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TECHNICAL EFFICIENCY IN BASMATI RICE PRODCTION

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Increasing competition in international markets, and increasing production costs, increases the need for greater efficiency in Basmati rice production. Levels of technical inefficiency which now exist were estimated via a frontier production function. The modal level of technical inefficiency at farm-specific resource levels among 115 Basmati rice producers was 20 per cent which translated into a modal yield loss of 0.4 tons/ha. The better educated households tended to be more technically efficient; late transplanting, and late fertilizer application and water shortages contributed significantly to farm-specific technical inefficiency.

I. Introduction

Basmati 370 rice is one of Pakistan's most important crops. Over 35 per cent of the nation's rice area – and most of Punjab's rice land – is planted to this variety. Therefore, a large amount of Pakistan's most productive land, labor and irrigation water are allocated to this crop. Nearly half of the Basmati rice harvest is exported, generating about 10 per cent of foreign exchange earnings from commodity trade. Pakistan has a comparative advantage in Basmati rice production [Azhar and Mahmud (1984)] and also enjoys a near monopoly in this highly specialized, but thin international market for aromatic (fragrant) rice [Efferson (1985)]. However,

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Pakistan now faces the possibility of increased competition from India, Thailand and the USA in this specialized market. The recent decline in oil prices has further reduced the demand in the Middle East, historically the destination for over 95 per cent of Pakistan's Basmati rice export.

Basmati rice yields in recent years have stagnated, while production costs have increased [Amir and Knipsheer (1986)]. This scenario, of declining export opportunities and increasing production costs, emphasizes the need to increase efficiency in Basmati rice production, to ensure Pakistan remains internationally competitive in this market. Two broad opportunities exist to increase resource use efficiency: the generation of cost-reducing technologies; and enhancing the efficiency of farmer's use of existing technology.

Rice scientists have not succeeded in raising the yield ceiling of Basmati due to its poor recombining ability when quality attributes are important breeding objectives. Nonetheless, there is strong evidence that the yield potential of Basmati rice is not being realized by farmers; there are short-run opportunities to increase Basmati productivity using existing technology, as demonstrated in the pilot Rice Maximization Project in Punjab [Muhammed (1985)].

This paper provides an estimate of existing potential yield under farmer conditions, an estimate of the level of technical inefficiency in Basmati rice production, and examines the sources of this inefficiency. The study area was Gujranwala district, at the heart of the 'Kalar Tract' which is world renowned for the production of fine grained Basmati rice. An appreciation of efficiency losses and potential gains from increasing production efficiency should add to the impetus of programmes designed to increase Basmati production in Pakistan.

II. Measuring Technical Efficiency

Economic efficiency consists of two components: technical efficiency and price (or allocative) efficiency [Farrel (1957)]. A technically efficient firm is one which produces the maximum quantity of output for a given quantity of input. A farm is price efficient if it applies that quantity of inputs which maximizes profit, given the production function and prices it faces. A farm is economically efficient if it is both technically and price efficient [Farrel (1957)]. Of particular concern in this paper is the measurement of comparative technical efficiency of Basmati rice growers in Pakistan Punjab.

Average, or farm-specific, technical efficiency is measured by comparing farmer's yields with best practice techniques, given the farmer's input level.

This potential may be interpolated from yields of researcher-managed plots [e.g., Herdt and Mandac, (1981)], or the most efficient farmers in a sample [e.g., Bagi (1982)], Kalirajan and Flinn (1983)]. The latter proxy was adopted in this study and so provides a comparative measure of technical efficiency of each farmer with respect to best farmer techniques, given that farmer's resource base. Research-based yields were not used because (a) the data was not available, and (b) even if it were, because researchers rarely face the same constraints as farmers, estimates of farmer's technical inefficiency derived in this manner will be biased and larger than is realistically the case under farmer's conditions.

The textbook definition of a production function holds that it maps the maximum possible output which can be produced for given quantities of a set of inputs [Yotopoulos and Nugent (1976)]. Therefore, failure to operate on the production surface results in technical inefficiency [Farrel (1957)].

