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# Semi-parametric analysis of agricultural production under dichotomy of inputs

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**Abstract**: Inputs used in agriculture play asymmetric roles during the production process. Growth inputs, i.e. water, nutrients, seed and soil environment, become a part of the biological growth of plants, whereas facilitating inputs, i.e. labour, capital and pesticides, help regulate the functions of growth inputs from outside of the plants. This insight about the asymmetric role of agricultural inputs has been incorporated into agricultural economics on the basis of agronomic principles of crop production. The objective of this study was to analyse the effect of facilitating inputs on the technical efficiency of growth inputs. This analysis has been carried out semi-parametrically by employing the double bootstrap procedure on farm household level data from Pakistan. The results indicate that pesticides, capital and family labour scale up the technical efficiency of the growth inputs, whereas hired labour significantly scales down this efficiency. We recommend the creation of alternative employment opportunities for the rural labour force, provision of effective agricultural extension services to farm families, a minimisation of trade barriers to the import agricultural machinery and an enhancement of the extent of farm mechanisation.

**Keywords**: damage control, data envelopment analysis, double bootstrap procedure, facilitating inputs, growth inputs, technical efficiency

A major part of the population in Pakistan is engaged in agriculture in some capacity. In this way, agricultural development is considered an effective way of alleviating poverty. However, in comparison to other developed countries, there is little evidence of productivity improvement in this sector. In developing countries in general, various factors and causes are responsible for the limited state of agricultural development. These factors and causes are also present in Pakistan and include non-economical land holdings and insufficient expenditure on indigenous research and development.

The agricultural production process differs from the industrial or non-agricultural production process. In contrast to the industrial production process, various factors in agricultural production are not under the control of the farmer. Moreover, not all the inputs used in agriculture play the same role during the production process. Rather, the inputs used in agriculture play asymmetric roles, e.g. the role of pesticide is different from than that of other inputs. The role of pesticides is to reduce the damage caused by various agricultural pests. The inputs that are applied to reduce damage are collectively termed damage control inputs. On the other hand, for example, farmers apply fertiliser nutrients to increase the level of output. The inputs that are applied in order to increase the level of output are sometimes called direct inputs. Because of this asymmetric nature of inputs, modelling the agricultural production function in the same way as the non-agricultural production function results in biased marginal product estimates (Lichtenberg and Zilberman 1986).

The study of Lichtenberg and Zilberman (1986) was probably the first to highlight the fact that agricultural production should be modelled in a way that allows the capture of the characteristic roles of inputs during the course of analysis. They argued that inputs such as pesticide have an asymmetric role as compared to the other inputs. In modelling the production function, pesticides are treated in the same way as other farm inputs. Headley (1968) and Carlson (1977) showed that treating the damage control inputs in the same way as the direct inputs

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produces biased results for marginal productivities of damage control inputs. This is because the marginal product of damage control inputs is dependent on the presence of damaging agents, i.e. insects and pests. These insights initiated a new strand of research that may be termed damage control econometrics.

The concept of damage control inputs in agriculture soon became popular in agricultural economics (Harper and Zilberman 1989; Babcock et al. 1992, Blackwell and Pagoulatos 1992; Carrasco-Tauber and Moffitt 1992; Fox and Weersink 1995), and various alternative specifications for production function were presented. The research in damage control econometrics established the separability of direct inputs and damage control inputs. On the basis of this separability embedded in production function, a damage control function was introduced. The basic structure of a separable production function is expressed in the following way:

$$Q = f[x, G(z)]$$

Where $f(.)$ production is function and $G(.)$ is a damage control function. The damage control function is in fact a scaling function which ranges [0,1]. When $G(.)$ equals 1, the actual output is realised without damage and when $G(.)$ equals 0 the whole output is lost to damaging agents. The popular forms of damage control function assumed in the literature are exponential Weibull, logistic and Pareto (Lichtenberg and Zilberman 1986).

However, these alternative forms have highlighted another problem in agricultural economics. It is true that damage control inputs play varying role in the agricultural production process that can be captured by an asymmetric specification of the production function, i.e. the specifications presented in Lichtenberg and Zilberman (1986) or Chambers and Lichtenberg (1994). The alternative forms mentioned above and many others produce inconsistent results of marginal products of damage control inputs. Some forms present high and others show negative marginal product on the same data. Hence, there is still no consensus on the choice of the functional form of the production function under asymmetric roles of inputs.

In view of this problem of parametric specifications, alternative semi-parametric specifications have also been proposed. Kuosmanen et al. (2006) proposed a two stage semi-parametric analysis in a separable production process. A multiplicative separability was assumed among direct inputs and damage control inputs in the following way:

$$Q = f(x).g(z) \qquad \text{or} \qquad g(z) = \frac{Q}{f(x)}$$

Here, the first stage comprised data envelopment analysis (DEA) in which the technical efficiency (TE) of the farms was computed. In the second stage, the TE scores were regressed on damage control inputs and damaging agents. Moreover, the analysis was done by employing a double bootstrap procedure that was developed by Simar and Wilson (2007).

