MEASURING THE DEGREE AND ISOLATING DETERMINANTS OF TECHNICAL AND ALLOCATIVE EFFICIENCY OF WHEAT FARMERS IN THE INDIAN VILLAGE OF PALANPUR

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Abstract

Using the concept of the stochastic frontier production function we estimate indices of technical and allocative efficiency for a sample of wheat farmers. These indices are used to derive an index of profit efficiency. The results show a substantial degree of both technical and allocative inefficiency. However technical inefficiency accounts for most of the loss in profits. The analysis is extended by isolating determinants of technical and allocative inefficiency. For the former we found good farming practice and credit availability to be important explanatory variables. With respect to allocative efficiency the determinants for some of the inputs were caste membership, acreage, and farmer and plot specific characteristics.

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1 Introduction

Farmer efficiency is comprised of allocative and technical efficiency.[1] The former is a behavioural concept and, assuming that farmers profit maximise, a measure of AE is given by the gap between marginal value product and marginal factor cost. Technical efficiency was defined by Farrell (1957) as the shortfall from the maximum output that a farmer may achieve subject to a given set of resources. Subsequently several authors have developed the econometric techniques to estimate parametric frontiers and thus obtain average Farrell output measures of TE. In particular the work by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) who independently developed the stochastic frontier production function proved a breakthrough. Their work was extended by Jondrow et al (1982) who showed how one may derive individual TE estimates in this context.[2] Joining the two concepts and estimating TE and AE simultaneously was first done by Schmidt and Lovell (1979). They assumed cost-minimisation while Kumbhakar (1987) modelled the case for profit-maximisation.

Studies measuring either AE or TE of farmers in developing countries are numerous. However with regard to the joint estimation of AE and TE applications are more rare. Kalirajan (1990) used a translog specification of production technology on data for commercial rice farmers in the Philippines. A more popular approach has been the estimation of profit frontiers. The shortfall from maximum profits is due to TI and AI, but the two effects cannot be separated for flexible functional forms.

In this paper we use the approach of Schmidt and Lovell (1979) to estimate TE and AE indices for the case of wheat farmers in the Indian village of Palanpur. These indices are used to obtain a measure of profit efficiency. The analysis is extended by isolating some of the determinants of TE, AE and PE. Several authors have examined the causes of TE but few have done so for AE.[3]

The paper is organised as follows: Section 2 describes the model and the estimation. The data set and the results are discussed in section 3. An analysis of determinants of TE, AE and PE is undertaken in sections 4.1, 4.2, and 4.3 respectively. Section 5 concludes the paper.

2 The model and the Estimation

We assume that the production relation is as shown in equation (1) below:

$$y_i = f(z_i, \mathbf{x}_i)e^{\epsilon_i} \tag{1}$$

[1]We use TE (TI), AE (AI) and PE (PI) to denote technical, allocative and profit efficiency (inefficiency) respectively.

[2]While only concerned with estimating a stochastic frontier, we note that this nests the deterministic frontier. In the deterministic case the shortfall from potential output is due entirely to factors within the control of the farmer. For surveys on this topic see Forsund, Lovell and Schmidt (1980), Schmidt (1985-86), and Bauer (1990).

[3]Rati (1980) and his analysis of the effect of education on AE is one study known to us. Ali et al (1994) examine the causes profit inefficiency.

where y denotes output; z is the fixed input; $\mathbf{x}$ is the vector of variable inputs; and the subscript i denotes the ith farm, $i = 1, ..., n$. The error term ϵ_i is composed of the terms v_i and u_i, such that $\epsilon_i = v_i - u_i$. The symmetric term v_i captures exogenous shocks, such as weather, supply side shocks, etc., and is assumed to be distributed as $N(0,\, \sigma_v^2)$. The term u_i captures deviation from the frontier due to factors within the farmers control and is assumed to be distributed as $|N(0,\, \sigma_u^2)|$.[4] The density of $v_i - u_i$, $g(v_i - u_i)$, is:

$$g(v_i - u_i) = \frac{2}{\sqrt{2\,\pi\,\sigma}} exp[\frac{(v_i - u_i)^2}{2\sigma^2}]\{1 - G[(v_i - u_i)\lambda/\sigma]\} \tag{2}$$

where $\sigma^2 = \sigma_v^2 + \sigma_u^2$; $\lambda = \sigma_u/\sigma_v$; and G is the standard normal distribution function, evaluated at $[(v_i - u_i)\lambda/\sigma]$.