Farrel (1957) further proposed that the production surface may be estimated using linear programming techniques. Others, as Aigner and Chu (1968), and Timmer (1970) extended the application of programming techniques to the measurement of efficiency. However, this approach has severe limitations [Aigner et al. (1977)]. For example, the approach does not take into account statistical random errors (e.g., errors of measurement, variability due to differences in the levels of excluded variables) which are accounted for, for example, in composed error techniques. It is for these reasons that Forsund et al. (1980) came out strongly in favor of the composed error model for the analysis of technical efficiency.

Programming models are also less advantageous when the technical efficiency of an individual crop is of particular interest. Nor does the approach readily allow the measurement of farm-specific technical efficiency. In this case, models based on variants of production function models have grater appeal. However, ordinary or generalized least squares techniques, the usual means by which production functions are estimated, result in the specification of an "average" production function; a frontier production function must be estimated to provide a measure of technical efficiency [Aigner et al. (1977)].

Composed Error Model

Several authors [for a comprehensive review see, Forsund et al. (1980)] have discussed the estimation of production frontiers of the form:

$$Y = f(X, \beta)\, e^{\epsilon} \tag{1}$$

where

$Y = n \times 1$ vector of output of the ith farm;

$X = m \times 1$ vector of inputs;

$\beta = m \times 1$ vector of parameters;

$\epsilon = n \times 1$ vector of error terms; and

e = the natural exponent.

The error term, ϵ, is composed of two independent terms,

$$\epsilon = v - u \tag{2}$$

where v is a symmetrical two-sided error term which captures the effects of random shocks outside the farmer's control, observation and measurement error, and other statistical noise. Thus, v allows the frontier to vary across farms, or over time for the same farm, and therefore the frontier is stochastic. Technical efficiency of the i-th farm relative to the stochastic frontier is

$$e^{-u_i} = Y_i / f(X_{ij}, \beta_j) \; e^{v_i} \tag{3}$$

which is captured by the one sided error component, $u_i \geqslant 0$.

Average efficiency has been estimated (from frontier functions) as the mean of the difference, or the ratio of actual to calculated output. However, this estimate of inefficiency includes the effect of the random error, v, in addition to the one-sided "technical" error term u, which is of primary interest. If the symmetric error v is assumed to be distributed as $N(0, \sigma_v^2)$, and the non-negative error u is assumed to be distributed as the absolute value of a half normal distribution, $N(0, \sigma_u^2)$,[1] then the population average technical efficiency is estimated as [Lee and Tyler (1978)]:

$$E[e^{-u}] = 2\, e^{(\sigma_u^2/2) \bullet [1-F(\sigma_u)]} \tag{4}$$

where $F(\bullet)$ is the standard normal distribution function evaluated at σ_u.

[1] As a Journal reviewer correctly pointed out, the assumption that u is half normal is not unique. Aigner et al. (1977) and Schmidt and Lovell (1979) for example, compared half normal and exponential distributions for u and found that both formulations of the one-sided error term gave similar results. Stevenson (1980) assumed u followed a gamma distribution which gave slightly better results, but was computationally more difficult than assuming u was half normal, given his data set.

Most analysis of technical efficiency has assumed u is half normal [e.g., Bagi (1982); Kalirajan and Flinn (1983)]. Clearly, the robustness of different error structures in frontier estimation requires closer examination.

Farm-Specific Efficiency

Jondrow et al. (1982) and Kalirajan and Flinn (1983) demonstrate that the expected value of u_i, i.e., the technical efficiency of the i-th farm may be calculated using the distribution of u_i, conditional on ϵ_i (i.e., v_i -- u_i). The estimating relationship is:

$$E(u_i/\epsilon_i) = \sigma_* \left[\frac{f(\epsilon_i\lambda/\sigma)}{1\text{-}F(\epsilon_i\,\lambda/\sigma)} - (\epsilon_i\lambda/\sigma)\right] \tag{5}$$

where F(•) is as previously defined, f(•) is the standard normal density function estimated at $(\epsilon_i\lambda/\sigma_i)$, and

$$\lambda = \sigma_u/\sigma_v,\ \sigma = (\sigma_u^2 + \sigma_v^2)^{1/2} \text{ and } \sigma_*^2 = \sigma_v^2 \bullet \sigma_u^2/\sigma^2 \tag{6}$$

The estimate of u_i is obtained by replacing ϵ_i by its estimated residual, $\hat{\epsilon}_i$, and the unknown parameters σ_*, σ and λ by their estimates which are also derived from the residuals of equation (1) given an error structure as equation (2). The technical efficiency of the i-th farm is then directly given by exp $(-u_i)$, or technical inefficiency by $[1\text{-exp}(\text{-}u_i)]$.

