], indicating that each contract farming participant was paired with the non-contract participant with the closest propensity score. However, the rest of the non-contract farmers were ignored for this step. This matching approach helped identify an alternative result for $E\left(Y^0|Z, D=1\right)$, statistical independence of $\left(Y^0,\ Y^1\right)$, and term $D$ conditional on $Z$ (contract farming participation is exogenous after conditioning on $Z$). This process is also called "selection on observables" [31]. We also confirmed that the conditioning on a propensity score *P(Z)* must be an independent condition [32]. This technique eliminates the dimensionality match on $Z$. If the assumptions of this method hold, then $E\left(Y^0|Z, D=1\right) = E\left(Y^0|Z, D=0\right) = E\left(Y^0|P(Z)\right)$, offering unbiased estimates of $E\left(Y^1 - Y^0|Z, D=1\right)$. Finally, we examined the relationships using the SFA and matched non-contract samples to test the hypothesis that these use a similar technology and compared their *TE* with the t-test results.

### *2.4. Data and Variables Description*

This study used a stochastic trans-log rather than the Cobb–Douglas production function. The stochastic trans-log model is relatively more flexible and restrictive on production and substitution elasticity [28]. Table 1 presents detailed information on the TE estimation's variables. We develop two models—the production model and the technical inefficiency model—to estimate the TE of contact farmers. In the production model, total land under rice production (ha), total rice seed cost per year, total fertilizer cost per year, labor expenditure per year, pesticide and chemical expenditure per year, total agriculture machine expenditure per year, and total rice output were taken as explanatory variables. The technical inefficiency model includes off-farm income, contact status, farmer age, education, rice farming experience, access to farm advisory service, and access to interest-free agriculture credit. Since smallholder farmers are eligible to avail interest-free credit, we used it rather than commercial banks' credit and information credit. Both include huge costs and interests in the study and, thus, can negatively affect the farmers' propensity to participate in contract farming.

Organic rice production information entails two harvests per year in Punjab, Pakistan. The total exported organic rice refers to a single output. Regarding the labor variable, we computed the total labor cost by including the per person per day expenditure of hired labor and considered the wage rate of permanently hired labor family labor. The farming area under rice production was taken in hectares. The total costs associated with seeds, fertilizer, and pesticides were computed for 2021. Machinery costs included purchasing agricultural machineries—such as irrigation equipment and land preparation machines—and agriculture tools were included in the machinery cost as the total expenditure. Since an organic rice farmer produces at a production frontier with a TE of 100%, we treated contract farming participation as a binary variable [8]. Likewise, based on the prior literature, seven key socioeconomic characteristics: contact participation, off-farm income, farmers' age, education level, rice farming experience, agriculture advisory, and access to interest-free credit were included in the technical inefficiency estimation. We expect that these variables will improve organic rice production and help farmers to optimize the organic rice output [33].

**Table 1.** Description of variables included in the estimation.

| Variable | Description |
|---|---|
| ***Production model*** | |
| Land | Total land under rice production per year (ton) |
| Seed | Total seed cost per year/ton |
| Fertilizer | Fertilizer expenditure per year/ton |
| Labor | Labor expenditure per year (PKR 1000) |
| Pesticide | Pesticide and chemical expenditure per year (PKR 1000) |
| Machine | Agricultural machines expenditure per year (land preparation-harvesting) (PKR 1000) |
| Output | Total output value of organic rice per year (ton) |
| ***Technical inefficiency model*** | |
| Off-farm | Total per year off-farm income (PKR 1000) |
| Contract | Contract farming participation status (1 = yes; 0 = no) |
| Age | Age of rice farmer (years) |
| Education | Number of schooling years of the farmer (1–16 years) |
| Experience | Rice farming experience (years) |
| Advisory | Farm advisory status (if received: 1 = yes; 0 = otherwise) |
| Credit | Credit availed (1 = yes; 0 = no) |
| ***PSM—Probit estimates*** | |
| Land | Total agricultural land under rice production |
| Member | Total active family members work on the farm |
| Age | Age of rice farmer |
| Gender | Gender of the rice farmer |