We further need to specify the production technology. In particular we choose the Cobb-Douglas specification as this has been very popular in research in agricultural production. Moreover the small sample size restricts the choice. Substituting the C-D form into (1) we get:

$$y_i = \beta_0\, z_i^{\beta_z} \prod_j^m x_{ji}^{\beta_j}\, e^{\epsilon_i} \tag{3}$$

where j denotes the jth variable input, $j = 1, ..., m$.

Since we are interested in both TE and AE we need to make some behavioural assumptions. We postulate that farmers maximise median profits[5] and the input and output prices are either known with certainty or are statistically independent of the production function. Moreover they are assumed not to observe v_i or u_i.[6] Our model is as in Zellner, Kmenta and Dreze (1966), except that we maximise median profits. The benefit of including the first order conditions is that this increases the efficiency of the parameter estimates (Schmidt (1985-86)). The resulting first order conditions, given our production technology is of the C-D type, are given by:

$$(\beta_k - 1)\, ln(x_{ki}) = -\,\beta_0\; - \;\beta_z ln(z_i) - \;\beta_j \sum_{k \neq j}^{m} ln(x_{ji}) + ln(c_{ki}) + \omega_{ki} \tag{4}$$

where x_{ki} is the kth variable input the ith farmer is maximising with respect to; and c_{ki} denotes the cost of the kth input to the ith farmer. The ω_{ki} reflect deviation from the profit maximising point for the kth variable input. That is they capture allocative inefficiency as the deviation of estimated marginal value of product of the jth input ($\widehat{MVP}_{ji}$) from the marginal factor cost (MFC_{ji}), i.e. $\widehat{MVP}_{ji}/MFC_{ji}$. They also captures random noise and measurement error. We assume that the vector of error terms, ω_{ik}, is distributed as multivariate

[4]Other distributional assumptions have been used, but this particular one has been the most popular.

[5]As in Kumbhakar (1987)

[6]Thus differing from Kumbhakar (1987) who lets farmers observe u_i, giving a rationale for considering the variable inputs as endogenous.

normal, with mean vector zero and covariance matrix $\mathbf{\Sigma}$. The density is given by:

$$h(\omega_i) = (2\,\pi)^{-m/2}|\mathbf{\Sigma}|^{-1/2}exp[-\frac{1}{2}\omega_i^{'}\Sigma^{-1}\omega_i] \tag{5}$$

As ϵ_i is assumed independent of the ω_i, the joint distribution is given by the product of the two densities. The log-likelihood follows as:

$$\begin{aligned} ln(L) \quad &= n\,ln(2) - n\,(m+1)\,ln(2\,\pi)/2 - n\,ln(\sigma^2)/2 - n\,ln|\mathbf{\Sigma}|/2 + n\,ln(r) \\ &- \tfrac{1}{2}\textstyle\sum_{i=1}^{n}[\omega_i^{'}\,\mathbf{\Sigma}\,\omega_i + (v_i - u_i)^2\,\sigma^2/2] + \sum_{i=1}^{n} ln\{1 - G[(v_i - u_i)\lambda/\sigma]\} \end{aligned} \tag{6}$$

where r is the jacobian of the transformations of ϵ_i and the ω_i into the y_i and x_{ji}. The covariance matrix $\mathbf{\Sigma}$ consists of the elements σ_{ij} where at the maximum the following holds:

$$\hat{\sigma}_{ij} = (1/N)\sum_{i=1}^{N}\hat{\omega}_{ij}\hat{\omega}_{ij} \tag{7}$$

This expression may be substituted into (6), yielding the concentrated likelihood function. This simplifies things since this version is maximised only with respect to the $\beta's$, λ, and σ^2, and not the elements of $\mathbf{\Sigma}$.

