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Efficiency estimation in a profit maximising model using flexible production function

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Abstract

This paper uses a flexible (translog) production function to estimate efficiency of 227 farms from West Bengal, India. We consider estimation of technical and allocative inefficiencies using a profit maximising framework which accommodates both endogenous and exogenous inputs. The maximum likelihood method of estimation developed in this paper is based on the production function and the first-order conditions of profit maximisation. Farm-specific technical and allocative inefficiencies are also estimated. Empirical results show that the mean level of technical efficiency is 75.46% while the best farm is 85.87% efficient (technically). So far as allocative efficiency is concerned the majority of the farms are found to be under-users of the endogenous inputs, viz., fertiliser, manure, human and bullock labour.

1. Introduction

The neoclassical theory of production is based on the notion of efficiency. This idea is emphasised in the textbook definition of a production function which gives the maximum possible output for given quantities of inputs. One problem with the notion of 'maximum' is that nobody can recognise it simply by observing the actual level of output unless the observed output is assumed to be the maximum. Such an assumption is not realistic since different producers do produce different levels of output even if they use the same level of every observed input. One way of explaining the difference in observed outputs among producers is through differences in productive efficiency. In the frontier approach a producer is said to be technically efficient [1] if the observed output is maximum, given the input quantities. Thus, the production frontier is defined as the locus of maximum possible outputs for each level of input use. A failure on the part of the farm to produce the frontier level of output, given the input quantities, is attributed to technical inefficiency.

[1] The concept of technical efficiency goes back to Farrell (1957). Another concept of efficiency is Leibenstien's X-efficiency (1966), which is often associated with poor quality or poorly trained/motivated labour force, lack of managerial effort, etc. In the context of farming, soil characteristics, climatic and some socio-economic factors may affect efficiency of a farm.

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Technical inefficiency is not the only inefficiency. If the producer makes mistakes in allocating inputs, the resulting inefficiency is labeled as allocative inefficiency. It is always associated with some behavioral objective like profit maximisation or cost minimisation. Mistakes in the allocation of resources and production of suboptimal level of output increase cost and, therefore, decrease profit. Consequently, identification of the inefficient producers is very important, especially for government policy designed to promote efficient utilisation of resources.

Econometric estimation of frontier functions goes back to Aigner, Lovell and Schmidt (1977) and Meeüsen and van den Broeck (1977). The methodology proposed by these authors is quite general and can accommodate any functional form of the underlying production technology. However, their approach is restricted to estimation of only technical inefficiency or cost therefrom. Extensions of the Aigner et al. (1977) model to incorporate both technical and allocative inefficiencies have been made in terms of production functions for which the cost or the profit functions can be derived explicitly from the optimising conditions (see, for example, Schmidt and Lovell, 1979, 1980; Kumbhakar, 1987, 1988). The major advantage of using such restrictive production functions lies in obtaining closed form algebraic formulae for costs of technical and allocative inefficiencies which are of primary concern to the producers. The disadvantage is that the production functions for which cost or profit functions can be derived explicitly are quite restrictive in nature.

This paper describes a method of estimating technical and allocative inefficiencies using a translog production function – the most widely used flexible functional form in applied works. Estimating a translog production function with inefficiency was first proposed by Greene (1980). He assumed, at least implicitly, the inputs to be exogenous or predetermined. The problem with such an assumption is that allocative inefficiency from suboptimal input use cannot arise since the use of input levels are no longer a choice variable.

In this paper, we depart from the Greene formulation by including endogenous and exogenous inputs. The endogenous inputs are chosen to maximise expected value of profit. Since the input demand and output supply functions cannot be derived explicitly, the parameters are estimated from the system of equations consisting of the production function and the first-order conditions of expected profit maximisation using the Maximum Likelihood (ML) method. Estimation of technical and allocative inefficiencies for each observation is also considered. The proposed method is applied to estimate efficiency of 227 farms in West Bengal, India.