Another variation of the separable production functions involves incorporation of the dichotomous role of inputs through the integration of agronomic principles into production functions. Zhengfie et al. (2006) argued that the separability of agricultural inputs was even broader than that previously described (Lichtenberg and Zilberman 1986). Inputs used in the agricultural production process are either growth inputs or facilitating inputs. The inputs that are responsible for the biological growth of the plants are growth inputs. In other words, the inputs that affect physiological processes within plants are termed growth inputs, i.e. nutrients, soil environment and water. The other category of inputs is represented by facilitating inputs, which affect the efficiency of growth inputs. Facilitating inputs are not part of the biological growth of the plant but critically affect the biological growth by altering the outer environment of the plant. These inputs are labour, capital, management and pesticides. Of course, some pesticides are also systemic even if they are not directly responsible for increases in yield. The role of pesticides is indirect as they reduce the gap between actual yield and potential yield.[1] Under this framework, Zhengfie et al. (2006) analysed the agricultural production process econometrically. They proposed a translog production function with an embedded scaling function. The scaling function in this analysis was composed of facilitating inputs, i.e. labour, capital and pesticides.

Kuosmanen et al. (2006) favoured non-parametric techniques since they are free from strong econometric assumptions about the choice of the functional form for the production function. They added that the non-parametric form performs equally well even under the ideal conditions of parametric analysis.

[1]The readers are referred to Zhengfie et al. (2006) for definitions of terms like actual output, potential output and the relevant economic and agronomic concepts.

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However, the scope for non-parametric analysis was limited by the fact that their results were lacking in statistical properties because of the nature of their mathematical programming. Fortunately, Simar and Wilson (2007) have developed a double bootstrap technique for contemporary econometrics that can incorporate statistical properties of the estimates.

In this study, the dichotomy of agricultural inputs is analysed using farm household data from Pakistan. To our knowledge, this is the first Pakistani study that incorporates the concept of dichotomy and separability of agricultural inputs. The purpose of the study in hand is to revisit the agricultural production function by including the concepts of separability and dichotomy of agricultural inputs. As discussed above, Zhengfie et al. (2006) studied the dichotomy of inputs by modelling the production function in translog settings. Thus, there is a need for studies that semi-parametrically analyse the proposed dichotomy of inputs. The study in hand aspires to be a modest contribution to the agricultural economics literature in the following ways: Firstly this is the first study that analyses the agricultural production process semi-parametrically by incorporating the dichotomous nature of growth inputs and facilitating inputs.[2] Secondly, the double bootstrap procedure developed by Simar and Wilson (2007) is employed for the first time in Pakistan. A SAS MACRO has also been developed that can carry out the double bootstrap procedure in an automated way.

## MATERIALS AND METHODS

The agricultural production process is different from other production processes primarily because of the former is highly dependent upon natural factors that include temperature, humidity, rainfall and pest pressure. These natural factors are usually beyond the control of farmers or managers. Secondly, the inputs used in the production process play asymmetric roles. Zhengfie et al. (2006), on the basis of agronomic principles, categorised these inputs either as growth inputs, i.e. water, soil environment, seed and nutrients or facilitating inputs, i.e. labour, capital and pesticides. Lichtenberg and Zilberman (1986) had previously introduced the concept of the separability of inputs. The general form of a separable production function is given as

$$Q = f[\mathbf{z}, g(\mathbf{x})]$$

Where $Q$ is output and $\mathbf{z}$ is a vector of direct inputs and $\mathbf{x}$ is a vector of damage control and state variables. State or environmental variables include weather, humidity, pest pressure, etc. $f(.)$ is a production function and $g(.)$ is a damage abatement function. The value $g(.)$ is a [0,1] interval. When $g(.)$ assumes the value of 1 the actual output equals potential output and when it assumes the value of 0, it means maximum destruction caused by the state variable, i.e. the insects or pests. When $g(0)$ then $Q = f[\mathbf{z},0]$ and when $g(1)$ then $Q = f[\mathbf{z},1]$. Therefore, in a production process that involves direct inputs, damage control inputs and that is prone to certain damaging agents like pests, a production function is modelled as the following separable structure under the Lichtenberg and Zilberman (1986) framework as $Q = F[\mathbf{x}, g(\mathbf{y},\mathbf{z})]$ where $\mathbf{x},\mathbf{y},\mathbf{z}$ are the vectors of direct inputs, damage control inputs and damage agents, respectively.