Individual TE estimates may now be derived by using the mean of the conditional distribution of u for a given ϵ (see Jondrow et al (1982)). Hence:

$$E(u_i|\epsilon_i) = \sigma_*[\frac{f(\epsilon_i\,\lambda/\sigma)}{1 - G(\epsilon_i\,\lambda/\sigma)} - (\epsilon_i\,\lambda/\sigma)] \tag{8}$$

where $\sigma_*^2 = \sigma_u^2\,\sigma_v^2/\sigma^2$. Estimates of AE and the covariance matrix are formed using equations (4) and (7) respectively.

3 The data and the Results

3.1 The data

The data were collected by Professors Bliss and Stern in the Indian village of Palanpur in 1974/75. This covers 47 wheat growing plots in the Rabi season.[7] A list and brief description of the data set is given in Table 1. Summary statistics are provided in Table 2. The fertiliser variable does not include the fertiliser applied at the time of sowing.[8] Instead we include a dummy variable for fertiliser at the time of sowing in the analysis of determinants of TE.[9] Moreover eight farms used no fertiliser at all. No particularly good way of dealing with this problem has been suggested. Johnson and Rausser (1971) list three possibilities: i) adding a constant to all the observations; ii) adding a constant to those observations which were recorded as zero; iii) adding a parameter to the variable in question and estimating this along with the other parameters. We chose to add a small constant to the zero input cases. This

[7]Some plots are farmed by the same farmer.

[8]23 farms used fertiliser at the time of sowing.

[9]The reason for not including such a dummy variable in the model is explained in the results section.

Table 1: List and description of variables used in model

Symbol	Description
Y	Wheat output, Kg.
PW	Price of wheat, rupees per Kg., a constant
A	Acreage, the fixed input
F	Fertiliser, Kg.
P	Number of ploughings
I	Number of irrigations
L	Standard man hours, (man=1, woman=1,child=0.5)
CP	Rupees per ploughing
CI	Rupees per irrigation
CF	Rupees per Kg. of fertiliser
CL	Rupees per standard man hour

was intuitively appealing in that the actual values were zero. We note that adding a small constant to all the observations makes no difference and that excluding the eight farms again yields very similar results to the method we actually used.[10]

Table 2: Summary statistics for variables

Symbol	*Mean*	*Standard Deviation*	*Range*
Y	604.03	329.74	153.76-1546.28
PW	1.30	-	-
A	0.73	0.35	0.25-1.72
F	22.34	16.32	0.0001-55.00
P	5.06	1.67	2.00-9.00
I	4.19	1.12	2.00-6.00
L	28.51	16.12	8.00-74.00
CF	12.97	5.91	3.75-28.66
CI	23.45	23.03	3.75-87.00
CP	12.97	5.91	3.37-28.66
CL	0.559	0.055	0.407-0.625

Our labour variable does not include those labour hours used for ploughing and irrigation. Rather we assume that the variables P and I capture the combined effect of the animal and labour power used. Finally we note that the price used for bullock services was the one recorded in the market for bullock services which, apparently, was minimal (See Bliss and Stern (1982, p.275)). This figure was adjusted for the actual time it took to plough the plot. We also used this figure to calculate the cost of irrigation by Persian wheel (as opposed

[10]See Croppenstedt (1993) for more detail.

to pumping sets).

3.2 The Results

The FIML estimates for the model are shown in Table 3.[11] All the parameter estimates are significant at least at the 5 percent level. Using a likelihood ratio test we tested and did not reject the hypothesis of constant returns to scale.[12] The parameter estimates were virtually identical and we report only the results for the unrestricted model.