Organisation of the rest of the paper is as follows. Section 2 gives an overview of efficiency studies in Indian agriculture. This is followed by the econometric model. Section 4 describes the data and the results are reported in Section 5. Conclusion and remarks are in Section 6.

2. Efficiency measures in Indian agriculture

Previous studies on efficiency of Indian farms can be classified broadly into the following three categories. First, studies based on the primal approach where the parameters were directly estimated mostly by using the ordinary least squares (OLS) method. These parameter estimates were then used to check whether the first order conditions of profit maximisation are satisfied (see, for example, Hopper, 1965; Sahota, 1968; Saini, 1979). Attempts were also made to model these deviations in terms of observable factors like education, experience, etc. (Ram, 1980). In the second category of studies, profit maximising behavior was explicitly taken into account by estimating the dual profit function. Again efficiency was modeled as a function of farm characteristics like size of land holding (Lau and Yotopoulos, 1971; Yotopoulos and Lau, 1973), size and form of tenancy (Junankar, 1980), variety of crops, and the degree of mechanisation (Sidhu, 1974). Finally, in recent years the frontier methodology of Aigner et al. (1977) was used by Huang and Bagi (1984), Huang (1984) and Kalirajan and Shand (1985), among others.

The present study follows the last approach, i.e., it uses the stochastic frontier method to estimate economic efficiency of farms in West Bengal, India. We extend the results of previous studies by incorporating allocative inefficiency together with technical inefficiency in a translog production function. This extension has two major advantages. First, in contrast to the previous frontier studies, we do not assume all inputs to be exogenous or predetermined. Instead, we include both exogenous and endogenous inputs in our analysis. Moreover, the assumption that the endogenous inputs are independent of technical inefficiency is not made. Second, we use a system of simultaneous equations to avoid possible bias that might arise due to the presence of the endogenous inputs and their correlations with technical inefficiency. [2] By including the first-order conditions of profit maximisation in the estimation process we hope to get more efficient parameter estimates.

3. Econometric model

It is well known that the production technology can be estimated by either the primal (direct) or the dual (indirect) approach. In the dual approach, one starts with a profit or cost function which can be directly estimated. Additional information can be obtained by using Hotelling–Shephard's lemma. [3] In this paper we use the primal approach where estimation of the production function is the main locus. Additional equations from the first-order conditions of profit maximisation are also used to make the model consistent in terms of the number of endogenous variables being equal to the number of equations. The production function is assumed to be represented by a translog form, which with both endogenous and exogenous inputs is written as:

$$\begin{aligned}\ln Y = {} & \alpha_0 + \alpha' \ln X + \theta' \ln Z + \tfrac{1}{2} \ln X' B \ln X \\ & + \tfrac{1}{2} \ln Z' \Lambda \ln Z \\ & + \ln X' \Delta \ln Z + \tau + \nu \qquad (1)\end{aligned}$$

where Y is output, X and Z are $n \times 1$ and $m \times 1$ vectors of endogenous and quasi-fixed inputs, respectively. The B and Λ matrices are square ($n \times n$ and $m \times m$, respectively) and symmetric whereas the Δ matrix is of order $n \times m$. These matrices contain all second-order coefficients. The first-order coefficients are contained in α and θ vectors. The symbol ν represents a random disturbance that captures exogenous shocks to the producer. Since these shocks can both be favourable and unfavourable, ν is allowed to take positive and negative values. On the other hand, technical inefficiency, τ, is represented by a non-positive random variable; $\tau = 0$ defines the production frontier which gives the maximum possible output given X and Z. The frontier is stochastic because of the presence of ν. A non-zero value of τ can be interpreted as the reduction in log output due to technical inefficiency. Therefore, given the inputs X and Z, the observed differences in output levels can be attributed to either technical inefficiency or random shocks or both. Similarly, the observed differences in (endogenous) input use, even if input prices are the same for all farms, can be explained in terms of differences in quasi-fixed inputs, and the presence of technical and allocative inefficiencies (defined in Eq. 2 below).

