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Stochastic Frontier and Technical Efficiency of Farms in Irrigated Areas of Pakistan's Punjab

Abid A. Burki and Haq Nawaz Shah

This paper presents new evidence on technical efficiency and its sources by examining the cost behaviour of 387 farms and whole-farm data from five irrigated districts of Punjab. Fitting translog variable cost frontier we find that technical inefficiency raises the cost of average sample farms by 24 percent that could have been saved had the farms been technically efficient. Our results enable us to conclude that farm efficiency is positively related to formal schooling of farm operators, abundance of canal water, and head reaches of *mogha*, and negatively to farm size, while the age of farm operators has no effect on efficiency.

Keywords: Agriculture, stochastic frontier, technical efficiency, Asia, Pakistan.

1. INTRODUCTION

Stagnation in agricultural production and technical inefficiency of farms are currently the top concerns of the policy-makers in Pakistan. The main issue is that in the post-Green Revolution period, despite growth in irrigated areas, rapid adoption of modern high-yielding varieties (HYV), spread of fertiliser, and irrigation water, crop yields and agricultural productivity have markedly slowed down [Byerlee and Siddiq (1994); Ali (1995); Khan (1998)].[1] The most striking trend is the finding that there is consistent decline in total factor productivity (TFP) in the agriculture sector.[2]

Abid A. Burki is Associate Professor, Department of Economics, Quaid-i-Azam University, Islamabad. Haq Nawaz Shah is associated with the Punjab Economic Research Institute, Lahore.

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[1]Pakistan is one of those developing countries where the earliest attempts to modernise agriculture with the so-called Green Revolution technologies were executed in the mid-1960s. The Green Revolution is the term used for biological, chemical, and mechanical innovations introduced in mid-sixties in the agriculture sectors of developing countries. More specifically, biological innovations include the high-yielding varieties of seed; chemical innovations include chemical fertiliser, pesticides, and insecticides; and mechanical innovations consist of tractors, tractor-driven implements, and tubewells, etc.

[2] For example, Khan and Barkley (1998) estimated that the annual growth in TFP, which was 3.45 percent during the Green Revolution period (1966–76), decreased to 2.2 percent between 1977–86, and to only 0.75 percent between 1987–90. Similarly, Byerlee and Siddiq (1994) reported that wheat production increased only at 1.4 percent per annum during 1977–90 as compared to 5.1 percent during 1966–76. This decline in productivity and crop yields raises concerns about "the sustainability of Pakistan's agricultural and irrigation systems" [Byerlee and Siddiq (1994)].

Pakistan's economy is already facing a high population growth rate, problems in the balance of payments, poverty, and the debt management, which continue to put pressure for increased agricultural production. However, agriculture seems to have no or little further potential to boost crop yields unless specific reform measures are introduced. For current policy debates it is important to quantify the magnitude of technical inefficiency and to identify its causes more precisely. To the extent that the sources of inefficiency are identified, we can predict about the likely effects of specific reforms on long-run efficiency and the revival of the agriculture sector.

The existing studies on technical efficiency in Pakistan's agriculture fail to give a clear picture of farmers' efficiency because they use farm-level data on a single crop (wheat and rice) and employ restrictive functional forms [Battese *et al.* (1993); Parikh and Shah (1996)]. Cost minimisation (or profit maximisation) decisions by farmers usually involve all categories of outputs and inputs. Therefore, studies based on the whole-farm data set are expected to produce more reliable evidence on inefficient farms. Moreover, flexible functional forms are known to be more suitable for empirical applications of stochastic frontiers because they envelope the data more closely [Schmidt (1985-86)].

We present new evidence on the magnitude of technical inefficiency in Pakistan's agriculture by examining the cost behaviour of 387 farms, and identify its causes by focusing on attributes of farms and farm operators, irrigation mechanism, loans, and farm size. We use data obtained from a survey of five irrigated districts of Punjab, Pakistan conducted by the Punjab Economic Research Institute (PERI), Lahore, Pakistan in the crop season 1991-92. We extend previous analysis in several different ways. First, in the estimation of a cost function, the assumption of static equilibrium may be violated if some farm inputs fail to adjust instantaneously to their optimal amounts because they are fixed in the short run. In this setting, the cost-minimising farmers can only adjust variable costs. For our analysis, we estimate a short-run variable cost frontier with quasi-fixed inputs. Second, we extend this analysis to whole-farm data which include all crop and non-crop outputs and all measurable inputs used on farm. Third, we specify a flexible cost frontier to avoid a possible bias that may result from the use of restricted functional forms. Finally, we specify a censored regression to evaluate the sources of measured efficiencies by focusing on attributes of farms and farm operators. In particular, we evaluate the impact of insufficient supplies of canal water to tail-end farmers and the use of poor quality of groundwater on technical efficiency of sample farms. Our results indicate that on a scale of zero to 100, technical efficiency of farms in our sample varies from a minimum of 29 percent to a maximum of 95 percent, with average efficiency at 76 percent. The robust finding that schooling improves efficiency confirms a crucial role for human capital, while the finding that the abundance of water is crucial for efficiency in agriculture conforms to the standard view of agricultural development. The paper also finds that farm efficiency is positively (negatively) related to head-reaches (tail-ends) of water outlets or *moghas* and negatively to farm size, while the age of farm operators and financing were not correlated with technical efficiency.