Table 3: Maximum likelihood estimates of the stochastic frontier Cobb-Douglas production function

Variable	*Parameter estimates*	*(t-ratios)*
Constant	6.6489	(102.670)*
Acreage	0.8749	(17.739)*
Fertiliser	0.0368	(2.576)*
Irrigation	0.0600	(3.681)*
Ploughing	0.0560	(5.115)*
Labour	0.0154	(3.603)*
σ^2	0.1485	(2.689)*
λ	3.4857	(2.472)*
Log likelihood value	-244.99	

Calculated using heteroskedastically-consistent covariance matrix
*Significant at least at the 5 percent level

With regard to technical inefficiency we note that our estimate of λ shows that factors within the farmers control dominate the disturbance term. We find that the average level of efficiency for the sample is 76 percent. That means that output could be 24 percent higher with the same level of inputs. The range is 95-38 percent, showing a wide range of observations. Table 4, which gives the frequency distribution for the TE estimates, shows that most of the farmers fall into the 100-80 percent range and very few fall to efficiency levels below 55 percent. Only one farm is in the top category and this farm scored 95.11 percent.

Turning to allocative efficiency we show the frequency distribution for the four variable inputs in Table 5. It is clear that there is very little allocative efficiency to be found. This is true even when, as in the case of ploughing, the mean suggests only an average level of under-utilisation of 1 percent. Only a small number of farmers lie within 5 percent of perfect allocative efficiency. Even considering the band of 25 percent on either side we find that only 40,

[11] We use the GAUSS package. Without any a priori reasons to use a particular one, we chose the BFGS algorithm. GAUSS allows one to derive the heteroskedastic-consistent covariance matrix.

[12] The likelihood value for the restricted model was -245.24.

Table 4: Frequency distribution of technical efficiency estimates

Range	*Frequency**	*Range*	*Frequency*
100 - 95.00	1	64.99 - 60.00	2 (40)
94.99 - 90.00	6 (7)	59.99 - 55.00	3 (43)
89.99 - 85.00	7 (14)	54.99 - 50.00	1 (44)
84.99 - 80.00	10 (24)	49.99 - 45.00	1 (45)
79.99 - 75.00	4 (28)	44.99 - 40.00	1 (46)
74.99 - 70.00	5 (33)	39.99 - 35.00	1 (47)
69.99 - 65.00	5 (38)		

*Figures in brackets denotes cumulative frequencies.

Table 5: Frequency distribution for allocative efficiency estimates

Range	*Fertiliser*	*Irrigation*	*Ploughing*	*Labour*
< 0.5000	5	16	5	4
0.5000 - 0.7499	9	4	12	5
0.7500 - 0.8999	12	1	6	9
0.9000 - 0.9499	0	0	3	2
0.9500 - 0.9999	2	0	3	1
1.0000 - 1.0499	2	1	4	1
1.0500 - 1.0999	0	0	0	3
1.1000 - 1.2499	3	1	3	10
1.2500 - 1.499	5	10	4	4
> 1.5000	9	14	7	8
$0.95 \leq \widehat{MVP}/MFC \leq 1.05$	4	1	7	2
$\hat{MEAN}$	0.90*	1.18	1.01	1.09

Excluding the eight farmers not using any fertiliser.

6, 40 and 55 percent of farmers reach this degree of AE for F, I, P and L, respectively.

The finding that a majority of farmers over-utilised fertiliser was surprising, in light of earlier findings by Bliss and Stern (1982).[13] They present a large amount of evidence showing that farmers under-utilise fertiliser and we are in no doubt that this is indeed the case.[14] A possible explanation of our results may lie in the interaction and timing of fertiliser and irrigation. Low levels of irrigation and bad input timing might shift the yield curve for fertiliser such that returns to this input fall off much earlier. It is also interesting that the estimate

[13]They found an $\widehat{MVP}$ to MFC ratio greater than 3 for fertiliser. We note that the result that a majority of farmers over-utilise fertiliser is also obtained if instead of adding a small constant we follow Bliss and Stern and add 25 to the fertiliser variable.