Kuosmanen et al. (2006) assumed a multiplicative separability among the production function and damage control function. Therefore, it may be represented mathematically as:

$$q = f(\mathbf{x})g(\mathbf{y},\mathbf{z}) \tag{1}$$

where $f$ and $g$ are production function and damage control function. The production function comprises direct inputs, i.e. all inputs other than the damage control inputs, whereas pesticides and the damaging agents are arguments of the damage control function. The inputs are said to be separable if the marginal rate of technical substitution (MRTS) between the inputs of a group is independent of the variation in the inputs that belong to the other set and *vice versa*. The separability is expressed as:

$$\frac{\partial}{\partial z_k}\left(\frac{\partial q/\partial x_i}{\partial q/\partial x_j}\right) = 0 \quad \forall i,\ j,\ k, \text{ and } i \neq j \tag{2}$$

$$\frac{\partial}{\partial x_k}\left(\frac{\partial q/\partial z_i}{\partial q/\partial z_j}\right) = 0 \quad \forall i,\ j,\ k, \text{ and } i \neq j \tag{2a}$$

The Equation 1 can be shown in the following way:

$$g(\mathbf{y},\mathbf{z}) = \frac{q}{f(\mathbf{x})} \tag{3}$$

[2]Zhengfie et al. (2006) analysed this dichotomy of inputs parametrically in translog settings.

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The right-hand side of the above expression is the reciprocal of Farrell's output-oriented technical efficiency measure. In studies of productivity, TE is measured both parametrically, i.e. using stochastic frontier analysis (SFA) or non-parametrically, i.e. using DEA. Jankowski et al. (2007) highlighted the lack of consensus among researchers in damage control econometrics about the choice of functional form in studies employing parametric analyses. Hence, agricultural economists like Oude-Lansink and Silva (2004) employed non-parametric methods for analysis purposes. Moreover, as mentioned by Kuosmanen et al. (2006), the non-parametric form performs equally well under the ideal situations of parametric analysis.

Zhengfie et al. (2006) proposed a separability between growth inputs and facilitating inputs. Therefore, we alter Equation 1 in the following way to get:

$$q = f(x_1, x_2, x_3).g(z_1, z_2, z_3, z_4) \tag{4}$$

Where $f(.)$ includes growth inputs (soil, water, nutrients and seed), whereas facilitating inputs (labour, capital and pesticides) are incorporated into $g(.)$. Therefore, after a minute manipulation, Equation 4 may be written in the following way:

$$g(z_1, z_2, z_3, z_4) = \frac{q}{f(x_1, x_2, x_3)} \tag{5}$$

Both the right-hand and left-hand sides contain unknowns that can be estimated. The right-hand side is estimated using a non-parametric method. Charnes et al. (1978) developed a non-parametric technique which is known as data envelopment analysis (DEA). The left-hand side is estimated using parametric truncated regression. In this way, it is a two-stage analysis. Usually, such two-stage studies comprise DEA in the first stage and some sort of regression in the second stage. Simar and Wilson (2007) identified several sources of bias in such two-stage studies. These sources of bias are upwards biased TE, serial correlation of the error term and a bounded, i.e. [0,1] nature of the TE. To address this issue of bias, the double bootstrap methodology proposed by Simar and Wilson (2007) is used for the analysis.[3]

**Econometric Procedure**

The first stage of the analysis is the DEA that can be explained with the following set of equations.

There are $n$ firms (or farms in the present case), $r$ outputs and $m$ inputs.

$$\max\theta = \frac{(u_1q_1)_o + (u_2q_2)_o + \ldots + (u_rq_r)_o}{(v_1x_1)_o + (v_2x_2)_o + \ldots + (v_mx_m)_o} = \frac{\sum_{i=1}^{r}(u_iq_i)_o}{\sum_{j=1}^{m}(v_jx_j)_o} \tag{6}$$

i.e. maximise the technical efficiency of the firm denoted as subscript 0, where $u$ is the weight assigned to the $r_{th}$ output and $v$ is the weight assigned to the $m_{th}$ input.

Subject to the following constraints:

$$(v_1x_1)_o + (v_2x_2)_o + \ldots + (v_mx_m)_o = \sum_{j=1}^{m}(v_jx_j)_o = 1 \tag{7}$$

$$\frac{(u_1q_1)_1 + (u_2q_2)_1 + \ldots + (u_rq_r)_1}{(v_1x_1)_1 + (v_2x_2)_1 + \ldots + (v_mx_m)_1} = \frac{\sum_{i=1}^{r}(u_iq_i)_1}{\sum_{j=1}^{m}(v_jx_j)_1} \le 1 \tag{8}$$

$$\frac{(u_1q_1)_2 + (u_2q_2)_2 + \ldots + (u_rq_r)_2}{(v_1x_1)_2 + (v_2x_2)_2 + \ldots + (v_mx_m)_2} = \frac{\sum_{i=1}^{r}(u_iq_i)_2}{\sum_{j=1}^{m}(v_jx_j)_2} \le 1 \tag{9}$$

$$\frac{(u_1q_1)_o + (u_2q_2)_o + \ldots + (u_rq_r)_o}{(v_1x_1)_o + (v_2x_2)_o + \ldots + (v_mx_m)_o} = \frac{\sum_{i=1}^{r}(u_iq_i)_o}{\sum_{j=1}^{m}(v_jx_j)_o} \le 1 \tag{10}$$