Estimates of the parameters of the stochastic frontier model (i.e., β, and as a result, σ^2, σ_u^2 and σ_v^2) are obtained using maximum likelihood or Corrected Ordinary Least Square (COLS) methods [Forsund et al. (1980)]. COLS estimates of the response surface are derived by adjusting the constant term by E(u), which is derived from the second and third moments of the OLS residuals [Richmond (1974)]. COLS estimates are easier to estimate than are MLE, although they are asymptotically less efficient [Forsund et al. (1980)]. Nonetheless, parameter estimates of the MLE and COLS models are similar [Olson et al. (1980)]. In this paper, the COLS method was used to estimate the Basmati frontier production function, equation (1), subject to the error structure of equation (2).

III. The Study Area

The Data

Basmati is produced in three ecologically homogenous districts of Punjab: Gujranwala, Sialkot and Sheikhupura. Gujranwala district was chosen as the study site as it is the district which produces the greatest quantity of Basmati rice in Punjab. In 1981-82, this district produced 23 per cent of all the rice produced in Punjab and about 30 per cent of the Basmati rice produced in Pakistan [PARC (1983)]. Gujranwala is predominantly a rice-wheat zone; these two crops occupied 75 and 72 per cent of the cropped area during Kharif and Rabi seasons of 1980-81 [Government of Punjab (1983)]. Sixty farmers were randomly selected as respondents from each of the two villages selected as survey sites. Data on farmer-management of their Basmati rice crop was collected on a plot-by-plot basis through repeat interviews for the 1982 rice crop.[2] Data from 115 of the 120 farmers interviewed was included in this analysis; the data set comprises 168 plots as many farmers had more than one plot of Basmati.

Respondents, on average, were 45 years old and had attended school for 3 years (Table 1). Mean farm size was 3 ha, with a range from 0.3 to

TABLE 1

Characteristics of sampled Basmati rice growers in Gujranwala district, 1982

	Units	Average value	Range	
			Lower	Upper
Household characteristics	(n = 115)			
Family size	no.	7	2	18
Operator's age	years	45	25	65
Schooling, operator	years	3	0	12
Schooling, adults	years	11	0	38
Tenure	owners	77	–	–
	tenants	26	–	–
	mixed	12	–	–
Rice production				
Farm size	ha	3	0.3	20
Problem soils	%	20	0	100
Compost	cart/ha	2	0	10
Fertilizer NPK	kg/ha	100	0	170
Labor-total	days/ha	59	35	100
-family	days/ha	34	0	100
-hired	days/ha	28	0	81
Labor-weeding	days/ha	7	0	25
-family	days/ha	4	0	25
-hired	days/ha	3	0	21
Irrigation	hrs/ha	115	35	215
Yield	t/ha	1.8	0.6	3.0

[2] A plot was defined as a contiguous piece of land grown to Basmati rice, under one system of tenure, management and irrigation source.

over 20 ha; about 20 per cent of the crop was grown on problem soils, largely due to salinity. Sixty seven (67 per cent) of the farmers sampled owned all the Basmati plots they farmed, while 26 (23 per cent) were tenants and 12 (10 per cent) of the respondents owned some of the plots of Basmati they farmed, but were tenants on others. In all cases, tenanted plots were farmed on a share basis, with the landlord receiving one third of output and paying for one third of input costs, other than for labor.

Input use for Basmati production varied between farms. For example, while the mean application rate of NPK fertilizer was 100 kg/ha, the range of fertilizer use varied from one farmer who applied no fertilizer, to another who applied 170 kg NPK/ha. Labor inputs ranged from 35 to 100 labor days/ha, with a mean of 59 days/ha. On average, family and hired labor was equally used to produce Basmati: the main use of hired labor was for transplanting, harvesting and threshing. Weeding labor – a variable included in the production frontier averaged 7 days/ha. Transplanting labor was not included, because, as transplanting is by hired labor, there was little variability in transplanting labor used between farms.