[14]Indeed farmers applied too little of both irrigation and fertiliser. See Bliss and Stern (1982, Ch.7).

Table 6: Frequency distribution of profit efficiency estimates

Range	*Frequency**	*Range*	*Frequency*
100 - 95.00	0	59.99 - 55.00	5 (30)
94.99 - 90.00	3	54.99 - 50.00	1 (31)
89.99 - 85.00	4 (7)	49.99 - 45.00	4 (35)
84.99 - 80.00	5 (12)	44.99 - 40.00	1 (36)
79.99 - 75.00	5 (17)	39.99 - 35.00	5 (41)
74.99 - 70.00	4 (21)	34.99 - 30.00	2 (43)
69.99 - 65.00	3 (24)	29.99 - 25.00	4 (47)
64.99 - 60.00	1 (25)		

*Figures in brackets denotes cumulative frequencies.

of $\sigma_{F,I}$ is negative, i.e. that mistakes in allocating fertiliser and irrigation move in opposite directions. This suggests that more irrigations would only have benefited those farmers that were found to be over-utilising fertiliser.[15]

It is useful to give a monetary interpretation to the degree of TI and AI found. Using the optimal variable input levels, as determined by the set of equations given by (4) we get the new output:

$$\tilde{Y} = \hat{\beta}_0 \, Z^{\hat{\beta}_Z} \, (X_j^*)^{\hat{\beta}_j} \tag{9}$$

where X^* denotes the optimal level of the jth input. Using this new output $\tilde{Y}$ we obtain potential output as $Y^* = \tilde{Y} \cdot e^{\hat{u}}$. Finally we calculate potential profits as

$$\Pi^* = PW\,Y^* - \sum_j^M C_{X_j}\,X_j^* \tag{10}$$

where C_{X_j} denotes the cost of the jth variable input. This figure is then compared to actual profits, Π. We found that on average farmers achieve only 62 percent of the maximum profits attainable.[16] The range is 94 to 28 percent. Table 6 gives the frequency distribution for the 47 farms. It is clear that profits could have been increased dramatically for most farms.

We may also separate that part of profit inefficiency caused by technical inefficiency from that caused by allocative inefficiency. We note that most of the shortfall from potential profits is due to TI since the average degree of PI due to allocative mistakes is only 6.98 percent. The range for profit inefficiency due to AI is 0.016 to 35.97 percent. Excluding the eight plots that used no fertiliser we find that the range is 0.016 - 6.10 percent and the average PI due to AI is 2 percent. It is in the case of no fertiliser use at all that AI contributed very substantially to profit inefficiency. The range of PI for the eight observations is 20.50 to 35.97.

[15] We note that the average number of irrigations were very close for farmers that over-utilised and those that under-utilised irrigation.

[16] Using micro-level data for South Indian farmers Kalirajan (1985) found a shortfall of 41 percent from potential profits. 25 percent of this was due to TI.

Table 7: List and description of determinants of TE and AE

Symbol	*Description*
DFS	Dummy for fertiliser applied at the time of sowing, 1 if yes, 0 otherwise
DSG	Dummy if sowing too place on or before December 1st, 1 if yes, 0 otherwise
DSEED	Dummy for seed type, 1 if RR21, 0 otherwise
DWEED	Dummy for weeding, 1 if done, 0 otherwise
DI30	Dummy for irrigation after 30 days of sowing, 1 if yes, 0 otherwise
EDU	Number of years of formal education
AGE	Age of farmer
CR	Dummy for credit for agricultural purposes, 1 if yes, 0 otherwise
DS	Dummy for soil type, 1 if bad, 0 otherwise
CASTE 1	Dummy for Thakur caste, 1 if member, 0 otherwise
CASTE 2	Dummy for Murao caste, 1 if member, 0 otherwise
DTEN	Dummy for tenancy, 1 if yes, 0 otherwise
VB	Value of bullocks
AC	Total acreage of land owned and cultivated
MAG	Number of males aged between 16 and 60 engaged solely in agriculture

