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Specification and Estimation Technical, Allocative, and Scale Inefficiency of Indian Rice Producing Farms

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This paper uses a system approach to measure simultaneously technical, allocative, and scale ineffciencies of Indian farmers using a stochastic frontier apporach. A quasitranslog stochastic production function is used to specify the production technology. Time and region dummies are introduced in the model. Interaction between region dummies and land variable is introduced to capture spatial differences in soil fertility across regions. The model is applied to farm level data. Empirical results indicate that Indian farmers, both large and small, are technical, allocative, and scale inefficient. Small farms are technically less effcient, but more scale effcient than large farms. The cost of allocative inefficiency is less for small farms.

I. Introduction

The inception of the green revolution since the mid 1960's and the consequent advent of modern technology have improved the economic efficiency of Indian agriculture. Since the publication of Schultz's (1964) *Transforming Traditional Agriculture* and consequent publication of Hopper's (1965) seminal paper on economic effciency of Indian farms, studies on the economic effciency of Indian farms gained momentum. Most of these studies found Indian farms econmically effcient.[1] Recently, however, economists have been more concerned with the post green revolution economic problems of Indian agriculture. It is sometimes argued that the benefical impacts of the

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green revolution have reached a saturation level and even the agricultural productivity is showing a downward trend. A reconsideration of the hypothesis of economic efficiency of Indian agriculture is, therfore, necessary in light of these changed scenario. The main purpose of this study is to examine the existence of different types of economic inefficiencies of Indian farms by applying a more up-to-date estimation methodology to a recent data set.

Earlier econometric studies on issues related to efficiency of Indian agriculture can be divided into two broad categories based on whether a stochastic functional specification or a traditional production of profit function have been used. Each of the category can again be divided into two subgroups based on whether a primal or a dual approach has been followed.

Studies which followed the primal approach have mostly estimated a Cobb-Douglas (CD) production function by the ordinary least squares technique (OLS)[2]. After obtaining the parameter estimates, marginal product (MP) of each endogenous input is calculated at the geometric mean of the data. The presence of allocative efficiency is then tested by equating value of MP of inputs with their respective prices.[3] On the other hand, the studies that followed the dual approach have mostly estimated a profit function along with the input demand or share (in profit) equations obtained using the Hotelling's lemma.[4]

Since a profit function accommodates allocative ineffciency, the hypothesis of profit maximization and allocative effciency are tested by imposing parmetric restrictions on the profit function.[5]

The studies that used average primal and / or dual functions can be characterized by at least one of the following problems. First, since these studies estimated nonstochastic production or profit function, they have basically measured the mean value of the observations rather than the maximum possible value defined by a production and/or a profit

[1] See Sampath (1979) for an exellent review of the studies on economic efficiency of Indian agriculture.

[2] e.g., Krishna (1964), Hopper (1965), Sahota (1968), and Sampath (1979) among others have used primal approach to address the efficiency issues of Indian agriculture.

[3] Single equation OLS estimation leads to inconsistent paramenter estimates as some endogenous inputs are correlated to the error in production function. As a result the measure of efficiency obtained from these parameters is likely to be inappropriate. This can be avoided by following a simultaneous equation estimation method.

[4] e.g., Lau and Yotopolous (1972, 1971), Yotopolous and Lau (1973), Sidhu (1974), Jununkar (1982, 1980), Kaliragan (1981a), and Kumbhakar and Bhattacharyya (1992) among others have used dual profit function to examine the allocative inefficiency of Indian farms.

[5] The advantage of using dual approach is that the price variables are exogenous and consequently there is no inconsitency even if a single equation is estimated.

function. From the point of view of economic behavior, it poses a serious problem, because in economic optimization one is interested in frontier value of a function rather than the mean value. Second, most earlier studies addressed the question of allocative inefficiency and/or the technical inefficiency under the hypothesis that the farms maximize profit. A farm may fall short of its profit maximizing goal even if it is allocatively and technically efficient, but scale inefficient (Fϕrsund, Lovell, and Schmidt, 1980). A profit maximizing farm can be on its profit frontier if, and only if, the farm is tecnically, allocatively, and scale efficient.