The paper is organised as follows. Section 2 gives a brief description of irrigation mechanisms in Pakistan. Section 3 lays out the stochastic translog variable cost frontier and discusses the techniques used to estimate the cost frontier. Section 4 describes the data and construction of variables. In Section 5, estimates of the frontier cost function are employed to compute the index and the extent of technical inefficiency. Section 6 utilises this index of technical efficiency and investigates important sources of technical efficiency by estimating a Tobit regression model. The conclusion and policy implications are given in the last section.

2. IRRIGATION MECHANISMS IN PAKISTAN

Pakistan has the largest contiguous irrigation system in the world. It has a total cultivated area of 21.55 million hectares, of which 17 million hectares (79 percent) is irrigated. From the total irrigated area, 72 percent is irrigated by canals, 22 percent by tubewells, and 6 percent by rains or other means. The Indus Water Treaty, signed between India and Pakistan in 1960 gave complete ownership of three eastern rivers (i.e., the Beas, the Sutlej, and the Ravi) to India, which also passed through Pakistan. Under the same treaty, dams were built on the river Indus and the river Jhelum to provide water in canals that were earlier fed by the rivers that went into Indian control. The World Bank provided financial assistance to construct the Tarbela and the Mangla dams on the rivers Indus and Jhelum, respectively, and for 9 link canals and 5 barrages.

A typical canal water distribution system in Pakistan has a barrage or headwork constructed on a river from where the canals emanate. The main canals are divided into branch canals, which are further divided into distributaries. These distributaries may or may not be divided into minors. Water outlets, called *mogha*, are provided on distributaries/minors. A water outlet or *mogha* on a distributary/ minor is a "masonary structure" through which water is admitted from a government distributary to a watercourse. The *mogha* is the border where the state control ends and farmers' joint management starts. The *mogha* is meant to pass a constant quantity of water. A water course runs through a number of fields and farmers located along a water course are provided with authorised cuts (*nakkas*) from where they get the water and carry it into their private watercourses to irrigate different parts of their fields. The settlement, irrigated by a watercourse, is called a *chak*, which is a kind of planned settlement made at the time of opening of a canal. Water requirements for the *chak* were determined on the basis of climate, soil conditions, cultivable area, and the type of crops that could be grown in that area. The size of the water outlet is designed on the basis of irrigation water requirements for a *chak* on each watercourse. The outlets are designed so that the irrigators take their authorised share of water and silt carried by the main channels. However, unequal water availability arises at the tail-end of distributaries and water courses due to water loss from seepage and rat holes. It is estimated that 40 to 50 percent of the water discharged from the water outlets of distributaries/minors into the watercourses is lost [Shahid *et al.* (1992)]. There is also evidence that water outlets are sometimes tampered with, by the farmers, and made oversized to get higher than the allocated water discharge.

It is obvious from the above that tail-end farmers on distributaries and watercourses face shortages of canal water, which they try to overcome by installing private tubewells. However, the quality of groundwater pumped out by tubewells is very poor as compared to canal water. For example, a survey on 1000 tubewells in the 1980s, conducted by Punjab Soil Fertility Institute, shows that only 25 percent of the tubewells supply usable water, 21 percent supply marginally usable water, and an overwhelming 54 percent supply hazardous groundwater [Byerlee and Siddiq (1994)]. A long-term use of unsuitable tubewell water produces sodicity, meaning hardening of the topsoil, which reduces seedling survival, water infiltration and, in turn, crop yields. Therefore, we expect that farms at the tail-end of distributaries and watercourses will have lower technical efficiency relative to their head-end counterparts.