4 Determinants of inefficiency

4.1 Determinants of technical inefficiency

We now turn to isolating some of the factors that are likely to affect technical efficiency. In particular we wish to consider two categories of factors: a) factors associated with good practice; and b) factors reflecting institutional characteristics. In table 7 we list and describe all variables used in sections 4.1 through 4.3. DFS, DSG, DSEED, DWEED, and DI30 fall into the category of good practice. DFS, and DWEED capture inefficiency by way of farmers deviating from what is considered good practice.[17] With DSG and DI30 we include two variables that capture good practice via the timing of inputs. With regard to DSEED we note that there are 29 farmers using Rust Resistant 21 (RR21) seed and since this seed type is considered to be inferior in quality a negative coefficient is expected.[18]

The variables CR, CASTE1, CASTE2, and DTEN relate to institutional

[17]We refer the reader to Bliss and Stern (1982, Ch. 7) who give a lengthy discussion of recommended input levels.

[18]The quality of RR21 is said to have declined since its introduction in Palanpur in 1970/71. Since it was easy to obtain with automatic credit facilities, those farmers that went to the trouble to obtain a different seed type are considered to be particularly enterprising and concerned with good agricultural practices.

Table 8: OLS estimates of determinants of Technical Efficiency

Variable	*Parameter Estimate*	*(t-ratio)*
Constant	0.6843	(21.024)**
DFS	0.1496	(3.998)**
EDU	-0.0058	(-1.550)
CR	0.0942	(1.978)*
DS	-0.0487	(-1.337)
DSG	0.0414	(1.176)
$\bar{R}^2$	0.30	
F-statistic	F[5,41] = 4.97	

* and ** indicate significance at least at the 10 and 5 percent levels resp.

factors which we feel might inhibit good practice. The availability of credit is frequently cited as an important factor in the production process. The variable we use is credit for agricultural purposes, i.e. credit for pumping sets or straw for the bullocks. Credit availability will capture the improved production technique due to the acquisition of a pumping set, and/or possibly the higher input levels due to the relaxed financial constraint of the farmer.

The CASTE dummies will show whether caste membership is of any importance. The idea is that higher caste members are generally better educated and have access to information that improves their performance which lower caste members do not have. Our caste dummies are for the top two castes and we would expect a positive correlation with efficiency. The tenancy variable will give an indication of whether or not there is any systematic difference between tenants and owner-cultivators.

We also included the variables EDU and AGE to proxy managerial abilities of the farmer; DS to capture differences in soil quality; and MAG, VB and AC to capture differences in endowments and scale effects.

We follow the approach taken by previous authors.[19] The relationship between TE and the explanatory variables is assumed to be of the form:

$$e^{-\hat{u}_i} = \alpha_0 + \alpha_m \sum_m x_{mi} + \epsilon_i \tag{11}$$

Where m denotes mth explanatory variable. We proceeded by including all the variables and then dropping in a step wise manner variables if their t-ratio was less than 1.

The results are given in Table 8. All coefficients except for education have the expected sign. However only DFS and CR are significant. Both explain much of the shortfall from the maximum output. The implications are that extension services and credit availability would greatly increase output.