With the development of stochastic frontier function methodology of efficiency estimation (Aigner, Lovell, and Schmidt, 1977, and Meeusen and van den Broeck, 1977) several studies have attempted to examine the economic efficiency of Indian farms. Most of these studies, however, have addressed the technical inefficiency by estimating a stochastic production function which appends an one-sided error term to a production function to capture farm level technical inefficiency.[6] This is no doubt an improvement over the traditional approach. However, the allocative and scale inefficiency of the farms and their cost implications were not addressed.

In this paper attempts have been made to extend the previous analysis in several ways. Use of a stochastic frontier specification facilitates the estimation of a production frontier representing the maximum possible level of output rather than average production. Assuming a behavioral model of unconstrained profit maximization, this paper presents a stochastic specification of the production function that permits radial measurement of all three types of inefficiencies (i.e., technical, allocative, and scale) for individual farm.[7] Since fixed factors limit the short-run expansion of output, interaction between fxied and variable factors has been accommodated in the production function specification. The data set used in this study was collected over a six year period across three agroclimatic regions of the Indian state of West Bengal. Time and region dummies are, therefore, incorporated in the model to capture time and region effects. Soil fertility is likely to vary across regions. Regional dummies are, therefore, interacted with the land variable to capture spatial differences in soil fertility. Application of the model to paddy cultivation shows

[6] e.g., Kalirajan (1981b, 1982, 1989); Battese and Coelli (1988, 1992); Battese, Coelli, and Colby (1989); Battese and Tessema (1982).

[7] Bhattacharyya and Glover (1983) estimated allocative and output inefficiencies and the consequent profit inefficiency of Indian paddy farmers using the non-radial measure. Technical efficiency component, however, was not separately identified.

that small farms are technically more inefficient than the large farms; but allocatively less ineffiecient than their larger counter part. Regarding scale inefficiency, both groups are found to be undersupplying output; but the small farms are less scale inefficient than large farms. The cost of allocative inefficiency is also found to be higher for large farms.

The rest of the paper is organized as follows. The following section describes the model and its basic characteristics. The estimation method is then analyzed and followed by a discussion of the data set. Empirical results are then presented. Concluding remarks stress the major findings of this paper.

Ⅱ. Model Specification

To capture the interaction between quasi-fixed inputs, $Z(=z_1, z_2, \ldots, z_J)$ and variable inputs $X(=x_1, x_2, \ldots, x_n)$, a quasi-translog production function is specified as:

$$(1)\quad y(X, Z)=a \prod_i x_i^{\alpha_i} \prod_j z_j^{\beta_j} \exp\left(\sum_i \sum_j \gamma_{ij} \ln x_i \ln z_j\right),$$

where y is the output, $i=1,\ldots, N$, and $j=1,\ldots, J$ index variable and quasi -fixed inputs, respectively. Such a specification allows for the derivation of closed-form solutions for the input demand and the output supply functions. Analyticlal specifications of all three types of inefficiencies as derived by Fφrsund, Lovell, and Schmidt (1980) are also possible with such a specification. Moreover, one can isolate the impact of individual inefficiency on the cost level which is of prime importance from a policy point of view.[8] Following Aigner, Lovell, and Schmidt (1977) and Messusen and van den Broeck (1977), a composite error structure is introduced in (1) by specifying the intercept term a as:

$$(2)\quad a=\alpha_0 \exp(\tau),$$

where $\tau \leq 0$. The stochastic variant of the production function(1)[9]

[8] Use of a fully flexible functional specification for similar purpose fails to isolate the impact of various inefficiency on the level of profit and/or cost (see Greene 1980). Recently, Kumbhakar (1991), Ferrier and Lovell (1990), Baure (1985) and Schmidt (1984) have tried to resolve this issue for the Translog cost function by imposing a pre-specified relationship between the value dual and its first order condition. However, these specifications are special case and impose specific structure on the translog functional form.

[9] The production function, (1), is assumed to satisfy convexity and monotonicity assumptions.

becomes

$$(1a)\quad y(X, Z) = \alpha_0 \prod_i x_i^{\alpha_i} \prod_j z_j^{\beta_j} exp(\sum_i \sum_j \gamma_{ij} \ln x_i \ln z_j + \tau + \epsilon),$$

where the error component ϵ represents symmetric statistical white noise which is beyond farms' control. The one-sided error term τ is the technical efficiency parmetèr that varies across farm but not observable. If $\tau = 0$, then the farm is producing the maximum level of output given the level of technology. If, on the other hand, $\tau < 0$, then the farm is producing below the technically feasible maximum, and hence technically inefficient.