Since the inputs X are endogenous, we have to introduce additional equations for consistency of the model. These equations are obtained from the optimising behavior of the producer. We assume that the objective of the producer is to maximise profit (conditional on its technical inefficiency) subject to the production function in (1).

[2] One can also avoid the endogeneity problem by estimating a profit function. Since the input and output prices are exogenous, consistent estimator of the parameters is obtained using a single-equation technique. There are, however, two problems associated with estimating a profit function. First, estimation of profit function requires price variability which might be a problem in a cross-sectional data (see, e.g., Junankar, 1989). Second, separating costs of technical and allocative inefficiencies (in terms of foregone profit) from a profit function is not always possible. Since our objective is to estimate both technical and allocative inefficiencies, we decided not to pursue the profit function approach in this study.

[3] Application of some of these models can be found in Cowing et al. (1983), Kopp and Diewert (1982) and Greene (1980). See also Schmidt (1985) for a critique of this approach.

In deriving the necessary conditions of profit maximisation (given technical inefficiency, τ) we assume that the effect of exogenous shocks ν is unknown.

Since profit is random due to the fact that ν is unknown, we follow expected profit maximisation criterion due to Zellner, Kmenta and Dreze (1966). The first-order conditions of expected profit maximisation can be written as:

$$\frac{\partial E(Y)}{\partial X_i} = \frac{W_i}{P}\exp(-u_i) \tag{2}$$

where P is the output price and W_i is the price of input i; u_i is interpreted as allocative inefficiency in the use of input i (Kumbhakar, 1987). If $u_i > 0$ (< 0), the ith input is used more (less) than its optimum level, given W_i and P. In other words, any deviation of the value of marginal product of an input from its price is attributed to errors in the allocation of input (allocative inefficiency). [4] We rewrite (2) to obtain:

$$-\ln Y^* + \ln X_i - \ln S_i^* + \ln W_i - \ln P - \ln c = u_i + \tau \tag{3}$$

where

$$\ln Y^* = \ln Y + \tau + \nu$$

$$S_i^* = \alpha_i + \sum_j \beta_{ij} \ln X_j + \sum_k \delta_{kj} \ln Z_k$$

$$j = 1,\dots,n \quad k = 1,\dots,m \quad \text{and}$$

$$c = E(\exp(\nu))$$

Eqs. (1) and (3) constitute a system of $(n+1)$ equations in $\ln Y$ and $\ln X_1,\dots,\ln X_n$. Since these equations are highly nonlinear, closed-form solution of $\ln Y$ and $\ln X_i$, i.e., output supply and input demand functions, cannot be obtained. However, consistent estimators of the parameters can be obtained from the ML method without deriving the input demand and output supply functions explicitly. Furthermore, estimators of τ and u_i can also be obtained for each observation.

The econometric model considered next is based on Eqs. (1) and (3).

To derive the likelihood function from the joint probability density function (PDF) of (ϵ_f, η_f) where $\epsilon_f = \tau_f + \nu_f$, $\eta_f = U_f + \iota\ \tau_f$, $U_f = (u_{1f}, u_{2f},\dots,u_{nf})'$ and ι is a $n \times 1$ column vector of ones, we make the following distributional assumptions on τ_f, U_f and ν_f. (The subscript f denotes farms, $f = 1, 2,\dots,F$.) These are:

- U is multivariate normal with zero mean and constant covariance Σ, and it is distributed independently and identically over farms.
- ν is i.i.d. $N(0, \sigma_\nu^2)$.
- The distribution of τ is the non-positive portion of an i.i.d. $N(0, \sigma_\tau^2)$ variable.
- ν and τ are independent of each other and are are also independent of the elements of the U vector.