The mean yield of Basmati rice over the sampled farms was 1.8 tons/ha of paddy rice, with a range from 0.6 to 3 tons/ha. Thus, there was over 1 tons/ha gap between the average and highest farm yield, suggesting that there are opportunities for increasing rice yields, given current technology. However, it is not clear how much of this yield gap is due to technical inefficiency and how much is due to constraints beyond the farmers control, as soil constraint.

Empirical Model

The empirically estimated production frontier for the Basmati rice production process was:

$$\ln Y_i = \ln a_o + \sum_{j=1}^{4} a_j \ln X_{ij} + b_1 D_i + v_i - u_i \tag{7}$$

where

Y_i = yield of Basmati of the ith farm, in kg/ha;
X_1 = fertilizer, in kg of NPK/ha;
X_2 = weeding labor, in days/ha;
X_3 = compost, in cart loads/ha;
X_4 = irrigation hours/ha;
D = dummy variable, D=0 for problem, and D=1 for good soils;
v = a disturbance term with normal properties;
u = farm specific error term as defined in equation (2).

The parameters of equation (7), as previously mentioned, were estimated using COLS procedures.

This model was estimated on a per hectare basis. There were three reasons for this: first, it is intuitively simpler to directly interpret efficiency on a per unit area as opposed to a (variable) per plot basis; second, farm size was collinear with other variables included in the model; and third, and anticipating the analysis, we later seek to determine whether plot specific inefficiency is related to farm size, an issue frequently debated with respect to Pakistan agriculture [e.g., Khan (1979)]. A translog expansion of equation (7) was also fitted to the data. This formulation was rejected in favour of the simpler, but clearly more restrictive, Cobb-Douglas model, because (a) there was high collinearity among the interaction terms, and (b) the assumption that all interaction terms were equal to zero could not be rejected as the calculated F-ratio for this constraint, 1.47 (n_1=20, n_2=139), was not significant at the 10 per cent level.

IV. Results and Discussion

Production Frontier Estimate

The COLS estimates of the stochastic production frontier for Basmati rice production are listed in Table 2. Yield was significantly related to the rate of inorganic fertilizer (X_1), farmyard manure (X_3), irrigation water applied (X_4), and to the soil quality dummy (D_1). However, yield was not significantly related to weeding labor inputs (X_2). The production elasticity for inorganic fertilizer (0.07) is low and consistent with expectation, as Basmati rice is not fertilizer responsive, when compared for example, to modern rice varieties as IRRI-6. The production elasticity for irrigation hours (0.25) is high, possibly indicating that the high price of pumping keeps irrigation water use comparatively low and so its marginal productivity comparatively high. However, the most important factor to increase rice productivity is the reclamation of problem soil areas. If constant returns to variable inputs are assumed to prevail, then the production elasticity of land (and other non-measured inputs) is about 0.67.

The marginal products of inputs included in equation (7) were calculated from the elasticities reported in Table 2 and the mean input levels, reported in Table 1. As shown in Table 3, the marginal products are highest for compost (6.6) and irrigation time (3.9), and lowest for fertilizer (1.2) and weeding labor (1.0). The real prices of these inputs – input price divided by rice price – are listed in the right most column of Table 3. The marginal products compare favourably with the real prices of inputs, indicating that

TABLE 2

COLS estimates of frontier production function, Basmati rice producers, Gujranwala district, 1982[1]

Variable[2]		Estimated coefficient	Standard error
$\ln a_0$	Constant	6.0107**	0.2897
$\ln X_1$	NPK fertilizer	0.0659*	0.0393
$\ln X_2$	Weeding labor	0.0040^{ns}	0.0062
$\ln X_3$	Compost manure	0.0073*	0.0033
$\ln X_4$	Irrigation hours	0.2517**	0.0566
D	Problem soil	0.4436**	0.0424
$\bar{R}^2$		0.4700	
F ratio (5, 162)		30.8700**	
$\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$		0.5506	
$\lambda = (\sigma_u^2/\sigma_v^2)$		0.6904	
σ_u^2		0.0978	
σ_v^2		0.2053	
$\theta = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$		0.3228	

1. **, *, +, ns implies significant at the 1, 5 and 10 per cent levels, and not significant.

2. $\bar{R}^2$ and F relate to the OLS estimates of equation (7).