One equation for each farm in the sample is defined including the farm for which technical efficiency is being calculated. The above Equation 10, for instance, shows the constraint of that farm for which technical efficiency is being calculated. The last constraint is

$$\frac{(u_1q_1)_n + (u_2q_2)_n + \ldots + (u_rq_r)_n}{(v_1x_1)_n + (v_2x_2)_n + \ldots + (v_mx_m)_n} = \frac{\sum_{i=1}^{r}(u_iq_i)_n}{\sum_{j=1}^{m}(v_jx_j)_n} \le 1 \tag{11}$$

[3]SAS MACRO was developed by Iqbal (2015) to conduct this analysis. Various researchers that have used double bootstrap procedures for their analyses have developed their own programming codes in different software, e.g. FEAR or Stata. Kousmanen et al. (2006) and Latrufet et al. (2007) reported that the *in silico* analysis is very time-consuming since it involves repeated iterations. The advantage of SAS MACRO is that it requires much less time for analysis compared to what has been reported in the literature. SAS MACRO can be modified easily by anyone intending to perform analysis using double bootstrap techniques (Iqbal and Sial 2015).

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$u_1, \ldots, u_s$ and $v_1, \ldots, v_m \geq 0,$

where θ*, $u$ and $v$ are output-oriented TE, optimal output weights and optimal input weights for the farm under consideration, respectively, and farms are 1 to $n$. This is the first stage of analysis in which the TEs of the growth inputs are calculated (Sherman and Zuo 2006; Cooper et al. 2007).

When Equation 7 equals 1 then the above model is written as:

$$\max \theta = (u_1 q_1)_o + (u_2 q_2)_o + \ldots + (u_r q_r)_o = \sum_{i=1}^{r} (u_i q_i)_o \quad (12)$$

subject to:

$$(v_1 x_1)_o + (v_2 x_2)_o + \ldots + (v_m x_m)_o = \sum_{j=1}^{m} (v_j x_j)_o = 1 \quad (13)$$

$$(u_1 q_1)_k + (u_2 q_2)_k + \ldots + (u_r q_r)_k \leq$$
$$\leq (v_1 x_1)_k + (v_2 x_2)_k + \ldots + (v_m x_m)_k \quad (14)$$

for all $k$ = 1 to $n$ number of farms including the farm for which technical efficiency is being analysed.

In more compact form, this can be written as follows:

$$\max \theta = (\sum_{i=1}^{r} u_i q_i)_o \quad (15)$$

subject to:

$$(\sum_{j=1}^{m} v_j x_j)_o = 1 \quad (16)$$

$$\sum_{i=1}^{r} (u_i q_i)_n \leq \sum_{i=1}^{m} (v_j x_j)_n \quad (17)$$

for all $n$ number of farms including the farm under analysis

$u_i, v_j \geq 0$

The above-mentioned constant return to scale model is estimated for each farm individually. By employing DEA in the first stage we obtain the TE scores of the growth inputs, which determine the ranking of each farm in the analysis. Farms with scores of 1 are said to be efficient farms; the rest are allotted scores of between 0 and 1.

In the second stage of analysis, these TE scores of growth inputs are regressed on the facilitating inputs using truncated regression. The whole analysis is run under a double bootstrap procedure to obtain robust results for TE and the sources of TE (Simar and Wilson 2007). Many other studies have employed this technique (Balcombe 2008; Barros and Dicke 2008; Latruffe et al. 2008; Blank et al. 2010). The right-hand side of the Equation 5 is estimated with non-parametric DEA, whereas the left-hand side is estimated with parametric maximum likelihood techniques.

Table 1. Names of districts and regions included in the analysis

| No | Name of districts | ID code | Region |
|---|---|---|---|
| 1 | Sargodha | 06 | 1 |
| 2 | Faisalabad | 10 | 1 |
| 3 | Toba Tek Singh | 11 | 2 |
| 4 | Jhang | 12 | 2 |
| 5 | Gujranwala | 13 | 3 |
| 6 | Hafizabad | 16 | 3 |
| 7 | Sheikhupura | 22 | 3 |
| 8 | Okara | 21 | 4 |
| 9 | Sahiwal | 24 | 4 |
| 10 | Pakpattan | 27 | 4 |

Districts are allotted different ID code according to Pakistan Social and Living Standards Measurement (PSLM) Survey for 2007–2008. The regions are classified 1–4 by the author.