## 3. Results and Discussion

### *3.1. Descriptive Statistics*

We computed the descriptive statistics for the production and technical inefficiency model (Table 2). It indicates the mean values and standard deviations for given variables. Likewise, it helps compare the contract participants, non-contract participants, and the sub-matched sample regarding sociodemographic characteristics and production inputs applied. Regarding the variable input's application, the mean values of the total sample, contract farmer, non-contract, and matched sample were quite similar. The average organic rice output of the total sample was 65.206 tons. Likewise, it was 62.238 tons, 66.175 tons, and 60.154 tons for non-contract, contract, and matched samples, respectively. The mean and standard deviation values of total yearly expenditures on pesticides, labor, and seed were almost similar in all categories. However, contract farmers had more land under organic rice production and slightly used more fertilizer than non-contract participants. It indicates that contract participation ensures higher profitability; therefore, farmers applied more fertilizer to enhance per-acre production. Thus, it confirms the appropriateness of inefficiency estimations and production frontier study hypotheses. Further, variables representing farmers' sociodemographic characteristics are almost alike and have no significant differences in mean values. We posit that these variables will likely affect organic farmers' technical efficiencies and export-oriented production in the study area.

**Table 2.** Descriptive statistics for production and technical inefficiency model.

| Variable | Total | | Non-Contract | | Contract | | Matched Sample | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| ***Production model*** | | | | | | | | |
| Land | 2.457 | 1.732 | 2.765 | 0.893 | 2.149 | 0.719 | 2.683 | 0.417 |
| Seed | 9.726 | 3.628 | 9.862 | 3.681 | 9.59 | 3.093 | 8.372 | 0.738 |
| Fertilizer | 22.721 | 15.922 | 19.755 | 10.826 | 25.687 | 17.534 | 23.835 | 3.833 |
| Labor | 15.374 | 7.975 | 16.627 | 6.128 | 14.121 | 7.581 | 16.576 | 2.378 |
| Pesticide | 13.966 | 7.188 | 11.274 | 5.076 | 16.658 | 8.109 | 12.501 | 2.935 |
| Machine | 36.781 | 17.828 | 37.886 | 19.462 | 35.676 | 16.471 | 32.432 | 4.627 |
| Output | 2.962 | 0.974 | 3.172 | 1.103 | 2.752 | 0.785 | 2.273 | 0.154 |

**Table 2.** *Cont.*

| Variable | Total | | Non-Contract | | Contract | | Matched Sample | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| *Technical inefficiency model* | | | | | | | | |
| Off-farm | 105.16 | 74.827 | 107.28 | 71.426 | 103.03 | 72.718 | 103.718 | 9.128 |
| Age | 41.282 | 15.272 | 38.983 | 13.818 | 43.581 | 14.107 | 39.812 | 8.616 |
| Education | 9.113 | 3.781 | 9.382 | 3.915 | 8.844 | 3.078 | 8.961 | 2.892 |
| Experience | 22.267 | 13.814 | 22.926 | 12.784 | 21.608 | 10.876 | 19.262 | 3.647 |
| Credit | 0.376 | 0.275 | 0.370 | 0.314 | 0.381 | 0.298 | 0.472 | 0.092 |
| Advisory | 0.573 | 0.442 | 0.561 | 0.467 | 0.585 | 0.472 | 0.452 | 0.082 |

Source: author's calculations based on field survey 2021.

### *3.2. Parameter Estimations*

#### 3.2.1. Determinants of Organic Rice Production Technical Efficiency

Table 3 represents the results of the production frontier with a full sample and sub-matched group. We assume contract and non-participants had the same technical efficiency in the full sample. In the matched sample, model specifications allowed the contract and non-participants to differ in technical efficiency. Likewise, log-normalized values reported the partial production elasticity of input coefficients at the mean value. The input elasticities for land (number of hectares) under organic rice production, seed, and machine expenditures were positive and significant.