[19] See for example Kalirajan (1990)

Table 9: OLS Estimates of factors affecting degree of AE

	Parameter Estimates for the Groups: (t-ratios)			
Variable	ω_F	ω_I	ω_P	ω_L
CONSTANT	5.6087	3.7788	1.6634	1.0446
	(5.982)**	(9.326)**	(8.707)**	(14.795)* *
CASTE1	-3.4702	0.2353	-0.3033	–
	(-2.734)**	(1.096)	(-1.472)	–
CASTE2	-4.0052	–	-0.6632	–
	(-3.351)**	–	(-3.247)**	–
DTEN	-2.2004	–	-0.2600	–
	(-1.615)	–	(-1.178)	–
EDU	–	-0.0410	–	–
	–	(-1.870)*	–	–
AGE	–	-0.0384	–	0.0112
	–	(-3.885)**	–	(1.857)*
DS	–	0.4750	–	-0.1646
	–	(2.538)**	–	(-1.182)
AC	–	-0.0065	-0.0064	–
	–	(-1.284)	(-1.780)*	–
$\bar{R}^2$	0.17	0.36	0.14	0.05
F-statistic	F[3,43]=4.15	F[5,41]=6.13	F[4,42]=2.83	F[2,44]=2.16

* and ** indicate significance at least at the 10 and 5 percent levels resp.

4.2 Determinants of allocative efficiency

Next we move to examine what factors determine the degree of allocative inefficiency. Given that the ω_i measures deviation from AE[20] we choose to estimate the following relationship [21]:

$$e^{abs(\hat{\omega}_{ji})} = \alpha_0 + \alpha_m \sum_m x_{mi} + \epsilon_i \tag{12}$$

where again j refers to the jth variable input and m denotes the mth explanatory variable. Equation (12) is estimated separately for each of the four ω's.

We chose to use the following variables: CASTE1, CASTE2, DTEN, EDU, AGE, VB, AC, MAG, and DS. The reasons for the choice of explanatory variables is as in section 4.1. DS was included since soil quality is observable at the start and may thus affect the farmer's input choices.

Results are shown in Table 9. The equation for ω_L fails the F-test at the 5 percent level and we concentrate on the remaining three equations. Caste membership is an important variable for fertiliser and ploughing. In both cases members of the Murao caste apply these inputs more efficiently. Tenancy was

[20] Although not only.

[21] As in Rati (1980)

Table 10: OLS Estimates of factors affecting degree of PE

Variable	*Parameter estimate*	*(t-ratio)*
CONSTANT	0.4000	(6.179)**
CASTE1	0.0911	(1.279)
CASTE2	0.1434	(1.961)*
DTEN	0.0972	(1.302)
DFS	0.2164	(3.777)**
DSG	0.0922	(1.998)*
CR	0.1538	(2.467)**
DS	-0.0880	-(1.935)*
EDU	-0.0074	(-1.580)
		$\bar{R}^2$=0.53
		F-statistic: F[8,38]=7.54

* and ** indicate significance at least at the 10 and 5 percent levels resp.

not found to be statistically significant, just failing at the 10 percent level for fertiliser.[22] The equation for irrigation had the best fit and here the education and age variables were significant and had the expected sign, i.e. farmers with more education and experience were likely to allocate inputs more efficiently. Farmers with soil of low quality generally did worse and over 60 percent of farmers in this group under-utilised irrigation. Acreage had the expected sign but was significant at the 10 percent level only for ploughing.

4.3 Determinants of Profit Efficiency

We also used our aggregate index of profit efficiency and regressed this on the variables used in sections 4.1 and 4.2. Most of the results are as expected, given the results in Tables 8 and 9. However DSG now appears as significant (p-value = 0.053), underlining the importance of good practice. The result for caste membership is also clear, i.e. there is a substantial difference between those farmers belonging to the Murao caste and the others. Soil quality scores a p-value of 0.060 and there is thus evidence that it does play an important role. This lends support to Kumbhakar's (1987) formulation were farmers are able to observe technical inefficiency.

5 Conclusion

In this paper we applied a simultaneous equation model based on the stochastic frontier production function and the profit-maximising conditions to data for wheat growing farmers. Production technology was characterised by CRS. The results are used to derive indices of technical and allocative efficiency. With regard to the former we found an average shortfall of 25 percent from the

[22] We note that there were 7 tenants and of these only 2 under-utilised fertiliser.

maximum possible output attainable. With regard to allocative efficiency we found that most farmers deviated 25 percent of more from the optimum. The averages hid this fact, showing that inputs were between 1 and 18 percent missallocated on average. Of interest was the result that most farmers over-utilised fertiliser. We feel this can be explained by the interaction of I and F. The simultaneous equation model allows for allocative mistakes to be correlated and gives more insight into how inputs are inter-related.