With these assumptions in place, the joint PDF of (ϵ_f and η_f) derived from the convolution formula is given by:

$$g(\epsilon_f, \eta_f) = \frac{2\sigma\Phi(-\mu/\sigma)}{(2\pi)^{(n+1)/2}\sigma_\nu\sigma_\tau|\Sigma|^{1/2}} \times \exp\left[-\tfrac{1}{2}\left(\eta'\Sigma^{-1}\eta - \sigma^2\left(\epsilon/\sigma_\nu^2 + \eta'\Sigma^{-1}\iota\right)^2 + \epsilon^2/\sigma_\nu^2\right)\right] \tag{4}$$

where $1/\sigma^2 = (1/\sigma_\tau^2 + 1/\sigma_\nu^2 + \iota'\Sigma^{-1}\iota)$ and $\mu = (\epsilon/\sigma_\nu^2 + \eta'\Sigma^{-1}\iota)\sigma^2$; $\Phi(\cdot)$ is the cumulative distribution function of a standard normal variable. The log likelihood function for a sample of F farms can, therefore, be written as:

$$L = \sum_{f=1}^{F} \ln g(\epsilon_f, \eta_f) + \sum_{f=1}^{F} \ln|J_f| \tag{5}$$

where ϵ_f and η_f are to be replaced by their observed counterparts from Eqs. (1) and (3). [5] Finally, J_f is the Jacobian of the transformation from ϵ_f and η_f to $\ln Y_f$ and $\ln X_{1f},\dots,\ln X_{nf}$.

[4] One can separate input-specific allocative inefficiency (u_i) from random errors in optimisation if panel data are available (see, e.g., Kumbhakar, 1988).

[5] Under the normality assumption on ν, $c = \exp(\sigma_\nu^2/2)$.

The determinant of the Jacobian of the transformation, J_f, is:

$$|J_f| = \frac{(-1)^n}{\prod_i S_{if}^*} \begin{vmatrix} 1 & -S_{1f}^* & \cdots & -S_{nf}^* \\ -S_{1f}^* & -S_{1f}^* - \beta_{11} & \cdots & -\beta_{1n} \\ -S_{2f}^* & -\beta_{12} & \cdots & -\beta_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ -S_{nf}^* & -\beta_{1n} & \cdots & -S_{nf}^* - \beta_{nn} \end{vmatrix}$$

The log likelihood functions defined in (5) can be maximised to get the ML estimates of the coefficients of the production function as well as σ_ν and σ_τ.

After estimating the parameters we consider estimation of technical inefficiency for each farm. Following Kumbhakar (1989) and Jondrow et al. (1982), point estimators of τ for each farm can be obtained from:

$$\hat{\tau}_f = \hat{u}_f - \hat{\sigma}\phi\left(\hat{\mu}_f/\hat{\sigma}\right)/\Phi\left(-\hat{\mu}_f/\hat{\sigma}\right) \qquad (6)$$

where $\hat{\mu}_f$, $\hat{\sigma}$ are the ML estimates of μ_f and σ, and $\phi(\cdot)$ is the PDF of a standard normal variable. The point estimator of technical efficiency is then obtained from:

$$\mathrm{TE}_f = \exp\left(\hat{\tau}_f\right) \qquad (7)$$

Once τ is estimated, allocative inefficiency u for each endogenous input and each farm can be estimated from the residuals of (3).

4. Data

The data set used in the present study has been collected by the Agro-Economic Research Centre [6] from three regions of the Indian state of West Bengal. These regions cover the entire paddy production belt of West Bengal. A cross-section random sample of 227 household farms has been selected for the present study. The survey was conducted during 1980–1985. Since different regions were surveyed in different years, it is not a panel. Over the last two decades, the advent of technological changes, introduction of high yielding seeds, security of land tenure, availability of production loans, relaxation of government control over purchase of output and sale of some vital factors (fertilisers, irrigation water, pesticides), etc., have made the agricultural production system very much market oriented. Under such an environment, use of the profit maximisation hypothesis on the part of the producers as a maintained hypothesis seems appropriate.