3. MODEL SPECIFICATION

We estimate technical efficiency by using the stochastic cost frontier where technical efficiency of a farm means producing crop and non-crop outputs by minimum possible costs observed within the sample. Farms producing on the cost frontier are technically efficient, while farms lying above the cost frontier are technically inefficient.[3] The stochastic frontier approach was originally suggested by Aigner *et al.* (1977), and by Meeusen and van den Broeck (1977). This approach employs the composed error structure for the disturbance term to differentiate technical efficiency from statistical noise, random shocks, and events outside a farm's control. The estimates of cost function implicitly require that inputs are used at their cost minimising values. However, if some inputs are fixed in the short run, then the cost minimising farms would only minimise variable costs. Therefore, to estimate technical efficiency we model the cost structure of each farm by using the translog variable cost frontier. In general form, the basic model for the variable cost frontier can be represented as

$$VC_i = C\ (y_i\ ,\ w_i,\ \bar{x})\, e^{\varepsilon_i} \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad (1)$$

[3]The concept of frontiers is conveniently applied to production, cost, and profit frontiers. The only distinction is that the observations are restricted to lie beneath production and profit frontiers, but above the cost frontier. For some recent reviews on this literature, see Cornwell and Schmidt (1995); Greene (1995); Lovell (1993); Bauer (1990); Lovell and Schmidt (1988) and Schmidt (1985-86). For the frontier literature on developing countries' agriculture, see Bravo-Ureta and Pinheiro (1993).

where VC_i is the observed variable cost, y_i is a vector of outputs, w_i is a vector of variable input prices, and $\bar{x}$ is a vector of quantities of fixed inputs. ε_i is the composed error term specified as

$$\varepsilon_i = v_i + u_i, u_i \geq 0, \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2)$$

where v_i is independently and identically distributed (iid) as $v_i \sim N(0, \sigma^2)$, while the elements of u_i follow exponential distribution. The elements of v_i's ands u_i's are independent of one another, and y_i's and w_i's. In this composed error model, the symmetric component, v_i, captures the random effects of measurement errors in costs, external shocks, and events outside a farm's control, while the asymmetric component, u_i, measures farm effect representing technical inefficiency. Therefore, a particular technically inefficient farm lies above the cost frontier either due to random shocks or due to its inefficiency.

For the underlying translog technology, the full stochastic variable cost frontier model is written as

$$\begin{aligned} ln\ VC = \alpha_0 &+ \sum_{i=1}^{3} \alpha_i \ ln\ w_i + \sum_{f=1}^{2} \theta_f\ ln\ \bar{x}_f + \sum_{k=1}^{3} \beta_k\ ln\ y_k \\ &+ \frac{1}{2} \sum_{i=1}^{3}\sum_{j=1}^{3} \gamma_{ij}\ ln\, w_i\ ln\, w_j + \frac{1}{2} \sum_{f=1}^{2}\sum_{g=1}^{2} \theta_{fg}\ ln\, \bar{x}_f\ ln\, \bar{x}_g \\ &+ \frac{1}{2} \sum_{k=1}^{3}\sum_{l=1}^{3} \delta_{kl}\ ln\, y_k\ ln\, y_l + \frac{1}{2} \sum_{i=1}^{3}\sum_{f=1}^{2} \lambda_{if}\ ln\, w_i\ ln\, \bar{x}_f \\ &+ \frac{1}{2} \sum_{i=1}^{3}\sum_{k=1}^{3} \rho_{ik}\ ln\, w_i\ ln\, y_k + \frac{1}{2} \sum_{f=1}^{2}\sum_{k=1}^{2} \mu_{fk}\ ln\, \bar{x}_f\ ln\, y_k + \varepsilon, \quad \ldots \quad (3) \end{aligned}$$

where w_i represents the $i = 1, 2, 3$ prices of variable inputs, $\bar{x}_f$ represent the $f = 1, 2$ quantity of fixed factors, y_k denote the k=1, 2, 3 output quantities, and ε is the composed error term described above. Moreover, *i*, *j* and *f*, *g* denote cross terms for prices of variable inputs and fixed inputs, respectively, and *k*, *l* denote cross terms for outputs. For the variable cost function to be well-behaved we assume linear homogeneity in variable input prices. Linear homogeneity is imposed by normalising variable cost and other variable input prices by one of the variable input prices, while symmetry is imposed in terms of parameters of the model.

The parameters of the translog cost frontier and the density functions of v_i and u_i are estimated by numerically maximising the log-likelihood function for normal-exponential distribution as

$$ln\ \mathcal{L} = log\left(\frac{1}{\sigma_u}\right) + \log\left[1 - F^*\left(-\frac{\varepsilon_i}{\sigma_v} + \frac{\sigma_v}{\sigma_u}\right)\right] - \left[\frac{\varepsilon_i}{\sigma_u} - \frac{\sigma_v^2}{2\ \sigma_u^2}\right], \quad \dots \quad (4)$$

where F^* is the standard normal cumulative distribution function [Aigner *et al.* (1977)]. In this parameterisation, a simple measure of inefficiency is $\lambda = \sigma_u/\sigma_v$, where σ_v and σ_u are the standard deviations of symmetric error and one-sided error, respectively. This measure indicates the relative variability of the two sources of the composed error for each farm in the sample. The model is estimated by using the maximum likelihood method, which gives consistent and asymptotically efficient estimates [Greene (1982)].