**Table 3.** Stochastic translog estimation for organic rice production in Punjab, Pakistan.

| Variable | Full Sample (650) | | Sub-Matched Group (574) | |
|---|---|---|---|---|
| | **Coeff.** | **SD** | **Coeff.** | **SD** |
| Lnland | 0.378 *** | 0.085 | 0.406 *** | 0.064 |
| Lnseed | 0.309 *** | 0.006 | 0.335 *** | 0.017 |
| Lnfertilizer | 0.627 | 0.561 | 0.562 | 0.472 |
| Lnlabor | −0.208 | 0.167 | −0.197 | 0.146 |
| Lnpesticide | −0.019 | 0.017 | −0.039 | 0.031 |
| Lnmachine | 0.152 *** | 0.006 | 0.138 *** | 0.004 |
| lnland × lnland | 0.365 ** | 0.156 | 0.413 ** | 0.224 |
| Lnseed × lnseed | 0.272 *** | 0.057 | 0.304 *** | 0.073 |
| lnfertilizer × lnfertilizer | −0.216 | 0.175 | −0.185 *** | 0.055 |
| lnlabor × lnlabor | 0.632 | 0.581 | 0.486 | 0.363 |
| lnpesticide × lnpesticide | −0.137 | 0.119 | −0.097 | 0.075 |
| lnmachine × lnmachine | 0.098 | 0.162 | 0.173 | 0.218 |
| Lnseed × lnland | 0.175 *** | 0.036 | 0.296 *** | 0.065 |
| Lnseed × lnfertilizer | 0.186 | 0.276 | 0.217 | 0.272 |
| Lnseed × lnlabor | 0.355 | 0.328 | 0.276 | 0.086 *** |
| Lnseed × lnpesticide | 0.007 | 0.044 | 0.014 | 0.037 |
| Lnseed × lnmachine | −0.017 | 0.026 | −0.034 | 0.025 |
| Lnfertilizer × lnland | 0.425 | 0.402 | 0.378 | 0.466 |
| Lnfertilizer × lnseed | 0.261 | 0.201 | 0.187 | 0.112 * |
| Lnfertilizer × lnlabor | −0.326 | 0.327 | −0.187 | 0.251 |
| Lnfertilizer × lnmachine | 0.063 | 0.048 | −0.113 | 0.096 |
| Lnlabor × lnland | 0.417 | 0.387 | 0.382 | 0.382 |
| Lnlabor × lnseed | 0.372 *** | 0.067 | 0.287 | 0.047 |
| Lnlabor × lnmachine | −0.119 ** | 0.075 | −0.104 | 0.017 *** |
| Lnpesticide × lnland | 0.007 | 0.018 | 0.011 | 0.026 |
| Lnpesticide × lnfertilizer | −0.092 | 0.068 | −0.113 | 0.097 |
| Lnpesticide × lnlabor | −0.076 | 0.065 | −0.045 | 0.077 |
| Lnpesticide × lnmachine | 0.091 | 0.117 | 0.127 | 0.114 |
| Constant | 0.262 | 0.062 | 0.314 | 0.075 |
| Number of observations | 650 | | 574 | |
| Prob > chi-square | 0.000 | | 0.000 | |
| Log-likelihood | 91.262 | | 88.414 | |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Sources: authors' own calculations.