**Data**

Farm household level data from the agricultural section of the Pakistan Social and Living Standards Measurement (PSLM) Survey for 2007–2008 (GOP 2009) was used in this research. Ten irrigated districts from the Punjab province were chosen for the purpose of analysis. The list of these districts along with their ID codes is provided in Table 1. Based upon the cropping patterns, four different regions were formed. Region 1 included the districts of Sargodha and Faisalabad; region 2 included the districts of Toba Tek Singh and Jhang; region 3 included Gujranwala, Hafizabad and Sheikhupura, and, lastly, Okara, Sahiwal and Pakpattan were included in region 4.

Definitions and summary statistics of the various variables used are given in Table 2.

## RESULTS AND DISCUSSION

The analysis comprises two stages. In the first stage, the TEs of the growth inputs were calculated using DEA, which has been explained in the previous section. DEA technical efficiency scores are calculated by forming a separate frontier for each district, meaning that each farm is compared with other farms that

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Table 2. Definitions and summary statistics of variables used

| Variable | Category of inputs | Definitions of variables | *N* | Mean | StdDev | Minimum | Maximum |
|---|---|---|---|---|---|---|---|
| Q | – | total production/acre (000 Rs) | 494 | 32.86 | 23.98 | 4.56 | 344.20 |
| X1 | growth input | total land under peration (acres) | 494 | 7.75 | 7.92 | 0.38 | 50.00 |
| X2 | growth input | expenditure on seed/acre (000 Rs) | 494 | 1.72 | 1.85 | 0.04 | 15.00 |
| X3 | growth input | expenditure on fertilizer/acre (000 Rs) | 494 | 3.47 | 2.88 | 0.18 | 28.50 |
| X4 | growth input | expenditure on water/acre (000 Rs) | 494 | 3.22 | 4.21 | 0.05 | 42.34 |
| Z1 | facilitating input | expenditure on pesticides/acre (000 Rs) | 494 | 1.85 | 2.17 | 0.02 | 13.11 |
| Z2 | facilitating input | rent on capital/acre (000 Rs) | 494 | 2.46 | 1.99 | 0.08 | 22.00 |
| Z3 | facilitating input | total family worker days in a household in a month | 494 | 9.08 | 8.23 | 0.00 | 73.68 |
| Z4 | facilitating input | expenditure on permanent and casual hired labor/acre (000 Rs) | 494 | 3.50 | 3.91 | 0.04 | 30.00 |

The variables labeled with *X* and *Z* are growth inputs and facilitating inputs respectively. Identification of variables (*X* and *Z*) is a common practice in damage control literature. The same practice is being followed by the author. *N* – number of observations; Rs – Rupees; StdDev – standard deviation

lie in the same district. This practice is also in line with the approach of Kuosmanen et al. (2006) who calculated the TE scores of farms separately for each village included in the analysis. However, for the second stage of analysis, all the observations were pooled in a common truncated regression.

In the double bootstrap procedure, biased and bias-corrected types of scores are calculated.[4] The TE is bounded [0,1], and the farms with a TE of 1 are efficient as compared to their peers. For example, the farms with IDs 21, 24, 33, 41, 42 and 52 in Sargodha (DIST = 6) were efficient farms, whereas other farms in this district were termed as inefficient ones since their scores were less than 1. For example, the farm with ID 2 had a score of 0.557, which means this farm was about 44% less efficient than its peers. Similarly, the farm with ID 11 in Sargodha with a score of 0.640 was about 34% less efficient than its peers in the group, and so on.

District-wise mean TE scores are given in Table 3. The variation in the mean TE among different districts can be observed from Table 3 and Figure 1.

Table 3. District-wise technical efficiency scores

| District | *N* | Mean | Stddev | Minimum | Maximum |
|---|---|---|---|---|---|
| Sargodha | 64 | 0.526 | 0.249 | 0.133 | 1.000 |
| Faisalabad | 44 | 0.563 | 0.233 | 0.248 | 1.000 |
| Toba Tek Singh | 33 | 0.540 | 0.212 | 0.202 | 1.000 |
| Jhang | 80 | 0.391 | 0.226 | 0.075 | 1.000 |
| Gujranwala | 40 | 0.459 | 0.235 | 0.138 | 1.000 |
| Hafizabad | 35 | 0.781 | 0.224 | 0.318 | 1.000 |
| Okara | 41 | 0.613 | 0.231 | 0.310 | 1.000 |
| Sheikhupura | 86 | 0.506 | 0.185 | 0.230 | 1.000 |
| Sahiwal | 39 | 0.320 | 0.261 | 0.069 | 1.000 |
| Pakpattan | 32 | 0.589 | 0.260 | 0.227 | 1.000 |

District-wise technical efficiency (TE) scores are estimated by nonparametric data envelopment analysis (DEA) and descriptive statistics are calculated by the author afterwards. *N* – number of observations; Stddev – standard deviation