A decomposition, suggested by Jondrow *et al.* (1982), of the composed error ε_i from the cost frontier is used to obtain farm-specific estimates of inefficiency. According to this method, the farm level estimates of technical efficiency are obtained by using the expected value of u_i given ε_i, as

$$E\ (u_i|\varepsilon_i) = \left[\frac{f^*(A)}{1 - F^*(A)} - A\right], \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (5)$$

where $f(u) = exp\ ((-u/\sigma_u)\ /\sigma_u\ )$, $A = (\varepsilon_i\ /\sigma_v) + (\sigma_v/\sigma_u)$, and f^* is the standard normal density function.

4. DATA AND ITS DESCRIPTION

This paper is based on data collected by the Punjab Economic Research Institute, Lahore from five districts of the Punjab province of Pakistan in the crop season from May 1991 to April 1992.[4] The sample districts are Vehari, Khanewal, Multan, Faisalabad, and Gujrat. The data were collected, by the interviewing method, from farmers operating small, medium, and large farms. The sample farmers were interviewed in multiple visits by trained enumerators. Detailed information was collected from 387 farms on inputs, outputs, and other production and business-related characteristics. Their distribution by district is 182 farms from Faisalabad, 93 from Khanewal, 66 from Vehari, 27 from Multan, and 19 from Gujrat. The sample districts were located in a radius of about 200 miles, and they had broadly similar per acre yields across districts.

[4]The data were obtained from a field survey by the Punjab Economic Research Institute, Lahore, Pakistan in connection with an irrigation project aimed at rehabilitation of irrigation water distributaries and saline or flood-water disposal. Therefore, the sample design of the survey focuses on three water distributaries and two drainage outlets selected by using stratified, proportionate, and random sampling procedures. A major consideration in sampling design was farm size and the distance of farms from the distributary, emanating from the canal and the point where a water outlet emanated from the distributary. For further details on the survey, see Shahid *et al.* (1992).

The estimation of production efficiency for each farm requires data on inputs and outputs. We use three categories of outputs for the analysis which include crops, livestock, and hiring-out services. The crops variable is an aggregate of wheat, *kharif* fodder, *rabi* fodder, *desi* cotton (local variety), American cotton, sugarcane, maize, and rice. The livestock variable aggregates milk and live animals sold, while hiring-out services are an aggregate for hiring-out of land, tractors, tubewells, and related farm machinery services other than family labour. In the total farm revenue of the sample, 58 percent was contributed by production of crops and 21 percent each by livestock and custom hiring-out services.

The inputs used in the study include three variable inputs, viz., fertiliser (F), hired labour (N) and miscellaneous inputs (MI),[5] and two quasi-fixed inputs, viz., land (L) and capital (K). For the prices of variable inputs we use fertiliser price (w_F) farm level wages of hired labour (w_N), and aggregate price of miscellaneous inputs (w_{MI}). The data on outputs and most categories of inputs are aggregated by first normalising each input and output price by its mean. Then, on the basis of these prices, the quantities derived from observed cost of inputs or observed revenue of outputs were aggregated into outputs or required input categories. Capital service to each farm is based on 10.95 percent return and assumed asset depreciation for buildings, machines and implements, and hand tools.[6]

5. EMPIRICAL RESULTS

In accordance with the assumption of linear homogeneity in variable input prices, we normalise variable cost (VC), w_F and w_N by w_{MI} , while symmetry condition is incorporated directly into the function. We solve the log-likelihood function in (4), which gives the maximum likelihood parameter estimates for the stochastic translog variable cost frontier presented in Table 1. The estimated value of 2.05 for λ indicates that technical efficiency due to internal sources is relatively more important. It implies, in other words, that about 67 percent of the total deviation in cost efficiency of sample farms is due to internal factors under farm-owners' control.

The farm-specific efficiency is obtained by $E(u_i | \varepsilon_i)$ given in (5). Farms that are away from cost frontier are not efficient because they incur higher costs per unit of outputs. The evidence on the degree of cost efficiency in sample farms is summarised in Table 2. It indicates that the cost efficiency of farms varies from a low of 29 percent to a high of 95 percent with mean efficiency of 76 percent. It implies that technical inefficiency raises cost of an average farmer to the tune of 24

[5]The variable input MI includes water, seeds, hired-in services of tractors/threshers, and animal feed.

[6]This rate of return is based on Pakistan (1996).