Land size (number of hectares) under organic rice production had the highest coefficient, indicating that there exist economies of scale in the organic rice sector in Pakistan. It implies that as the area under productive increases, it improves the cost-effectiveness of organic rice production because each additional input unit lowers the total cost of production. Hence, the average cost per unit of production decreases as the size of the farm increases. The economies can occur because the farmer is able to spread more production over the same level of fixed expenses. Prior studies found the presence of economies of scale in the conventional rice sector [34,35]. To the best of our knowledge, our work is the first to report that economies of scale also exist in organic rice production in Pakistan. In general, the input coefficients of land and seed are larger in the matched sample than in the full sample. The coefficients of expenditures on labor and pesticides are negative and statistically insignificant. Regarding the inverse influence of labor on technical efficiency, one possible reason might be the higher labor cost because a greater labor transformation has shifted a big chunk of agricultural labor into the industrial sector. These findings are in line with [33]. Over the years, agriculture sector growth has shown a stagnant and negative trend; however, the industrial sector exhibits an increasing trend. Thus, lower wages in the agriculture sector and gradual expansion in the country's industrial sector played a crucial role in the labor shift to the industrial sector [36,37].

The negative connection between expenditure on pesticides and technical efficiency is due to the negative residual effect of pesticides on rice grain. Previous studies also reported similar results [38,39]. Upon selling the rice produce, excessive application of pesticides leaves longer-term health impacts, which upon detection, it lowers the final prices of harvest. Last, the positive association between expenditures on machines and technical efficiency reveals the importance of investment in agricultural mechanization to modernize Pakistan's agriculture in the wake of improving the range of exported commodities [12,20]. Further, improving the state of machine inventory is also important because a greater labor shift has transferred almost 80% of labor out of agriculture [40]. Hence, agriculture machines have a more prominent role in filling this labor gap vis-à-vis helping achieve higher technical efficiency in Pakistan agriculture.

#### 3.2.2. Inefficiency Estimates for Organic Rice Production in Punjab, Pakistan

Seven determinants of inefficiency for organic rice production were examined and are represented in Table 4. Amongst, the farmer's age and agriculture advisory service have positive coefficients. However, off-farm income, contract participation, farmer education, rice farming experience, and access to interest-free credit negatively influence organic rice technical efficiency. The negative coefficients show that the variable positively impacts the organic rice technical efficiency. The positive and significant coefficient of the farmer's age on technical efficiency indicates that age negatively affects technical efficiency and old farmers tend to have lower technical efficiencies than younger farmers. These results support prior studies indicating that older farmers are less oriented toward modern technology adoption [41,42]. Among the negative coefficients, contract participation (−0.527) has a significant and positive impact on technical efficiency, followed by access to interest-free credit (−0.379) and off-farm income (0.370).

Regarding the positive impacts of contract farming on technical efficiency, our findings are similar to the existing studies [5–8], complementing the fact that contract farming (being an institutional arrangement) offers easy and timely access to crop-improving inputs and enhances smallholder farmers' market access (and, therefore, improves technical efficiency). Such a finding is consistent with smallholder farmers' local and economic scenarios, where farmers lack funds and credit to meet quality crop inputs [14]. Hence, contract farming might be a plausible gauge to promote organic rice production and the technical efficiency of smallholder organic rice farmers in Punjab, Pakistan. Likewise, regarding access to interest-free credit and off-farm, our prior debate inculcates that lack of funds and poor access to marketing are the major constraints that inhibit the smallholder's technical efficiency [43]. Therefore, improving the means of farmers' income—both by off-farm and improved interest-free credit access—would help relax credit constraints and allow farmers to choose among the contract farming and marketing channels vis-à-vis improving technical efficiency. These findings are consistent with [42], indicating that smallholder farmers participate in contract farming to reduce the risk associated with production to processors and put the cost burden, i.e., seed, pesticides, and fertilizer, on the processor and/or exporters.