Allocative inefficiency results from employing inputs in incorrect proportions. Following Schmidt and Lovell (1979, 1980), a farm is allocatively inefficient if the marginal rate of technical substitution between factors differs from their ratio of prices, i.e., $MRTS_{qs} \neq (w_q / w_s)$. This can be specified as:

$$(3)\quad \frac{f_q}{f_s} = \left\{\frac{x_q}{w_s}\right\} \exp(u_q);\ \forall\, q,\ s = 1, \ldots, N;\ q \neq s.$$

where w is hiring price of the subscripted factor, f represents the marginal productivity of the subscripted factor, and u_q can take any value. Given (1a) and (3), allocative ineficiency of the qth input relative to the sth input can be expressed as:

$$(3a)\quad \exp(u_q) = \left\{\frac{x_s w_s}{x_q w_q}\right\} \left\{\frac{(\alpha_q + \Sigma_j \gamma_{qj} \ln z_j)}{(\alpha_s + \Sigma_j \gamma_{sj} \ln z_j)}\right\}\quad .$$

Technical and allocative effciency are necessary but not sufficient for profit maximization. A farm could still be scale inefficient if MC $\neq$ p, where MC is marginal cost and p is output price. Scale inefficiency can be specified as:

$$(4)\quad \exp(\xi) = \left\{\frac{1}{p}\ \frac{\partial C^*}{\partial y}\right\}$$

where $C = \sum_{i=1}^{n} w_i x_i$ and $*$ denotes the optimum level. The parameter

ξ measures the deviation of observed output from the profit-maximizing output supply. If $\xi = 0$, then the farm is supplying the profit-maximizing level of output, given p. ξ is positive (negative) if the farm is supplying more (less) than the optimum level. Given our production tion (1a), (4) can be expressed as:

$$(4a)\quad p \exp(\xi) = \theta y^{(\theta - 1)} \left\{ \sum_i (\alpha_i + \sum_j \Upsilon_j \ln z_j) \prod_i w_i^{\theta(\alpha_i + \Sigma_j \Upsilon_{ij} \ln z_j)} \prod_i z_j^{(-\theta\beta_j)} \right\}$$

$$\left\{ \left\{ \alpha_0 \prod_i (\alpha_i + \sum_j \gamma_{ij} \ln z_j)^{(\alpha_i + \Sigma_j \gamma_{ij} \ln z_j)} \right\}^{-\theta} \right\}$$

where

$$\theta = \frac{1}{(r+k)} : r = \sum_i \alpha_i, \text{ and } k = \sum_i \sum_j \gamma_{ij} \ln z_j.$$

Equations (1a), (3a), and (4a) represent the full system of equations incorporating technical, allocative, and scale inefficency. Taking logarithms of (1a), (3a), and (4a), the following system of equations is obtained

$$\text{(1b)} \ \ln y = \ln \alpha_0 + \sum_i \alpha_i \ln x_i + \sum_j \beta_j \ln z_j + \sum_i \sum_j \gamma_{ij} \ln x_i \ln z_j + \tau + \epsilon;$$

$$\text{(3b)} \ \ln x_s - \ln x_q = \ln w_q - \ln w_s + \ln \left\{ \alpha_s + \sum_j \gamma_{sj} \ln z_j \right\} - \ln \left\{ \alpha_q + \sum_j \gamma_{qj} \ln z_j \right\} + u_{qj}$$

$$\text{(4b)} \ \ln y = \frac{1}{(r+k-1)} \left\{ \ln \alpha_0 + \sum_j \beta_j \ln z_j - \sum_i (\alpha_i + \sum_j \gamma_{ii} \ln z_j) \ln w_i + \sum_i (\alpha_i + \sum_j \gamma_{ij} \ln z_j) \ln(\alpha_i + \sum_j \gamma_{ij} \ln z_j) \right\} + \frac{1}{(\theta - 1)} \ln p + \frac{1}{(\theta - 1)} \xi$$

The system of equations (1b), (3b), and (4b) involve$(n + 1)$ equations in $(n + 1)$ unknowns ($\ln y$ and $\ln x_i$, $\forall i = 1, \cdots, n$). A solution to these $(n+1)$ equations gives in unconditional input demands and output supply. The conditional input demands can be obtained from the first n equations, and the output supply from (4b). To be economically efficient, (to maximize profit), all three inefficiency parameters (τ, u_q, and ξ) must be equal to zero, both individually and simultaneously.