Table 1

Parameter Estimates for the Stochastic Variable Cost Frontier

Parameter	Estimate	Asymptotic t-Statistic	Parameter	Estimate	Asymptotic t-Statistic
α_0	8.39	1.41*	δ_{33}	−0.08	−0.88
α_1	−1.33	−1.12	λ_{11}	0.06	0.40
α_2	−1.56	−1.42*	λ_{12}	0.02	0.11
θ_1	0.33	0.52	λ_{21}	0.12	0.96
θ_2	−0.63	−1.39*	λ_{22}	0.22	1.83**
β_1	0.54	1.19	ρ_{11}	−0.06	−0.58
β_2	−0.15	−0.73	ρ_{12}	0.06	0.47
β_3	−0.06	−0.54	ρ_{21}	−0.02	−0.31
γ_{11}	0.18	1.24	ρ_{22}	0.10	1.35*
γ_{12}	0.02	0.16	ρ_{31}	0.03	0.91
γ_{22}	0.06	0.73	ρ_{32}	−0.05	−2.11**
θ_{11}	0.11	1.80**	μ_{11}	−0.23	−3.14**
θ_{12}	−0.02	−0.69	μ_{12}	−0.03	−1.03
θ_{22}	0.03	1.68**	μ_{13}	0.01	0.75
δ_{11}	0.10	3.91**	μ_{21}	0.03	0.40
δ_{12}	0.03	1.94**	μ_{22}	0.02	1.92**
δ_{13}	−0.02	−0.31	μ_{23}	0.02	−0.10
δ_{22}	0.01	0.25	σ_u	0.379	12.22**
δ_{23}	−0.03	−0.95	σ_v	0.185	8.85**
λ	2.05	5.87			
Log-likelihood[a]	−165.72	–			
N	387	–			

[a]The convergence for the log-likelihood function was achieved after 913 iterations at 0.0001 tolerance level. The hypothesis that the given set of parameters are jointly zero was rejected by the Wald test at the 1 percent level. The χ^2 test statistic was 34.50.

*Significant at the 10 percent level.

**Significant at the 5 percent level.

Table 2

Frequency Distribution of Cost Efficiency by Farms

% Level of Efficiency[a]	Number of Farms	% of Total
90–100	40	10.34
80–89	156	40.31
70–79	82	21.19
60–69	50	12.92
50–59	38	9.82
49 or Less	21	5.43
Full Sample Means Efficiency (%)	76	–
Std. Dev. of Efficiency (%)	14	–
Number of Farms (N)	387	–

[a] This index is bounded between zero and 1 where a score of 1 depicts the most efficient farm and 0 the least efficient.

percent, which could have been saved had the farmers could have been technically efficient.[7] More specifically, about 10 percent of farms are found to be most cost-efficient. Out of 387 farms, 196 or about 51 percent of the sample farms were operating at observed costs of up to 20 percent higher than the frontier costs, while 34 percent of the farms were operating at observed costs ranging between 21 percent and 40 percent higher than the frontier costs. About 5 percent of sample farms were operating at observed costs of more than 50 percent. The cost inefficiency across farms may be caused by a host of farm-specific factors, of which the most important could be the poor decision-making by the management and misuse of resources. In the following section, we attempt to relate the observed degree of cost inefficiency of farms to the potential sources of such inefficiency.

6. SOURCES OF TECHNICAL EFFICIENCY

For agricultural policy, a question of considerable importance is: Why do efficiency differentials occur across farms? They may be a reflection of technical knowledge and managerial abilities of farm operators, timely availability of essential inputs, quality of inputs and farm size, etc. Because efficiency index is truncated, we use a Tobit regression model to evaluate the sources of estimated differences in cost efficiency of farms.

The explanatory variables used in Tobit regressions are farmers' level of education, age, three variables on access/location of farm from irrigation facility, one variable on access to institutional credit, two variables on area operated and size of land holding, and five variables on geographic location. Farm characteristics and the definition of variables are presented in Table 3. It shows that the mean age of farm operator is 46 years while mean schooling is approximately 4 years. Most of the farms are canal-irrigated (88 percent), while mixed irrigation or tubewell irrigation is practised on the remaining area. About 81 percent of sample farms operate an area of less than 12.5 acres. The land ownership pattern shows that only 21 percent of farms in our sample own 12.5 acres or more. The use of institutional credit varies from zero to Rs 0.48 million in the study period.

To avoid collinearity between some irrigation variables and area owned and operated, we introduce five sets of variables which generate five models. Allowing for efficiency differentials across districts, the Tobit maximum likelihood estimates for each of the five models are shown in Table 4. The dependent variable is measured in units of efficiency, bounded between zero and one, so that a 1 percent increase in the dependent variable implies that the farm could raise its cost efficiency by 1 percent.