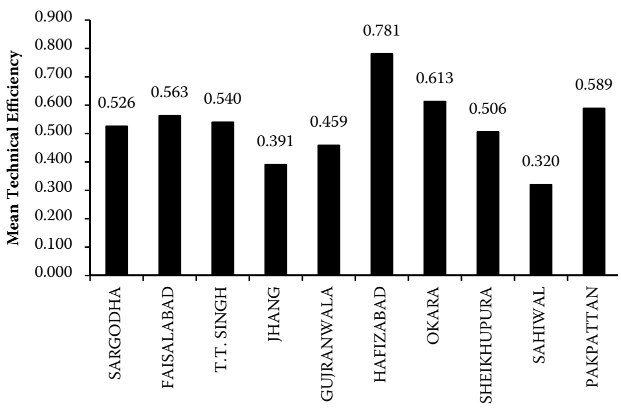


Figure 1. District-wise mean technical efficiency scores
Source: Graph drawn by author based upon the calculations of technical efficiency (TE).

[4]Biased and bias-corrected TE scores are available upon request from the authors.

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Table 4. Results of $t$-test for difference in mean technical efficiency scores

| District | Sargodha | Faisalabad | Toba Tek Singh | Jhang | Gujranwala | Hafizabad | Okara | Sheikhupura | Sahiwal |
|---|---|---|---|---|---|---|---|---|---|
| Faisalabad | –0.77 | – | – | – | – | – | – | – | – |
| Toba Tek Singh | –0.28 | 0.43 | – | – | – | – | – | – | – |
| Jhang | 3.4*** | 4.0*** | 3.2*** | – | – | – | – | – | – |
| Gujranwala | 1.37 | 2.04** | 1.55 | –1.52 | – | – | – | – | – |
| Hafizabad | –5.0*** | –4.2*** | –4.5*** | –8.5*** | –6.0*** | – | – | – | – |
| Okara | –1.8* | –1.00 | –1.40 | –5.1*** | –3.0*** | 3.0*** | – | – | – |
| Sheikhupura | 0.57 | 1.52 | 0.88 | –3.6*** | –1.22 | 7.0*** | 2.8** | – | – |
| Sahiwal | 4.0*** | 4.5*** | 3.9*** | 1.53 | 2.5** | 8.1*** | 5.3*** | 4.6*** | – |
| Pakpattan | –1.15 | –0.46 | –0.82 | –4.0*** | –2.2** | 3.2** | 0.42 | –1.9* | –4.3*** |

Standard $t$-test procedure for difference in means is applied to get results. ***, **, * indicate 1%, 5% and 10% level of significance respectively

Many of the mean TE scores differ significantly from each other. Therefore, a separate DEA was conducted for each district. The results of the $t$-test for the differences in the means are given in Table 4.

## Effect of facilitating inputs on the technical efficiency of growth inputs

Next, a maximum likelihood method in a truncated regression was used to explain variation in the TE of growth inputs due to facilitating inputs (i.e. pesticides, capital and labour) by using the specification given by Equation 5. Due to the bounded nature of the dependent variable [0,1], truncated regression is used by setting a lower bound of 0 and an upper bound of 1. Despite the existence of other forms, i.e. ordinary least squares (OLS), tobit/censored regression functions have been used for this purpose. Nevertheless, Simar and Wilson (2007) favoured truncated regression because of its consistency with the underlying data generating process (DGP). Most studies terminate their investigation after this step, but, again, for the reasons mentioned earlier, this may produce misleading results. To tackle this problem, a double bootstrapping technique is used and the final results of this procedure are given in Table 5.

Almost all of the estimated coefficients are significant except the coefficient of region 3. The coefficient of pesticides has a positive sign indicating that the use of pesticides by the farms helped to increase the TE of the growth inputs. Shafiq and Rehman (2000) also concluded that pesticides were a productive input. However, in Pakistan, the use of pesticides is extremely crop-specific. Most pesticides are used on the cotton crop. More than 60% of the cotton cropped area receives pesticides, followed by rice, 39% of whose area is covered by plant protection measures (GOP 2010). The use of these chemicals is extremely low for the other crops grown in the country. Another issue in estimating the marginal effects of pesticides is that most of the data including those used in the present analysis, do not include the negative externalities that emerge due to the use of pesticides. These negative effects take the shape of environmental degradation that disturbs the terrestrial, aquatic and subsoil environments. Therefore, it may be assumed that pesticide productivity is overestimated, since the analysis does not account for the

Table 5. Effect of facilitating inputs on technical efficiency of growth

| Variable | Description | Coefficient | SE | $t$–value |
|---|---|---|---|---|
| Intercept | – | 0.8186*** | 0.0134 | 61.3110 |
| Z1 | pesticides | 0.0178*** | 0.0042 | 4.2570 |
| Z2 | capital | 0.0183*** | 0.0055 | 3.3399 |
| Z3 | family labor | 0.0039*** | 0.0011 | 3.5971 |
| Z4 | hired labor | –0.0074** | 0.0025 | –2.9171 |
| R2 | region 2 | 0.0416** | 0.0166 | 2.5051 |
| R3 | region 3 | –0.0119 | 0.0134 | –0.8878 |
| R4 | region 4 | –0.0251* | 0.0147 | –1.7047 |

Inputs: Double bootstrap estimation. The above results have been attained by completing a 7 step procedure of double bootstrap estimation. In the first loop 100 iterations are used to get bias corrected technical efficiency (TE) of growth inputs. In the second loop 2500 iterations are used to get robust estimates of the coefficients. ***, **, * indicate 1%, 5% and 10% level of significance respectively; SE – standard error

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environmental degradation costs. The results indicate that all agricultural regions are statistically different from region 1, except for region 3. This is perhaps due to the different cropping patterns prevalent in these regions.