Ⅲ. Estimation method

Direct estimation of the production function gives consistent estimates only when inputs can be treated as exogenous. Zellner, Kmenta, and Drèze (1966) argue that expected profit maximization treats inputs as exogenous only if technical inefficiency is completely unknown to the farm. Since sources of technical inefficiency include poor management, the condition of capital stock, and local labor quality, the assumption of unknown technical inefficiency may not be fully justified. If technical inefficiency is known to the farm, the estimate of the production function parameters obtained directly from the production function will be inconsistent. This inconsistency can be avoided if a simultaneous equation approach is used that allows estimation of all three inefficiency parameters(Kumbhakar, Biswas, and Bailey, 1989).

A simultaneous equation method such as the full information maximum likelihood (FIML) also gives inconsistent estimates of the parameters. If τ is known to the farm, then the use of FIML give upward bias to the intercept. On the other hand, if τ is unknown, then it is not possible to distinguish between the effects of τ and ϵ. Use of the maximum likelihood estimation (MLE) method is required because an assumed distribution for each disturbance terms can be specified, and the individual inefficiency effects could be identified. A simultaneous equation MLE method has been used here for estimation of the model. Prior to estimation, the probability density function (*pdf*) of the error vector with specified distributional assumptions for each error term needs to be derived. The error vector from the system of equations (1b), (3b), and (4b) is

$$(5) \quad \begin{pmatrix} \tau+\epsilon \\ \underline{u} \\ \xi \end{pmatrix}$$

where $\underline{u}$ = $[u_2,..., u_n]'$. Following assumptions are made regarding distribution of error terms:

1. $\tau \sim i.i.d.\ N(0,\ \sigma_\tau^2)$ truncated at zero from above;
2. $\underline{u} \sim MVN(\mu,\ \Sigma)$, i.e., *i.i.d.* normal over farms;
3. $\xi \sim i.i.d.\ N(0,\ \sigma_\xi^2)$;
4. $\epsilon \sim i.i.d.\ N(0,\ \sigma^2)$; and
5. τ, μ, ξ, and ϵ are independent of each other and also independent of w_i and all exogenous fixed factors z_j.

Given the above set of assumptions the *pdf* of the error vector is

$$f(\tau,\ \epsilon,\ \xi,\ u) = f(\tau)\, f(\epsilon)\, f(\xi)\, f(u),$$

and after suitable transformation the concentrated likelihood function for a single farm can be expressed as:

$$(6)\ L_C=k - \left(\frac{d}{2}\right)+\ln\sigma+\ln\Phi\left(-\ \frac{\mu_\tau}{\sigma}\right)-\ln\sigma_\xi-\ln\sigma_\tau-\ln\sigma_\epsilon-\frac{1}{2\sigma_\xi^2}$$
$$+\ln\left\{(\theta\text{-}1)\sum_i \alpha_i\right\}-\frac{1}{2}\ln\ |\ \Sigma\ |,$$

where $\Phi(\bullet)$ is the cumulative density function (*cdf*) of a standard normal, $|\ \Sigma\ |$ is the variance-covariance matrix of the error vector u

$$\kappa = \ln 2 - \frac{n+1}{2}\ln 2\pi - n + 1,\ \sigma^2 = \left\{\frac{\sigma_\tau^2\sigma_\epsilon^2}{\sigma_\tau^2 + \sigma_\epsilon^2}\right\},\ \mu_\tau = \left\{\frac{b_1\sigma_\tau^2}{\sigma_\tau^2 + \sigma_\epsilon^2}\right\}$$
$$\text{and } d = \left\{\frac{b_1^2}{\sigma_\tau^2 + \sigma_\epsilon^2}\right\}$$

κ is a constant and can be eliminated during estimation. The log-likelihood function for the full sample of T farms is thus

$$\text{(6a) } \ln L = \sum_{i=1}^{T} \ln L_c$$

The MLE of α_i, β_i, γ_{ij}, σ_τ, σ_ϵ, and σ_ξ can be obtained by maximizing (6a).