The agricultural production activities of the state of West Bengal are spread over at least two crop seasons. Here we consider the monsoon paddy as our subject of investigation. [7] This choice is due to the fact that monsoon paddy is produced by all farms in the region under investigation. Moreover, during this season, markets for the inputs become quite competitive.

Output (Y) is measured in quintals (100 kg) of paddy. The endogenous inputs are: fertiliser (F), manure (M), human labour (N) and bullock labour (B). We treat land (L) and capital (K) as quasi-fixed inputs. The human labour includes both family labour and hired labour and is measured in hours. Bullock labour is also measured in hours. Fertiliser and manure are measured in kg. Land is measured in acres. Prices of paddy, fertiliser, manure, labour and bullock labour are all measured in Indian rupees.

The capital variable used here is a weighted average of rental value of services from irrigation and other farm equipment. The land under cultivation has been used as a quasi-fixed input because its market is not well developed especially in leasing out. It is measured in acres and it includes the area under monsoon paddy only.

Productivity differences due to different types of soil, terrain, weather and land sizes are controlled by including regional and farm-size dummy variables in the production function. We hope that these regional dummies will capture the differential effects of soil, terrain and weather since we do not have data on these variables.

[6] An agricultural research centre under the Ministry of Agriculture, Government of India.

[7] Data on input usage are related to the production of paddy only. Inputs used other than in paddy are not considered here.

5. Empirical results

Estimated parameters of the model outlined in (1) and (3) are reported in Table 1. The coefficients are of right signs and most of them are statistically significant. The first order coefficients are all positive. These coefficients can be interpreted as the elasticity of output with respect to the inputs at the normalized data point. This is because the elasticity of output with respect to ln X_i, E_i (the farm subscript f is dropped) is:

$$E_i = \alpha_i + \sum_j \beta_{ij} \ln X_j + \sum_k \delta_{ik} \ln Z_i \tag{8}$$

which equals α_i at the normalized data point. These E_i can also be used to calculate (short-run) returns to scale (RTS) which are defined as the sum of the (endogenous) input elasticities. We find RTS to be equal to 0.9898 at the normalized data point.

The production function is said to be well behaved if it is monotonically increasing and concave in input quantities. Monotonicity is satisfied since the estimated input cost shares (cost of input as a ratio of total value of output) are found to be positive. Concavity is checked by verifying the negative semidefiniteness of the matrix:

$$\left[\hat{W} \frac{\partial^2 Y}{\partial X \, \partial X'} \hat{W} \right] / Y = B - \hat{S} + SS' \tag{9}$$

where $\hat{W} = \text{diag}\,(W_1, \ldots, W_n)$, $\hat{S} = \text{diag}\,(S_1, \ldots, S_n)$, $S = (S_1, \ldots, S_n)$ and $S_i = W_i X_i / PY$. Concavity is satisfied at the normalized data point since the above matrix is found to be negative semidefinite.

Technical efficiency for each farm is calculated as TE $= Y/Y_{\max} = \exp(\tau)$, where the estimate of τ is obtained from (6). This measure of technical efficiency is called output augmenting since it suggests that actual output is below the frontier output by $[1 - \exp(\tau)] \times 100\%$. Alternatively, output could be increased by $[1 - \exp(\tau)] \times 100\%$ if the farm becomes technically efficient. The frequency distribution of TE is reported in Table 2. None of the farms in the sample is fully technically efficient. The mean efficiency of these farms is 75.46%; the maximum is 85.87% and the minimum 55.45%. Thus, potential output of these farms, given their input usage, is much higher.