[7]Ali (1995) finds resource use inefficiency of 30 percent, on average, in basmati rice production by farmers in Gujranwala district of Punjab. However, these magnitudes are different from our results.

We first consider the effect of education on efficiency. We treat education as a proxy for managerial ability and efficiency in decision-making because education is generally expected to enhance farmers' managerial ability by allowing them to allocate resources more optimally [Fane (1975)]. In Pakistan, where most of the farmers are illiterate, education improves the ability of farmers to collect and process business information, especially on technological innovations and input and output prices. Thus, education is expected to improve their managerial ability, which, in turn, enhances their relative technical efficiency. We find that years of formal schooling have a significantly positive effect in all the models, which indicates that farms managed by more educated farmers are relatively more cost-efficient. The coefficients in Model 1 through Model 5 indicate that, other things remaining constant, one additional year of schooling increases cost efficiency of sample farmers by 3.6 to 4 percent. These results are very similar to those found by Lockheed *et al.* (1981) in a survey of works across LDCs, and generally corroborated

Table 3

Farm Characteristics and Definition of Variables

Variable	Definition	Mean	Std. Dev.	Min.	Max.
Personal Characteristics					
Schooling	Years of formal schooling	3.93	4.59	0.00	16.00
Age	Age in years	46.27	15.49	12.00	90.00
Irrigation Systems					
Canal	= 1 if only canal irrigated, 0 if canal + tubewell, or only tubewell irrigated	0.88	0.32	0.00	1.00
Water Outlet	= 1 if located near the water outlet, 0 otherwise	0.31	0.46	0.00	1.00
Drainage Sample	= 1 if from the saline drainage sample, 0 otherwise	0.35	0.48	0.00	1.00
Farm Size					
Area Operated	= 1 if area operated is 12.5 acres or more, 0 otherwise	0.19	0.40	0.00	1.00
Area Owned	= 1 if land owned is 12.5 acres or more, 0 otherwise	0.21	0.41	0.00	1.00
Others					
Loan	Institutional loan (Rs)	9354.21	34415.20	0.00	487200.00
District 1	= 1 if in Faisalabad district	0.47	0.50	0.00	1.00
District 2	= 1 if in Khanewal district	0.24	0.43	0.00	1.00
District 3	= 1 if in Vehari district	0.17	0.38	0.00	1.00
District 4	= 1 if in Multan district	0.07	0.26	0.00	1.00
District 5	= 1 if in Gujrat district	0.05	0.22	0.00	1.00
N	Sample size	387			

Table 4

Sources of Technical Efficiency Using Tobit Regressions

Variable	Dependent Variable is Index of Technical Efficiency				
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.752	0.755	0.738	0.800	0.788
	(11.21)**	(11.38)**	(11.00)**	(12.44)**	(12.10)**
Personal Characteristics					
Schooling	0.038	0.036	0.036	0.040	0.040
	(2.42)**	(2.31)**	(2.28)**	(2.56)**	(2.48)**
Age	–0.016	–0.017	–0.012	–0.019	–0.014
	(–0.65)	(–0.71)	(–0.50)	(–0.78)	(–0.58)
Age^2	0.0002	0.0002	0.0001	0.0002	0.0002
	(0.72)	(0.77)	(0.51)	(0.91)	(0.65)
Irrigation Systems					
Canal	0.056	0.058	0.062	–	–
	(2.52)**	(2.69)**	(2.87)**		
Water Outlet[a]	0.048	0.056	0.055	–	–
	(2.55)**	(3.43)**	(3.31)**		
Drainage Sample	–0.015	–	–	–0.049	–0.047
	(–0.86)			(–3.32)**	(–3.16)**
Farm Size					
Area Operated	–0.013	–	–0.043	–	–0.043
	(–0.54)		(–2.34)**		(–2.33)**
Area Owned	–0.045	–0.054	–	–0.060	–
	(–1.88)**	(–2.90)**		(–3.17)**	
Others					
Loan	0.000	0.000	0.000	0.000	0.000
	(1.06)	(0.98)	(0.71)	(1.29)	(0.96)
District 1[b]	–0.042	–0.052	–0.045	–0.010	–0.033
	(–1.27)	(–1.66)*	(–1.41)*	(–0.32)	(–0.11)
District 2	0.017	0.083	0.012	0.046	0.049
	(0.52)	(0.26)	(0.36)	(1.38)*	(1.46)*
District 3	–0.031	–0.041	–0.041	0.089	0.066
	(–0.85)	(–1.16)	(–1.16)	(0.26)	(0.19)
District 4	–0.071	–0.078	–0.096	–0.044	–0.065
	(–1.77)**	(–1.98)**	(–2.48)**	(–1.10)	(–1.63)*
σ^2	0.129	0.129	0.130	0.132	0.133
	(27.82)	(27.82)	(27.82)	(27.82)	(27.82)
Log-likelihood	242.68	242.09	240.63	235.27	233.00
N	387	387	387	387	387

Notes: These results are based on a Tobit regression censored below at 0 and above at 1. Numbers in parentheses are asymptotic *t*-values.