**Table 4.** Inefficiency estimates for organic rice production in Punjab, Pakistan.

| Variable | Full Sample | | Sub Matched Sample | |
|---|---|---|---|---|
| | **Coeff.** | **Z** | **Coeff.** | **Z** |
| Off-farm income | −0.370 *** | 0.028 | −0.408 *** | 0.045 |
| Farmer's age | 0.269 *** | 0.051 | 0.398 *** | 0.073 |
| Contract participation | −0.527 ** | −0.214 | −0.543 ** | −0.229 |
| Years of schooling | −0.009 | −0.018 | −0.027 | −0.049 |
| Rice farming experience | −0.074 | −0.123 | −0.106 | −0.096 |
| Credit access (interest-free) | −0.379 *** | −0.007 | −0.427 *** | −0.015 |
| Agriculture advisory service | 0.197 | 0.236 | 0.231 | 0.276 |
| Constant | −3.251 ** | −1.59 | −4.18 ** | −2.11 |
| Observations | 650 | | 574 | |

Note: *** $p < 0.01$, ** $p < 0.05$; sources: authors' calculations based on field survey 2021.

#### 3.2.3. Effects of Contract Farming Participation on Technical Efficiency

Table 5 illustrates the technical efficiency scores and levels of production performance for organic rice farmers in Punjab, Pakistan. The results show that the full sample has a technical efficiency score equal to 0.879. It implies that, on average, organic rice farmers in Punjab, Pakistan, produce 87.9% of the potential output. However, technical inefficiency loses 12.1% of the maximum output. In the full sample, the technical efficiency of rice farmers ranges between 86.6% for non-contract farmers and 90.3% for contract farmers. Likewise, in the matched sample, the technical efficiency score equals 0.882. It implies that, on average, organic rice farmers produce 88.2% of the maximum output in the matched sample. At the same time, 11.2% of the potential output is lost because of technical inefficiency. Contract farmers have higher technical efficiency (89.9%) than non-contract farmers (86.8%), confirming that contract participation leads to improved technical efficiency. Further, the two-sample t-test of TE-mean values indicates a significant difference between contract and non-contract farmers, complementing prior results that contract participation improves the organic farmer's technical efficiency.

**Table 5.** Technical efficiency score for export-oriented rice production in Punjab, Pakistan.

| S | Obs. | | Mean | Std. Dev. | Std. Err. | Min | Max |
|---|---|---|---|---|---|---|---|
| ***TE (full sample, N = 650)*** | | | | | | | |
| Full sample | 650 | | 0.879 | 0.061 | 0.003 | 0.512 | 0.952 |
| Non-contractor farmer | 300 | | 0.856 | 0.057 | 0.007 | | |
| Contract farmers | 350 | | 0.903 | 0.061 | 0.005 | | |
| Degrees of freedom = 648 | ***t*=** | **−3.76 ***** | | | | | |
| ***TE (sub-matched sample, N = 574)*** | | | | | | | |
| Full sample | 650 | | 0.882 | 0.063 | 0.003 | 0.571 | 0.916 |
| Non-contract farmers | 262 | | 0.868 | 0.065 | 0.785 | | |
| Contract farmers | 312 | | 0.897 | 0.076 | 0.766 | | |
| Degrees of freedom: 572 | ***t*=** | **−3.15 ***** | | | | | |

Note: *** $p < 0.01$; sources: authors' calculations based on field survey 2021.

### *3.3. Propensity Score Matching*

The probit estimates represent the propensity of contract farming participation, as illustrated in Table 6. Among others, the farmer's age and distance to the market have negative and significant connections with the likelihood of participating in contract farming. Among these, the distance to the market has a greater coefficient value (−0.382), indicating that the propensity to participate in contract farming declines as the distance from the market increases [44]. One possible justification is that most contract farming, rice purchasing, marketing, and exporting companies are city-centered and located in the big cities in Pakistan—for example, Engro-rice. Thus, distant farmers have the least access to such companies. Simultaneously, poor road and transport infrastructure conditions increase the information and transaction costs associated with the contract and marketing of final products [45]. Regarding the negative influence of the farmer's age, prior literature shows that older farmers rarely engage in contract farming [41,42]. Farmer education, rice farming experience, access to interest-free agriculture credit, number of livestock heads, and presence in the kalar track are positively and significantly associated with contract farming participation. These findings imply that educated and experienced farmers tend to engage more in contract farming. These findings are amply related to the prior literature on contract farming participation [38,46]. Likewise, regarding the positive and significant influence of access to interest-free credit and the number of livestock heads on contract farming participation, the justification is that most smallholder farmers are resource-poor and seek credit from market intermediaries, i.e., input provider-cum-traders, assemblers, etc. [47]. Most stakeholders engage in the course and basmati rice trade, influencing farmers' decision-making. Therefore, access to interest-free credit and the number of livestock heads help farmers meet immediate cash needs for crop input and allow farmers to decide whether to participate in contract farming or not. Thus, these findings imply that farmers with a sufficient resource base prefer to participate in contract farming than resource-poor farmers [14]. Based on this, improving the farmer's resource base through multiple means—such as livestock provision and interest-free credit—would provide supplementary support to boost contract farming participation, export-oriented organic rice production, and improve smallholders' income and export earnings.