Table 1
Parameter estimates (standard errors in parentheses)

Parameter	Estimated value	Parameter	Estimated value	Parameter	Estimated value
α_0	−0.4127 (0.1255)	β_{FN}	−0.0078 (0.0027)	δ_{NK}	−0.0078 (0.0097)
α_F	0.1541 (0.0088)	β_{FB}	−0.0092 (0.0016)	δ_{NL}	−0.0697 (0.0426)
α_N	0.5663 (0.0327)	β_{FM}	−0.0090 (0.0018)	δ_{BK}	−0.0051 (0.0031)
α_B	0.1582 (0.0103)	β_{NB}	−0.0480 (0.0042)	δ_{BL}	0.0070 (0.0139)
α_M	0.1119 (0.0133)	β_{NM}	−0.0292 (0.0048)	δ_{MK}	−0.0053 (0.0040)
θ_K	0.1352 (0.0403)	β_{BM}	−0.0097 (0.0024)	δ_{ML}	0.0187 (0.0169)
θ_L	0.1759 (0.3001)	λ_{KK}	−0.0438 (0.0172)	σ_v	0.5388 (0.0421)
β_{FF}	0.0277 (0.0015)	λ_{LL}	0.0022 (0.4479)	σ_τ	0.5238 (0.0526)
β_{NN}	0.1199 (0.0128)	λ_{KL}	−0.0033 (0.0680)	Region 1	−0.0084 (0.0344)
β_{BB}	0.0675 (0.0048)	δ_{FK}	0.0005 (0.0023)	Region 2	−0.0691 (0.0345)
β_{MM}	0.0364 (0.0043)	δ_{FL}	−0.0146 (0.0096)	Small	0.0648 (0.0317)
				Medium	0.0971 (0.0443)

F, fertiliser; N, human labour; B, bullock labour; M, manure; K, capital; L, land.

Table 2
Frequency distributions of technical efficiency

Technical efficiency (%)	Frequency	Percent of total
Below 58.5	1	0.44
58.5–61.5	4	1.76
61.5–64.6	8	3.52
64.6–67.6	24	10.57
67.6–70.7	23	10.13
70.7–73.7	68	29.96
73.7–76.7	68	29.96
76.7–79.8	25	11.01
Above 79.8	6	2.65
Total	227	100

Table 3
Distribution of technical efficiency across regions and farm sizes

	Mean	Maximum	Minimum	Standard deviation
Region 1	75.20	83.16	65.91	3.94
Region 2	75.17	85.17	55.45	5.51
Region 3	76.62	85.87	66.28	4.20
Small	75.98	82.12	63.05	3.83
Medium	75.16	85.87	62.41	4.82
Large	75.53	85.17	55.45	4.77
Total	75.46	85.87	55.45	4.59

From the view point of a resource scarce economy these findings have obvious policy implication. By improving technical efficiency of these farms, output could be increased, on average, by 24.54%. [8]

In Table 3 we report the level of technical efficiency by region and farm size. To conserve space only the mean, maximum and minimum values are included. The mean efficiency levels are very similar across regions and size groups but not the minimum values. This difference in the distribution of technical efficiency is also reflected in the standard deviations (reported in the last column of Table 3). It can be seen that the small farms are more efficient (higher mean values and smaller standard deviations). However, the best farm in the small size group is not more efficient than those in the medium and large size groups.

Readers familiar with the empirical applications of stochastic frontier production functions are not surprised by the above results on technical efficiency. The mean level of technical efficiency is comparable to other similar studies. [9] There are, however, certain factors which can affect the estimate of technical efficiency. First, since we are dealing with cross sectional data, farm-specific factors cannot be controlled. Thus, unobserved farm effects are confounded with technical efficiency. As a result, farms which are found to be most inefficient might not be so if individual effects are controlled. This can be done only when panel data are available [see, for example, Kumbhakar and Hjalmarsson (1993) for such an application]. Second, the role of non-physical inputs like experience, information, supervision, etc., might influence the ability of a producer to use the available technology efficiently. These factors are not taken into account because of non-availability of such information in the present data.