Given the estimates of the parameters, τ, μ, and ξ can be estimated for each observation. Following Jondrow, Lovell, Materov, and Schmidt (1982), τ can be separated from ϵ by estimating the conditional *pdf* of τ given b_1, where $b_1 = \tau + \epsilon$ is the residual of the production function. Following Kumbhakar (1987), it can shown the τ given b_1 is normally distributed with mean μ_τ and variance σ_τ^2 truncated at zero. Thus the point estimate of τ for each observation can be obtained from the mean or mode of τ which are

$$\text{(7a) } \tau_{\text{mean}} = \mu_\tau - \sigma\frac{\phi(\mu_\tau/\sigma)}{\Phi(-\mu_\tau/\sigma)};$$
and

$$\text{(7b) } \tau_{\text{mode}} = \begin{cases} \mu_\tau, & \text{if } (\mu_\tau/\sigma) \leq 0; \\ 0, & \text{otherwise.} \end{cases}$$

where $\phi(\bullet)$ is the density function of a standard normal. Given estimated values of μ_τ and σ, τ can be estimated. Given X and Z, the percentage loss of output due to tecnichnical inefficiency, τ, can be obtained from

$$\text{(8) } YL_\tau = \frac{y - y^*}{y^*} = 1 - \exp(\hat{\tau}),$$

where y^* is the frontier level output, y is the observed output, and $\hat{}$ indicates the estimated value.

The relative allocative inefficiency of T farms for (n-1) inputs (relative to input s) can be obtained from

$$\text{(9) } \hat{u}_q = \ln x_s - w + \ln x_q + \ln w_s - n\, w_q + \ln\left\{\frac{\hat{\alpha}_q + \Sigma_i\gamma_{qi}\ln z_i}{\hat{\alpha}_s + \Sigma_j\gamma_{sj}\ln z_j}\right\}.$$

Following Schmidt and Lovell (1979), the cost of allocative inefficiency can be measured from

$$(10)\ \ln C(W, y, Z) = \ln K + \theta \ln y + \theta \sum_i (\alpha_i + \sum_j \gamma_{ij} \ln z_j) \ln w_i$$

$$-\theta \sum_i \beta_j \ln z_j + \{\rho - \ln(\gamma + k)\} - \theta(\epsilon + \tau);$$

where

$$\rho = \ln \left\{ \alpha_s + \sum_j \gamma_{sj} \ln z_j + \sum_q \left\{ \alpha_q + \sum_j \gamma_{qj} \ln z_j \right\} \exp(-u_q) \right\}$$

$$+ \theta \sum_q (\alpha_q + \sum_j \gamma_{qj} \ln z_j) u_q,$$

and

$$\ln K = \ln(\gamma + k) - \theta \ln \alpha_o - \theta \sum_i (\alpha_j + \sum_j \gamma_{ij} \ln z_j) \ln(\alpha_i + \sum_j \gamma_{ii} \ln z_i).$$

The cost of allocative inefficiency is represented by the term

$$(11)\ CA = \{\hat{\rho} - \ln(\hat{\gamma} + \hat{k})\}$$

Clearly σ is minimized when $\mu_2 = \mu_3 = \cdots = \mu_n = 0$ and equals $\ln(\gamma + k)$. In that case, the cost function does not contain any allocative inefficiency parameter. Otherwise, the values (non-negative) of $\{\rho - \ln(\gamma + \kappa)\}$ are the addition to the logarithm value of cost, $\ln C(W, y, Z)$, due to allocative inefficiency.

Schmidt and Lovell (1979) has shown that the conditional demand for input will increase by the same proportion due to the presence of technical inefficiency. However, the presence of technical inefficiency reduces output supply which in turn, requires less input.

The net effect would be reduced demand for each input (Kumbhakar 1987) which will reduce the cost of production. It is, therefore, interesting to check the impact of all three inefficiency parameters.