*Significant at the 10 percent level.

**Significant at the 5 percent level.

[a]The first one-third length of the branch distributary from its outlet in the main canal is defined as near the water outlet or *mogha*.

[b]Farms located in Gujrat district are the excluded category.

by Phillips (1994) and others.[8] There are strong similarities between the impact of education on efficiency in agriculture to that found by Burki and Terrell (1998) for small manufacturing firms in Pakistan. It is surprising that Azhar (1991) found little or no association between education and efficiency from a 1976-77 sample of basmati rice-producing farmers in a traditional production relationship. Azhar's finding may be explained by the fact that his sample of farmers used traditional production technology, which required no formal education. In the new production environment since 1980s, technical and economic needs of farmers have drastically changed and explain the observed positive association between education and farmers' technical efficiency.

Age of the farmers is found to have no significant influence on technical efficiency of farms in any of the models. This suggests that, on average, older farmers are equally efficient in their use of resources as their younger counterparts.

Irrigation water has played a central role in the adoption of modern varieties (MVs) of seed and fertiliser during the Green Revolution and post-Green Revolution periods.[9] Increased supplies of water on partially irrigated lands increase crop yields. Therefore, interrupted supply of water due to unscheduled canal closures or tubewell breakdowns is found to increase technical inefficiency of rice-growing farmers in Punjab [Ali (1995)]. Nonetheless, in canal irrigation system, the distance of farm location from the head of a distributary or a water outlet influences water availability per cultivated acre that may explain the variability of cost efficiency. For example, Punjab farmers located near the head of distributaries get 1.6 times higher water discharge from their water outlets than farmers located near the tail-ends [Shahid *et al.* (1992)].[10] The availability of detailed information on the location of farms from canal water outlets, as well as farm location near saline drainage water, gives an opportunity to investigate possible linkages between irrigation mechanisms and cost efficiencies. Therefore, in Table 3 we define *canal* dummy variable which equals one if farms used only canal irrigation and equals zero if farms practised mixed-irrigation or used only tubewell irrigation. The *water outlet* dummy variable equals one for head-end farmers and equals zero for tail-end farmers, while *drainage sample* equals one for farms located along saline and flood-water disposal drains.

Access to sufficient canal water and farm location near *mogha* or water outlet are found to have positive and significant impact on technical efficiency of farms. As expected, the positive and significant coefficients for canal dummy predict that

[8]See, for instance, Stefanou and Sexana (1988); Kalaitzandonakes and Dunn (1995); and Ali (1995).

[9]During the Green-Revolution period (1966–76), MV's of wheat were rapidly adopted in over two-thirds of the wheat-growing area. However, in the post-Green Revolution period (1976–90), the use of MV's of wheat was slowly extended to almost all the irrigated areas of Pakistan [Byerlee and Siddiq (1994)].

[10]Similar problems of tail-end versus head-end farms were reported for India by Panda (1986) and Srivastava and Gupta (1992).

farmers exclusively depending on canal irrigation are about 6 percent more cost-efficient than those who use only tubewells, or practise mixed irrigation. Due to better quality of canal water than the tubewells, mixed irrigation is practised only when either farmers have no access to canal irrigation, or their authorised discharge of water is uncertain due mainly to their location at the tail-end of watercourses or distributaries. The evidence from the sample survey shows that some of the farmers at the tail-end of the distributaries had permanently closed their *moghas* due to insufficient water supply. The significant coefficient for canal may be further explained by the poor quality of groundwater from tubewells as compared with canal water.

The dummy variable for water outlet sheds further light to explain this scenario. The significantly positive effect of water outlet or proximity of farms to *mogha* indicates an additional gain in cost efficiency ranging from 4.8 to 5.6 percent, implying that farms located near head-end of *mogha* have significant cost advantage over the tail-end farmers. Farms near *mogha* have relatively more supply of water, which together with MV's and fertiliser increases cropping intensity and crop and livestock yields.

Due to obvious collinearity between water outlet and drainage sample, farmers' location near saline drainage watercourses appears to have no statistical relationship with technical efficiency in Model 1. However, treating this variable separately explains the negative and significant relationship between resource-use efficiency and location of farmers near saline drainage watercourses. Our results predict that, other things remaining constant, farm efficiency on average falls in the range of 4.7 to 4.9 percent for farms located in the drainage sample.