To compose a management index that describes how management is reflected in the level of input utilisation, we run an auxiliary regression of technical efficiency, which can be used as an index of 'management', on all of the inputs. [10] The results show positive correlation between technical efficiency and (endogenous) input use. In other words, an inefficient farm tends to use less of every (endogenous) input and produce less output (Kumbhakar, 1987). This finding suggests that:

- The OLS results based on the production function without the management variable are biased.
- Even if technical inefficiency is introduced into the analysis [as in Huang and Bagi (1984), Huang (1984), Kalirajan and Shand (1985), among others], the assumption that technical inefficiency is independent of the inputs is inappropriate. Consequently, the parameter estimates are inconsistent if the production function alone is used in estimation.

[8] Two alternative models, viz., a single-equation translog model and a simultaneous equation Cobb–Douglas (CD) model, were also considered. About 90% of the parameters were found to be statistically insignificant in the first model. Because of this we did not pursue the single-equation translog model further. The CD model is a special case of the translog model considered in this study. We, therefore, test the restrictions for the CD model using the likelihood ratio test. The test rejects the CD specification at the 1% level of significance. The distribution of technical efficiency generated from this model shows much greater variability – ranging from 20% to 87% with a mean value of 67.13%. Since this model is rejected by the data, we decided not to report the results in details.

[9] See the survey by Battese (1992) and the references cited there for a variety of applications in agricultural economics using data from different countries.

[10] This regression "does not explain what determines the performance of the management" (see Mundlak, 1961, p. 49).

In view of the 'belief' that there is an inverse relation between land size and productivity in Indian agriculture, we looked at the coefficient of the land variable in the auxiliary regression. The coefficient is negative and statistically significant. This finding supports previous results that small farms are technically more efficient. [11]

Now we examine whether these farms are using their inputs efficiently by calculating allocative inefficiency for each farm from (3), viz.

$$u_{if} = -\ln Y_f^* + \ln X_{if} - \ln S_{if}^* + \ln W_{if} - \ln P_f - \tfrac{1}{2}\sigma_v^2 - \tau_f \quad (10)$$

where Y^*, S^* and σ_v^2, τ are to be replaced by their estimates. A zero value of u_i means that the input i is efficiently used whereas a negative (positive) value means under-utilisation (over-utilisation). [12] In view of this, we separate positive and negative values of u for each input and report their mean values in Table 4. The distribution of farms is shown by their percentages in each category. Table 4 shows a clear pattern of input use. Under-utilisation of the inputs is a common problem to most of these farms: 53.75% underutilised fertiliser and 62.56% underutilised manure. The percentage of farms underutilising human and bullock labour are 57.71 and 55.95, respectively.

These results on allocative inefficiency seem to contradict the Schultz hypothesis (1964) that Indian farms are poor but allocatively efficient. Schultz, like Hopper (1965), calculated allocative (in)efficiency for the whole sample, not for individual farms. Thus, to relate our results to those of Schultz, one has to look at the mean values of u_i which are very close to zero. This is what Schultz's conclusion is. Thus, in the aggregate level our results do not contradict the Schultz hypothesis.

Table 4
Allocative inefficiency and the distribution of farms

	Allocative inefficiency			
	u_F	u_N	u_B	u_M
Over-utilisation	0.0228	0.1518	0.0347	0.0488
	(46.25%)	(42.29%)	(44.05%)	(37.44%)
Under-utilisation	−0.0201	−0.1151	−0.0281	−0.0281
	(53.75%)	(57.71%)	(55.95%)	(62.56%)
Average	−0.0003	−0.0022	−0.0004	0.0007

However, it is to be noted that the concept of efficiency is essentially micro. One cannot draw any conclusion regarding allocative efficiency of individual farms from the aggregates. Our results on allocative inefficiency are based on individual farms. In reporting these results we grouped farms as under- (over-)user of inputs and calculated their mean values. What is interesting here is that one can look at the magnitude of these values for each input and farm to identify those which are under- or over-user of a particular input. The aggregative picture conceals such information. From a policy point of view, the main advantage of this type of micro analysis is that it gives some information about the inefficient farms to the policy makers so that outside help of experts may be directed to those who need it most.