TABLE 3

Marginal value product of variable factors, Basmati rice production, Gujranwala district, 1982

Input	Unit	Marginal product[1]	Real price[2]
NPK Fertilizer	kg/ha	1.19	1.45
Weeding labor	days/ha	1.03	1.10
Compost manure	carts/ha	6.57	6.00
Irrigation	hrs/ha	3.94	4.40

[1] Calculated as $\bar{Y}/\bar{X}_i * b_i$ where $\bar{Y}$ is average yield (1.8 t/ha); $\bar{X}_i$ is average value of variable input; and b_i is input elasticity from Table 2.

[2] Calculated as input price divided by rice price.

Basmati rice producers, on average, are tolerably price efficient.

The ratio of the standard errors of u and v (i..e. λ) is 0.69, implying that the random error v dominates the sources of variation among Basmati rice producers. The value of θ [i.e., $\sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$] is 0.32, implying that about 32 per cent of the variability in actual yields from best practice yields is due to technical inefficiency.

Technical Efficiency

Average (population) technical efficiency, estimated via equation (3) is 0.79, or 79 per cent. In other words, estimated average population technical inefficiency is 0.21 (i.e., 1- 0.79), or 21 per cent; and represents the average degree of failure to produce maximum output from a given level of inputs. The distribution of plot-specific technical inefficiencies, estimated via equation (5), are dispalyed in Figure 1(a). The modal level of technical inefficiency was 20 per cent, with a minimum value of 16 per cent and a maximum value of 34 per cent, three-quarters of the sample plots exhibited technical inefficiencies of less than 25 per cent.

The mean yield loss due to technical inefficiency was 0.45 tons/ha. The yield-loss distribution was positively skewed, with a mode of 0.39 tons/ha; with a minimum yield loss of 0.27 tons/ha and a maximum yield loss of 0.72 tons/ha [Figure 1(b)] . The implication from an extension viewpoint is while there are opportunities to increase the yields of average farmers towards best-farmers' techniques, there may also be potential to increase the yields of farmers now realizing higher yields, given input levels applied. Nonetheless, these results indicate that the yield shortfall between the average farmer's actual practice and if he adopted best practice techniques was somewhat less than the 1 tons/ha-or-more yield difference often thought to exist betwen the yields of typical farmers and those following best practice techniques.

Determinants of Technical Inefficiency

To determine the association between farm household characteristics and technical inefficiency plot specific estimates of technical inefficiency were regressed against these characteristics using ordinary least squares.[3]

[3] A Tobit transformation of this model is also logical [Amemiya (1984)] as technical inefficiency is a continuous variable falling in the range of (0, 1). However, as there were no observations and certainly no clustering of observation at the limit points, and because none of the predicted values of the OLS model lay outside the limits of (0, 1) the OLS model was used as it permits direct interpretation of the estimated partial regression coefficients.