**Table 6.** Probit estimates of the contract farming propensity.

| Variable | Coef. | Z |
|---|---|---|
| Farmer's age | −0.275 *** | −0.036 |
| Gender | 0.428 | 0.564 |
| Education | 0.187 ** | 0.092 |
| Farm size | 0.081 | 0.076 |
| Labor availability | 0.065 | 0.059 |
| Rice farming experience | 0.361 *** | 0.015 |
| Credit access (interest-free) | 0.271 *** | 0.009 |
| Off-farm income | 0.156 | 0.176 |
| Machine | −0.007 | −0.017 |
| Distance from market | −0.382 *** | −0.067 |
| Mobile phone | 0.154 | 0.124 |
| Livestock heads | 0.216 *** | 0.034 |
| Kalar track | 0.287 ** | 0.163 |
| Constant | −0.478 *** | −0.045 |
| Observations | 650 | |
| Log-likelihood | −34.213 | |
| McFadden pseudo-R-square | 0.574 | |
| Correctly classified | 78.63% | |

Note: ** $p < 0.05$, *** $p < 0.01$.

Further, we compute the propensity scores based on probit estimates for each group, i.e., full sample, contract farmers, and PSM subsamples. Next, we create the subsamples of the non-contract farmer to match contract farmers by selecting each contract farmer with the non-contract farmer having the closest propensity score that of the contract farmer, see Figure 2. The kernel density estimates of propensity score distribution for contract farmers, full sample, and PSM subsample are shown in Figure 2. As expected, the propensity score distribution for the PSM subsample is skewed toward zero. Likewise, the distribution of matched subsample is more closely related to the contract farmers.