The estimates of allocative inefficiency, presented here, are subject to two caveats. First, the use of the risk neutral assumption where farms are risk averse may result in 'apparent allocative inefficiency'. The present study implicitly assumes risk neutral behavior while using the expected profit maximisation behavior where only the output variable is uncertain. Under risk averse behavior the first order condition is:

$$E\left(U'(\pi)\left[P\frac{\partial Y}{\partial X_i} - W_i\right]\right) = 0 \quad (11)$$

where $U(\pi)$ is utility from profit, π, and $U'(\cdot)$ is the first derivative of $U(\cdot)$. The second derivative of $U(\cdot)$, $U(\cdot)''$, is assumed to be negative (zero) for risk-averse (risk-neutral) behavior. Thus, the

[11] See Saini (1979, chapter 7) for a review of some of these studies. It is, however, to be noted that the present methodology is econometrically much more sophisticated and rigorous.

[12] It is to be noted that the idea of allocative efficiency used here is based on the profit maximisation hypothesis. Since the profit maximising behavior is embedded into the model, it is not possible to test the profit maximisation hypothesis as such (Junankar, 1980).

condition under risk neutrality [$U''(\cdot) = 0$ or $U'(\cdot) = \text{constant}$] is:

$$E\left(\left[P\frac{\partial Y}{\partial X_i} - W_i\right]\right) = 0 \tag{12}$$

which is the first-order condition of expected profit maximisation in (3) without allocative inefficiency ($u_i = 0$). Since the solution of X_i from (11) is less than that of X_i from (12), the estimates of input over-utilisation will be biased upward if risk-neutral behavior is imposed when producers are risk-averse. Second, the output and input markets may not be competitive as assumed. In the Indian context one may cite government intervention in the input markets, e.g., fertiliser and labour markets as well as in the output market. The presence of such restrictions distorts prices which may result in 'apparent allocative inefficiency'.

6. Conclusion and remarks

The main contribution of this paper is in the use of a flexible (translog) production function in estimating technical and allocative efficiencies using farm-level data from West Bengal, India. We used the expected profit maximisation criterion which accommodates both endogenous and exogenous (quasi-fixed) inputs and estimated both technical and allocative inefficiencies for each farm. The possibility of bias or inconsistency in parameter estimates resulting from correlation of technical inefficiency and input use is eliminated by using a simultaneous equation approach instead of a single equation method.

The empirical results show that there is substantial scope for improving technical efficiency of these farms. None of the farms in our sample is fully technically efficient. The most efficient farm is about 14% below the production frontier. We also find that technical efficiency is positively correlated with fertiliser, manure, labour and bullock labour but negatively with land size. The last result shows that small farms are more efficient (technically). This finding is important so far as the land reform policy of the government is concerned. Concerning allocative inefficiency, we find that more than 50% of the farms in our sample under-utilise fertiliser, manure, labour and bullock labour. The extent of under-use, however, varies from farm to farm. This phenomenon of inefficient use of inputs may be due to distortions in the input and output markets resulting from government regulations as well as social and cultural constraints. Imperfect market conditions may also be responsible for this misallocation.

The present research can be extended in several ways. First, factors like land size, land tenure, credit availability, education, extension services, etc., may be introduced to explain differences in technical and allocative efficiencies. Second, if the product and factor markets are not competitive because of government regulations, social and cultural barriers, etc., or some of the factors are immobile and farms are risk averse, imposition of the expected profit maximisation (risk neutrality) hypothesis may lead to erroneous conclusions, especially regarding allocative inefficiency. Finally, availability of panel data would be helpful to control for farm-specific effects which cannot be separated from technical inefficiency using cross sectional data. We hope to address some of these issues in the future.

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