Note, CA is defined for a given level of output from the cost function, $\ln (W{:}y, Z)$ for $\tau = 0$. Under profit maximization, the cost function is not conditional on a given level of output, In $C(W, p{:}Z)$. This can be derived by substituting the output suply function, $\ln Y(W, p{:}Z)$ in the constant output cost function. This becomes profit maximizing minimum cost. The cost of allocative inefficiency alone under profit maximization can be obtained from

$$(12a)\ CA\pi = \frac{1}{(\theta - 1)} \left[\left\{ \rho - In(r + k) \right\} (\theta - 2) \right]$$

One important point to note is the inclusion of the scale inefficiency parameter in the cost function. The output supply equation is derived under the optimizing condition, $\frac{\partial C^*}{\partial y} = p$, where $C^* = \Sigma_i^n w_i x_i^*$, is the efficient cost (net of allocative and technical inefficiency). But one can estimate the scale inefficiency under full cost by defining MC based on actual cost $C = \Sigma_i^n w_i x_i^{**}(w, \mu_i, p, \tau : Z, y)$. In the second case, the output supply function is affected by allocation and technical distortions in addition to the pure scale inefficiency. In the first case, the distortion is pure scale inefficiency as defined by Fϕrsund, Lovell, and Schmidt (1980).[10] One can therefore derive an alternative measure of scale inefficiency; based on actual cost and efficient cost. In the former case, three sources of inefficiency are complement to one another. In the alternative measure, the optimal output of a farm is conditional on its technical and allocative inefficiency.

The efficient scale inefficiency parameter, ξ_0, for each observation can be measured from

$$(13)\ \hat{\xi}_o = (\hat{\theta}-1)\ln y - \ln p - \hat{\theta}\ln \alpha_o + \hat{\theta}\sum_i\left\{\hat{\alpha}_i + \sum_j \hat{\gamma}_{ij}\ln z_j\right\}\ln w_i$$
$$-\theta\sum_j \hat{\beta}_j \ln z_j + \theta\sum_i(\alpha_i + \sum_j \gamma_{ij}\ln z_j)\ln(\alpha_i + \sum_j \gamma_{ij}\ln z_j).$$

The loss of output due to scale inefficiency alone, derived from the output supply equation (4*b*) is

$$(14)\ YL_{\xi_o} = \frac{\hat{\xi}_o}{(\hat{\theta}-1)}.$$

On the other hand the loss of output supply due to scale inefficiency under actual cost can be derived from the output supply equation

$$(15)\ \ln y(p, W, \xi, \tau, u : Z) = \frac{1}{(\theta-1)}\left\{\ln p - \left\{\ln\theta + \ln K + [\rho - \ln(r+k)]\right.\right.$$
$$\left.\left.+\theta\sum_i(\alpha_i + \sum_j \gamma_{ij})\ln w_i - \theta\sum_j \beta_j \ln z_j - \theta(\nu+\tau) - \xi_a\right\}\right\}.$$

Note equation (15) is not independent of $\underline{u}$ and τ. This measure focuses on finding the optimal level on output for each farm conditional on its technical and allocative inefficiency. It can be shown

[10] See Kumbharkar, Biswas, and Bailey (1989) for a discussion on this point.

that the optimum level of output defined by (4*b*) is greater than that defined by (15). Since inefficiency involves cost, the MC curve defined by (15) will be to the left of the MC curve that underlies equation (4*b*). So the alternative measure(based on actual cost) gives a more narrow measure of scale inefficiency.

The loss of out put under this condition, therefore, is

$$(14a)\ YL_{\xi_a} = \frac{\hat{\xi}_a}{(\hat{\theta}-1)},$$

where $\hat{\xi}_a$ is the estimated scale inefficiency using (15).

Ⅳ. Data Description

The data set used in this study was collected by the Agro-Economic Research Center[11] from three agro-climatic regions[12] of the state of West Bengal in India The data set was collected over the period 1980 –1985. A cross section sample of 300 household farms is used in this study.

Three regions represent the entire rice production belt of West Bengal. Agricultural production activities of West Bengal are spread over at least three crop seasons during a one-year production cycle. The monsoon paddy is the single most important crop in all three regions. This crop is produced by almost all peasants and almost 70% of total arable land is used for this particular cultivation (Dasgupta 1987). The monsoon crop is the only production activity considered in this model.