The results reveal that the use of farm machinery significantly contributes in a positive way and is the most productive among the facilitating inputs. Expenditure, as rent for tractors and other forms of farm machinery, helps increase the technical efficiency of growth inputs. Although the extent of farm mechanisation is increasing in the country, Pakistan remains a capital-deficient country. In the context of the present technological relationship among inputs and output, the use of machinery has contributed to increasing the agricultural productivity of the country. However, this result is in contrast to the study by Zhengfei et al. (2006) which was done in the Netherlands, where it was shown that the value of the marginal product of capital was significantly lower than its opportunity cost. These authors concluded that capital was overused in the Netherlands. In Pakistan, capital has bright prospects and it must be promoted in order to achieve more agricultural productivity. On the other hand, this result is in agreement with previous studies carried out in Pakistan (Bakhsh et al. 2004, Hassan et al. 2005). This prospect is also being realised by the private farms in the country, since the extent of farm mechanisation is increasing over time in Pakistan as more and more land is cultivated with the use of farm machinery (GOP 2010).

Family labour significantly scales up the technical efficiency of growth inputs. Every extra day spent on farm work by the members of a farming family during a month contributes to enhancing productivity. The marginal technical efficiency of growth inputs increases by nearly 0.4% in response to one extra day of family labour. It can be inferred from the results that TE is nearly 9.3% at the mean value of family workers. This result is agreement with the assertion of Ahmad (2003) that family workers are helpful in increasing productivity.

The results indicate that hired labour is extremely overemployed in the agricultural sector of the country since it significantly dampens the technical efficiency of the growth inputs. Every extra 1000 rupees spent on hired labour reduces the technical efficiency by about 0.7%. Shafiq and Rehman (2000) reported that hired labour had a negative productivity in the farm sector. This is partially because of the fact that Pakistan is a labour-abundant country. Most of the labour force that is employed in the agricultural sector of the country is unskilled. The present cropping pattern and the technological relationship that exists between agricultural inputs and outputs, hint that hired labour is employed beyond the optimum level. In this situation, the country has either to choose an alternative cropping pattern that can soak up the extra labour, or to promote alternative employment opportunities in the rural sector.

These labour issues, i.e. positive contributions of family labour and overuse of hired labour, is partially reflected in the recent structural changes in the socioeconomics of the country's agriculture. The number of farms as well as the percentage of family farm workers is increasing in the country (GOP 2010). Coefficients for regional dummies indicate that different regions exhibit different technical efficiencies primarily because of differences in cropping pattern practices.

The results reported in Table 5 were obtained using a double bootstrap procedure. For this purpose, truncated regression was run 2500 times. Therefore, 2500 different sets of estimates of each facilitating input variable were produced, one for each regression. Figure 2 shows the histograms for the bootstrapped estimates of the facilitating inputs. Obviously, the bootstrap estimates for regions were also obtained but they are not shown here as histograms.

## CONCLUSION

The concept of a divergent role of inputs in agricultural production process was first formulated by Lichtenberg and Zilberman (1986) and further extended by Zhengfei et al. (2006). In this study, we empirically verified the dichotomous role of inputs used in agriculture, by using input-output data of 10 districts from an irrigated part of the Punjab province.

Analysis was conducted in a two-stage semi-parametric fashion. Because of the econometric flaws in the traditional two-stage studies, the double bootstrap procedure proposed by Simar and Wilson (2007) was used.

The *t*-test suggests that the districts are statistically different from each other in mean TE. Therefore, the technical efficiency of farms belonging to different districts was calculated by considering each district as a separate set of farms. Similarly, Kuosmanen et al. (2006) calculated the technical efficiency of farms for each village separately instead of pool-