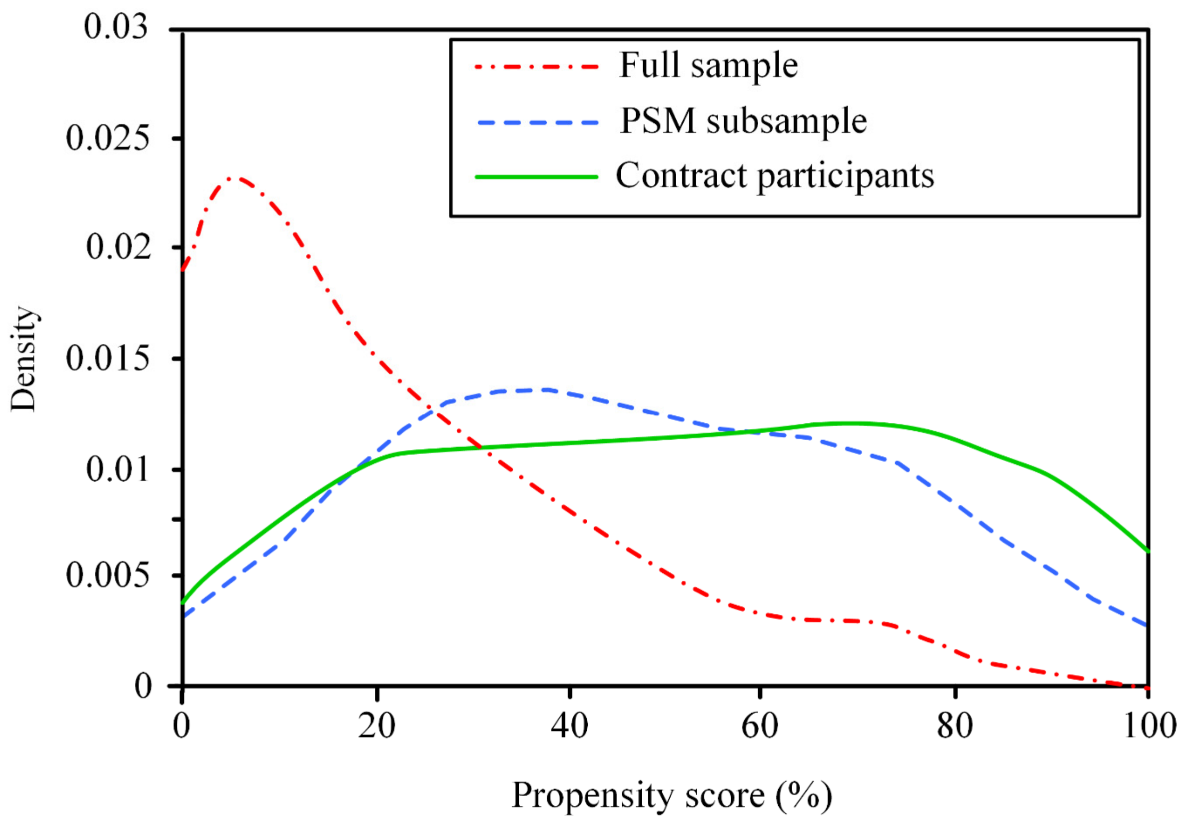


**Figure 2.** Kernel densities for propensity scores.

Based on the probit estimates, PSM is generated and satisfies the balancing property. Given the similar socioeconomic characteristics of contract and non-contract farmers, the propensity score before and after matching indicates that contract farming participation significantly creates differences in technical efficiencies. Similarly, nearest-neighbor match estimates and ATET are positive and significant. The results in Table 7 show strong positive effects of contract farming participation on the technical efficiency scores. This implies that contract farming participation improves the organic rice farmers' technical efficiency level from 86.8% to 89.7% and, therefore, there are lower technical inefficiency losses among contract farmers. Put simply, it reinforces that organic farmers are producing 10.3% below the maximum capacity and, therefore, with proper farm management and better organic rice training they have the potential to increase current output by 10.3% without needing to increase crop inputs. From these findings, participation in contract farming would help achieve potential output among organic rice farmers. These results nullify self-selection bias and support prior studies on the subject [8,48,49]. The findings support the notion that contract farming participation would be a potential means to improve smallholder farmer welfare by improving output and income in Pakistan.

**Table 7.** Mean and standard deviation of technical efficiency in PSM matching estimations.

| | Contract | Non-Contract | Difference in Means | *t*-Test |
|---|---|---|---|---|
| | **Mean** | **Mean** | | |
| | *TE—Probit model (n = 650)* | | | |
| Unmatched | 0.913 | 0.876 | 0.024 | 3.02 * |
| **ATT** | 0.897 | 0.868 | 0.027 | 3.25 ** |

Note: * $p < 0.10$, ** $p < 0.05$.

## 4. Conclusions and Policy Recommendation

Contract farming plays a profound role in smallholder agriculture by improving smallholder farmers' income and well-being in developing countries. Many studies have investigated the influence of contract farming participation on income, productivity, and yield; little is known about how contract participation effect smallholder organic rice farmers' technical efficiency and export-oriented production in developing countries. This study builds on a strong theoretical framework and stochastic frontier methodology to examine the impact of contract farming participation on technical efficiency and export-oriented production using a cross-sectional data set of 650 rice farmers in Punjab, Pakistan. Specifically, this study applies PSM to appropriately address the plethora of econometric challenges, confounding factors, and sample self-selection bias to guide policymakers and stakeholders through consistent and robust findings. This work contributes to the strand of literature on contract farming and technical efficiency. The study's findings provide practical insights for policies and practices to promote contract farming, export-oriented organic production, farmers' income, and well-being.