The index of profit efficiency shows an average shortfall from potential profits of 38 percent. Significantly most of this inefficiency is due to TI. Consequently the emphasis ought to be on improving TE which our results show can be done by improving the availability of credit and by providing extension services. Results for the factors affecting AE are less clear cut, but caste membership, education, age, soil quality and the acreage are important factors in explaining the deviation from profit maximisation. Results for the determinants of PE are illuminating in that apart from extension services and credit availability we find that caste membership and soil quality unambiguously play an important role.

References

[1] Aigner, D.J., C.A.K. Lovell and P. Schmidt, 1977, "Formulation and Estimation of Stochastic Frontier Production Functions Models," Journal of Econometrics, 6, pp. 21-37.

[2] Ali, F., A. Parikh, and M.K. Shah, 1994, "Measurement of profit efficiency using behavioural and stochastic frontier approaches," Applied Economics, 26, pp. 181-188.

[3] Bauer, P.W., 1990, "Recent Developments in the Econometric Estimation of Frontiers," Journal of Econometrics, 46, pp.39-56.

[4] Bliss, C. and N. Stern, 1982, Palanpur: The Economy of an Indian Village, Oxford: Clarendon Press.

[5] Croppenstedt, A., 1993, An Empirical Study of Technical and Allocative Efficiency of Wheat Farmers in the Indian Village of Palanpur, Unpublished Ph.D. Dissertation (University of Essex, Colchester, England).

[6] Farrell, M.J., 1957, "The Measurement of Productive Efficiency," Journal of the Royal Statistical Society, A 120, part 3, pp. 253-290.

[7] Forsund, F.R., C.A.K. Lovell, and P. Schmidt, 1980, "A Survey of Frontier Production Functions and of their Relationship to Efficiency Measurement," Journal of Econometrics, 13, pp. 5-25.

[8] Johnson, S.R. and G.C. Rausser, 1971, " Effects of Misspecification of Log-Linear Functions When Sample Values are Zero or Negative", American Journal of Agricultural Economics, 53, pp. 233-238.

[9] Jondrow, J., C.A.K. Lovell, I.S. Materov and P. Schmidt, 1982, "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model," Journal of Econometrics, 19, pp. 233-238.

[10] Kalirajan, K.P., 1985, "On Measuring Absolute Technical and Allocative Efficiencies," Sankhya, 47, Series B, Part 3, pp. 385-400.

[11] Kalirajan, K.P., 1990, "On Measuring Economic Efficiency," Journal of Applied Econometrics, 5, pp. 75-85.

[12] Kumbhakar, S.C., 1987, "The Specification of Technical and Allocative Inefficiency in Stochastic Production and Profit Frontiers," Journal of Econometrics, 34, pp. 335-348.

[13] Meeusen, W., and J. van den Broeck, 1977, "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error," International Economic Review, 18, pp. 435-444.

[14] Ram, R., 1980, "The Role of Education in Production: A Slightly New Approach," Quarterly Journal of Economics, 95, pp. 365-373.

[15] Schmidt, P., 1985-86, "Frontier Production Functions," Econometric Reviews, 4, pp. 289-328.

[16] Schmidt, P. and C.A.K. Lovell, 1980, "Estimating Technical and Allocative Inefficiency Relative to Stochastic Production and Cost Frontiers," Journal of Econometrics, 9, pp. 343-366.

[17] Zellner,A., J. Kmenta and J. Dreze, 1966, "Specification and Estimation of Cobb-Douglas Production Function Models", Econometrica, 34, pp. 784-795.