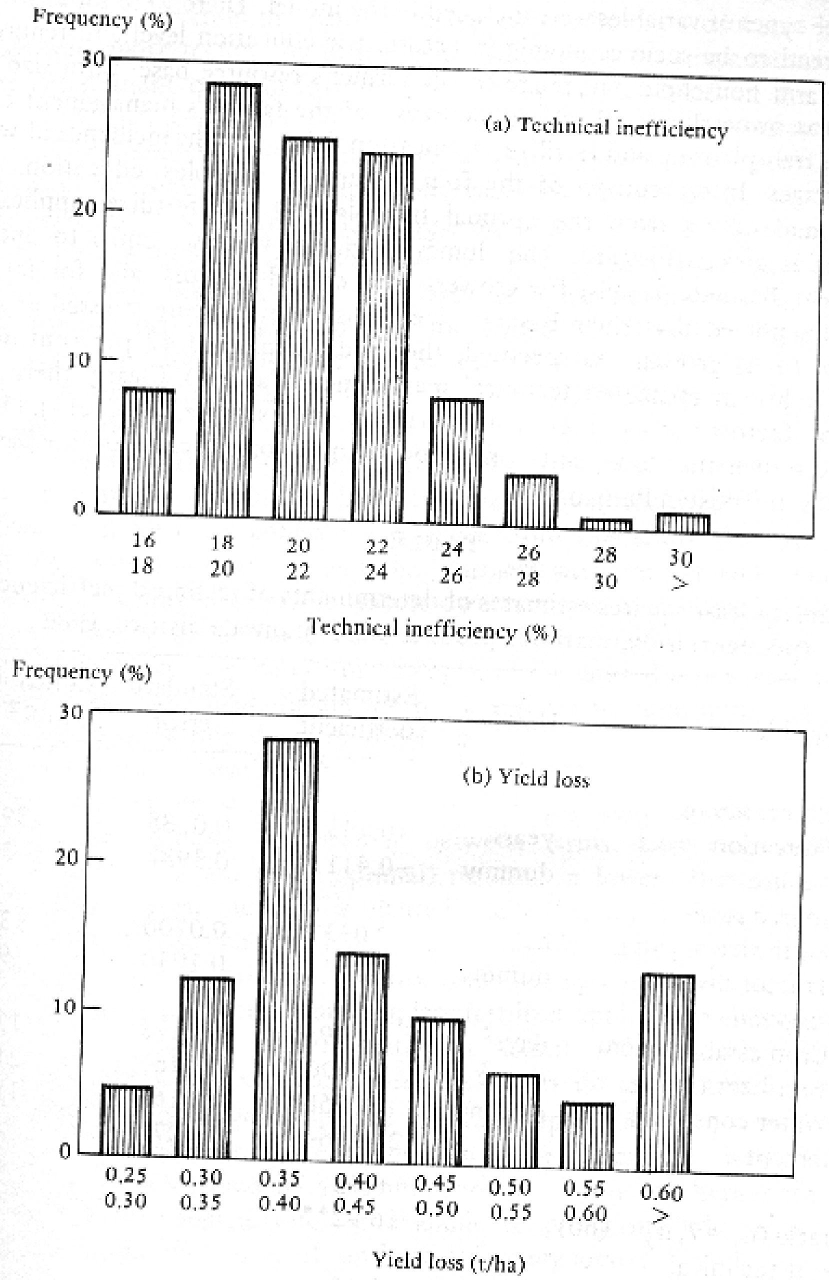

Figure 1

Frequency distributions of plot-specific (a) technical inefficiency, and (b) yield loss due to technical inefficiency in Basmati rice production, Gujranwala District, 1982

Three types of variables were included in the model. There were those which: (a) tend to be socio-economic in nature: the education level and tenure of the farm household; (b) relate to the farmer's resource base: farm size and tractor ownership; and (c) are indicative of the farmer's management capacity: transplanting and fertilizer application dates, and the incidence of water shortages. Interpretation of the four continuous variables: education, farm size and delays from the optimal transplanting and fertilizer application dates is straightforward. The dummy variables were set equal to one for owned Basmati parcels; for growers who owned tractors; and for farmers who reported that their Basmati rice crops were moisture stressed at some stage of its growth. As specified, the model explained 42 per cent of the variability in estimated technical inefficiency (Table 4). Clearly there were many factors not captured in the analysis. For example, Amir, et al. (1984) have shown that low plant population is an important cause of low Basmati yields in Pakistan Punjab.

TABLE 4

Ordinary least squares estimates of determinants of technical inefficiency (per cent) in Basmati rice production, Gujranwala district, 1982.

Variable	Units	Estimated coefficient[1]	Standard error	Contribution to R^2 (%)
Socio-economic				
Education	years	-0.1431^{**}	0.0188	39
Tenure	dummy	-0.4111^{ns}	0.3987	5
Resource base				
Farm size	ha	0.0337^{ns}	0.0700	3
Tractor owner	dummy	0.1121^{ns}	0.1930	9
Managerial				
Crop establishment	$days^2$	0.0395^{*}	0.0173	12
Fertilizer timing	$days^2$	0.0990^{**}	0.0261	21
Water constraint	dummy	0.0368^{*}	0.0169	11
Intercept		21.4364	0.5272	
$\overline{R}^2$		0.42		
F ratio ($n_1 = 7, n_2 = 160$)		16.92^{**}		
SE of technical inefficiency		2.15		

[1] **, * and ^{ns} implies significant at the 1 and 5% levels, and not significant.

[2] Days from optimal.