The findings of the study have four-fold insights. First, the SFA results reveal that the technical efficiency score of rice farmers in Punjab, Pakistan, is 89.7%, which can still be improved by 10.3% at the current sociodemographic characters and input levels. Second, the key production inputs are the number of hectares under rice production, expenditures on seed, and agriculture machines. Further, among the socioeconomic factors, off-farm income, contract participation, farmer education, rice farming experience, and access to interest-free credit positively and significantly influence organic rice technical efficiency. However, farmers' age negatively and significantly impacts technical efficiency. Notably, our findings show that there exist economies of scale in organic rice production in Pakistan because land size (number of hectares) under organic rice production has the highest coefficient. Third, probit estimates for propensity to participate in contract farming reveal that farmer education, rice farming experience, access to interest-free agriculture credit, number of livestock heads, and presence in the "kalar track" have a positive and significant association with contract farming participation. The findings indicate that access to interest-free credit and off-farm improves farmers' financial conditions as most are resource-poor, cash-strapped, and dependent on market intermediaries and local traders for inputs and immediate cash. Hence, under relaxed credit constraints, organic rice farmers prefer contract farming in Punjab, Pakistan. Last, nearest-neighbor match estimates and ATET are positive and significant, reinforcing that contract participation strongly affects technical efficiency scores. Moreover, these results nullify the presence of sample self-selection bias.

Based on the study findings, the following policy implications are suggested. First, to improve the technical efficiency of exported-oriented organic rice in Punjab, Pakistan, there is a need to revisit and upscale the current contract farming ventures. Currently, almost all of the current farming companies are private businesses. Further enhancing and developing contract farming schemes through public–private sector partnerships would help boost contract farming participation and smallholder welfare. Likewise, it would be interesting to increase the prevalence of contract farming by promoting it as an objective of economic policy and an institutional tool to overcome the flaws and loopholes in the current contract regimes. By doing so, a wider promotion and participation in contract farming can be achieved, which would shed a ripple effect on smallholders' income, technical efficiency, export-oriented quality rice production, and export earnings for the country. Second, the broader provision interest of interest-free credit and/or livestock head might strengthen the farmer's resource base. As discussed earlier, most smallholder farmers are cash-strapped and directly depend on informal traders for their cash needs, lowering their contract farming participation, technical efficiency, and welfare. Likewise, there is a need to create awareness and education regarding contract farming and its associated benefits because educated farmers tend to participate more in contract farming. Organizing farmer field schools, field visits, and seminars can better solve the purpose. Third, the government should improve the transport and road infrastructure connecting rural areas to cities. Such an intervention is desirable because it can help integrate the rural–urban market linkages, which profoundly impact rural revitalization, poverty alleviation, and farmers' well-being. Last, the government should lease out public land (over thousands of hectares are currently not in use) in rice-growing districts to private companies and other stakeholders for export-oriented organic rice production. Moreover, establishing state-of-the-art organic rice production technologies on similar land would help generate knowledge and information spillovers to facilitate a broader trajectory in contract farming, export-oriented organic rice production, technical efficiency, and farmers' well-being.

While our findings give a deeper look at the effect of contract farming on the technical efficiency of export-oriented organic rice production, it would be better to study the aggregate effect of contract farming on smallholders' income and well-being. This study uses rice farmers' cross-section data set for two cropping seasons (one-year data) of 2020–2021. Future studies should conduct investigations with three years or longer period panel data set to verify the findings reported herein. Moreover, this paper ignores the transaction costs related to contract farming. Therefore, it is a matter of core interest to examine the transaction costs, because if they are too high, it will be more profitable not to participate in contract farming.

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