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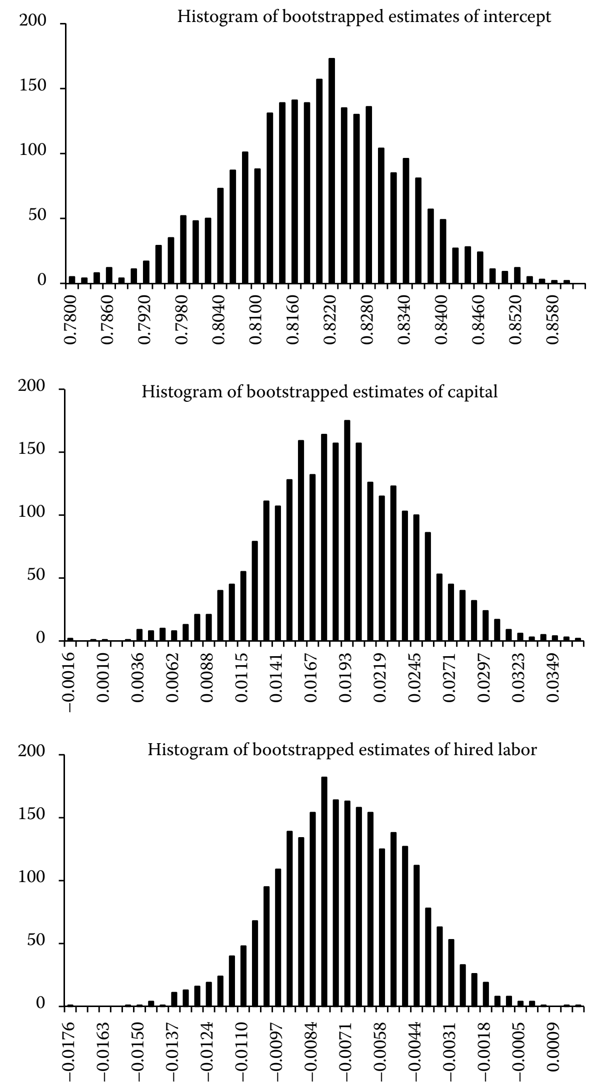


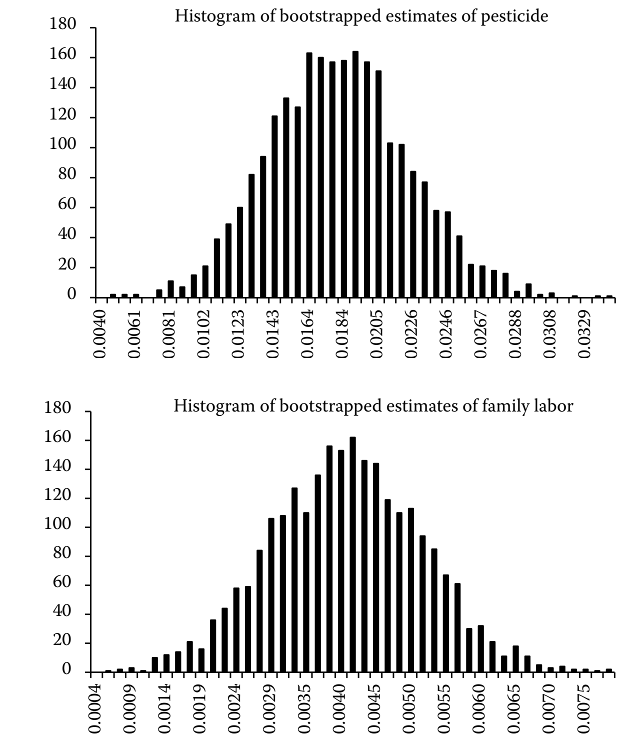


Figure 2. Histograms of the bootstrapped estimates of the facilitating inputs

Source: Graphs drawn by author based upon the calculations of technical efficiency (TE)

ing all farms into a common group. However, the underlying factors behind this variance in technical efficiency among districts were not analysed as they are beyond the scope of the current study.

It was observed that capital contributes positively to the TE of growth inputs. In the present technological relationship that exists among various inputs, there is a possibility for further development towards more and more farm mechanisation. The analysis showed that family farm labour makes a significant positive contribution towards the technical efficiency of the farms. Perhaps this is one of the reasons why family farm labour has increased more than proportionately to the increase in farm area over time in Pakistan. In the decade from 2000 to 2010, there was an increase of 4.74% in total farm area, but, over the same time, there was an increase of about 24% in family labour in the country (GOP 2000; GOP 2010). On the other hand, other forms of labour, i.e. permanent hired and casual hired labour, act negatively on TE. The results indicate that these forms of labour are being overly employed in the agricultural sector. It is therefore recommended that the rural labour force be employed in some alternative enterprises so that the pressure on agricultural land be relieved. The results indicate that plant protection measures adopted by the farmers positively contribute to the TE of the growth inputs.

Policy intended to foster agricultural development in the country should particularly address the issues of mechanisation and labour force. The extent of farm mechanisation may be increased by providing easy credit facilities, minimising trade barriers to the import of modern agricultural technology and farm machinery and enhancing research and development in farm machinery. Family farm workers should be provided with effective and modern agricultural

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extension services. Alternative employment opportunities might be created for the rural labour force in order to reduce the effects of negative productivities of casual and hired labour.

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