The socio-economic variables as a group accounted for 44 per cent of the explained variation in technical inefficiency. The more educated households were more technically efficient; this factor was the single most important determinant of yield loss identified, based on the values of the marginal R^2 (39 per cent). The positive association between education and productivity is consistent with the observations of Jamison and Lau (1982). The sign for tenure was negative but was only significant at the 30 per cent level. As Feder et al. (1985) aruge, the observed effects of tenancy on efficiency are probably indirect, through the implied relationship between tenure and for example, access to credit, technical information, and input and product markets. Therefore, if these factors are directly included in the model, or indeed they are not important in the specific social system being studied, then tenants and owners may exhibit similar levels of technical efficiency.

The farmers' resource base, as reflected in farm size and tractor ownership, were not significantly related to differences in technical inefficiency. Therefore, there is no conclusive evidence from this study that larger farmers are more (or less) efficient than farmers with smaller land holdings. The lack of significance of the tractor ownership variable possibly indicates that the time available for land preparation between wheat and rice is not a major constraint, compared for example, to the limited turnaround period between rice and wheat (Salam 1978). There was no significant difference in mean transplanting dates of those who owned, hired tractors, or used bullocks for rice cultivation which reinforces this contention.

Management constraints contributed 44 per cent to the explained variability in technical inefficiency between farms. Late crop establishment (late July is said to be optimal) resulted in lower efficiency as rice yields decline when the crop is planted late and so matures into the cool, winter season. Reasons cited by farmers for late transplanting included waiting for the monsoon rains before commencing cultivation, and a shortage of transplanting labor. Similarly, late fertilizer application -- the optimal date is just prior to panicle initiation, about 50 days after seeding – results in significant efficiency loss. Lack of credit and fertilizer supplies, and a lack of knowledge of optimal fertilizer application time were reasons advanced by farmers for late application of fertilizer. The water supply constraint, approximated by a dummy variable to reflect whether the crop had been water-stressed, due for example to pump breakdown or canal closure, also contributed significantly to efficiency losses.

Caveat to the Study

A possible limitation of this analysis is that the farm-specific technical efficiency estimates were based on a single time period when in fact, resource allocation decisions are often long-term, and based on projections and expectations over more than one time period [Dawson (1985), Timmer (1970)]. Single period estimates may also be of limited value since events in the sampled year may be year-specific, and may also affect some farmers but not others. Clearly, multi-year observations are necessary to estimate relative technical efficiency between farms, over time. However, the necessary panel data is rarely available in developing countries to allow estimation of efficiency in this dynamic sense. Therefore, as was the case in this study, analysts frequently have no option but to use cross sectional data in the estimation of technical efficiency. We are confident, nonetheless, that our estimates are useful from a policy viewpoint because: (a) agriculture in Gujranwala district is not now undergoing substantive technical change; and (b) Basmati yields and the weather in 1982 were typical given long-term averages for Punjab, nor were there major shifts in relative prices in that year [PARC (1983)]. Thus, our subjective belief is that year specific events during the study year were unlikely to have caused our estimates to deviate substantially from longer term estimates.

V. Policy Implications

Better application of existing technology provides an opportunity to increase Basmati production in Gujranwala District using existing input levels. While there are opportunities to increase the technical efficiency of the comparatively less efficient farmers, there also appear to be opportunities to increase the productivity of the comparatively more efficient Basmati producers.

Farm households with greater education had comparatively higher technical efficiency. These farmers tend to be identified as "progressive" households who in general have better access to markets, extension services and information. This supports Jamison and Lau (1982) and Ram's (1980) contention that increased education leads to greater productivity, in part, through reducing the acquisition cost and increasing the household's capacity to use technical information. These advantaged farmers are often the farmers better known to the agricultural services sector and have better access to markets; they are often the ones in effect, for whom technology is designed, as opposed to the less prosperous farmers whose circumstances may be less advantageous [Chambers and Ghildyal (1985)]. Therefore, there may be merit in adapting and targeting extension to the needs of the less progressive farmers if the objective is to increase their productivity.

Management factors (i.e., late transplanting and fertilizer application, water shortages) significantly contributed to yield loss and so to technical inefficiency. Clearly, extension could promote the benefits of timely application of inputs. However, it is necessary to determine with greater clarity why farmers do not complete these operations on schedule. This analysis would provide the insights to determine which of these constraints can be realistically removed through better extension advice or changes in the technology delivery system, or where research may be necessary to alleviate constraints which prevent farmer's undertaking operations in a more timely manner.

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