Both short-term and long-term loans are available to farmers in Pakistan. Short-term loans are generally available to purchase seeds, fertiliser, and other such inputs, while long-term loans are used to purchase assets, such as tubewells, tractors, and tractor-driven implements, etc. Although both kinds of loans reflect embodied technical change, investment on assets takes a longer period to increase technical efficiency of farmers. Ideally, we need separate information on short-term and long-term loans, which was not available from the sample survey. The composite loan variable is positive but surprisingly it has no significant effect on technical efficiency of farms. One possibility could be that the loans used for long-term investments obscure the impact of technical change on the technical efficiency index. However, we cannot rule out another possibility that in violation of the terms and conditions of loans, the creditors may be mis-employing their loans for consumption purposes.

The dummy variables for area operated and area owned are expected to have strong collinearity for obvious reasons. Therefore, the two farm size variables, when included together, do not give unbiased results in Model 1. However, in alternative specifications both are significantly negatively related with technical efficiency. These results indicate that farmers operating smaller farm sizes (less than 12.5 acres) are 4.3 percent more efficient than farms operating 12.5 acres or above. Similarly, our results predict that farms with land-holdings of 12.5 acres or more are about 5 to 6 percent less efficient than the excluded category. The cost advantage to small farms can be attributed to their intensive use of land, machines/tools, and family labour.

7. CONCLUSION AND POLICY IMPLICATIONS

In this article we have estimated cost efficiency on a sample of 387 farms drawn from five irrigated districts of Punjab, Pakistan. A translog variable cost frontier relating three variable inputs (fertiliser, hired labour, and miscellaneous inputs), two quasi-fixed inputs (land and capital), and three composite outputs (crops, livestock, and hiring-out services) to variable cost was fitted to the survey data which generated an index of farm-level technical efficiency. Our results based on whole-farm data show that technical inefficiency raises the cost of an average farm in our sample by 24 percent. The observed technical efficiency of sample farms pointed to a positive association between technical efficiency and education of farm operators, abundance of canal water, and head-reaches of *mogha*. The farm-size, however, was found to be negatively correlated with technical efficiency. Moreover, we found no relationship between the age of farm operators and their technical efficiency. At the same time, our data did not permit us to reach a clear conclusion on the role of institutional loans in farm efficiency. Since long-term loans take a longer period to increase technical efficiency, their effect on technical efficiency may be enigmatic. Moreover, if these loans are mis-employed by their users, then the key policy change should be to eliminate existing distortions.

The most obvious policy implications from the above conclusions are that sound policies regarding investment on education of rural households and canal irrigation management will have a positive effect on technical efficiency of farms in Pakistan. The robust conclusion that schooling improves efficiency confirms a crucial role for human capital. Therefore, human capital investments by the government to provide public education and to raise the quantity and quality of education should enhance farm-level cost efficiency and total factor productivity. The results from this study conform to the standard view of agricultural development. For instance, the abundance of water, which is long understood as crucial for agricultural development, also leads to greater technical efficiency of farms in Pakistan. Hence farms with sufficient supply of canal water were found to have much better efficiency than those which exclusively used tubewell water or practised mixed-irrigation. In Pakistan, the shortage of water at tail-end of watercourses arises from water loss due to seepage and rat-holes. An even bigger problem is that water outlets or *moghas* are tampered with and made oversized by the farmers in connivance with the canal water functionaries. Watercourses are also cut by the farmers due to which such losses increase along the length of a watercourse. This shortage of water is met by tubewells, as indicated by the average number of tubewells per canal water outlet towards the tail-end of distributaries that were more than the number towards the head-reaches. The result that tail-end farms tend to be less efficient than the head-end farms is consistent with the result that canal water abundance has a positive impact on technical efficiency. These results confirm that public investments by the provincial irrigation department on cleaning and desilting of canals, paving watercourses, and redressing the grievances of tail-end farmers about unequal access to water undoubtedly have large returns in the form of increased farm-level efficiency. In this regard, community-based organisations can play a very effective role in overcoming the grievances of tail-end farmers, especially if proper support is provided by the government.

Our analysis again raises the issue of efficiency of small versus large farms. Contrary to the evidence on the basis of data of a single-crop, that small and large farms are equally efficient [Ali (1995)], our results on the basis of whole-farm data show that small farms are more efficient due to their intensive use of land, machines, and family labour. Our advice to the policy-makers is that government programmes aimed at supporting small farms can improve farm efficiency. However, direct intervention by the government should be carefully planned; otherwise it may prove to be counter-productive. For example, government support programmes for small farms should not in any way hinder the growth of large farms, which have the potentials for specialisation, economies of scale, and revenue generation in the form of taxes.

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