The survey provides a wide range of information about both fixed and variable factors of production. Among inputs, fertilizer (F), manure (M), human labor (H), and bullock labor (B) are used as endogenous variable inputs, while land (L), capital (K), off-farm income (O), and years of education (E) are used as quasi-fixed inputs. Fertilizer is measured in terms of kilograms, while both types of labor are measured in terms labor hours. Total amount of paddy (Y) produced is the only output in this model, which is measured in terms of quintal. Manure is also measured in terms of hundred kilograms.

Both bullock and humman capital play inportant roles in indian

[11] It is a central organization for agricultural research under the Ministry of Agriculture, Government of India.

[12] Region I covers two districts, Nadia and Murshidabad. Region II covers the district of Burdwan and Birbhoom, and region III covers the district of Howrah, Hooghly, 24 Parganas, and Midnapore. A district is equivalent to U. S. county.

agriculture. Humman labor includes both family and hired labor. In this study market wage rate has been used to represent hiring prices of all labor. It has been argued (Saini 1971, Sampath 1979) that in the context of Indian agriculture, valuation of family labor at the prevailing market wage rate is justified. Although the market for animal labor is highly localized. during the peak season, such as the monsoon season, the market for animal labor is competitive. Another group of variable factors is fertilizer and manure. Fertilizer represents the total dose of chemical fertilizer used during that cropping seasoon. The market for manure is highly localized. Due to alternative use of manure, the market is competitive, particularly during the monsoon season.

Beside these four variable endogenous inputs, four quasi-fixed inputs are also considered in this model. Area under cultivation is considered as land input. capital is defined as a combination of values of all durable farm assets, namely the farmhouse, irrigation equipment, and farm equipment. The total value of capital is weighted by the total user cost of capital, defined as the sum of the yearly depreciation rate and the market rate of interest less the yearly inflation rate, assuming a straight line depreciation. Off-farm income is measure in terms of hundred rupees. In developing countries the degree of stochastic elements involved in agriculture is very high and the need for on-the -spot decisions is very important. If the farmer is engaged in off-farm employment, he probably can not make such quick decision, which means productivity and output may fall. On the other hand, off-farm employment allows the farmer to invest more cash in his farming that might increase productivity. Therefore , exact signs of the impact of off-farm income on productivity are difficult to determine *a priori* and empirical analysis is needed to assess the direction.

Since the seminal paper of Ram (1980) and Huffman (1977) on the impact of education production decisions and allocation scarce inputs, treatment of education as a regressor input has become a commonplace. In this model, maximum years of education of adult male members of the farm household are entered as a quasi-fixed factor. In the Indian situation, educated members of large farms are usually employed in off-farm positions in the services or trade sector awayfrom their village, so they take away with them the education input that could enhance efficiency of the farm. On the other hand. they contribute a part of their income to the family which, in turn, might influence productivity of the family farm. Small farmers, on the other hand, usually stay in village, and their off-farm jobs usually are in local services or in large farms as laborer. As a result, the human capital and off-farm income stays in the household. Since there are some zero values in for the education variable in the data set, it is used in the model without log-transformation.

The data set shows that the hiring prices of factors and output prices vary not only between years covered by the survey but also across regions. Variation in input and output prices can be attributed in part to differnences in transportation cost, storage cost, types of forward contracts, and types of land tenancy contracts. Quality differences in output and inputs may also be factors responsible for these price variations.[13] The price received by an individual farmer for his produce also depends on how long he can hold-off the sale. Larger farms are expected to hold their sale longer than their smaller counterparts, or they can sell their output in portions over time. This is probably why the data set reflects the fact that large farms receive higher prices for output. The data set also reveals that large farms pay lower price for their inputs, except for manure. The pattern of agriculture in India to a great extent depends on the mercy of the monsoon, to which farmers match their farming schedules. This is another reason for wide fluctuations in prices of some inputs like fertilizer, bullock labor, and human labor.

Ⅴ. Empirical Results

In view of the diverse farms size and wide dispersion of cost and output, observations have been divided into two subsets of large and small farms. Land holding size has been used to characterize farms in to these two subgroups. Following Bardhan (1977), this study chose seven acres as the dividing line between large and small farms. The model is further fine tuned by incorporating region (denoted as Reg_k where $k = 1, 2, 3$) and year (denoted as Yr_h where $h = 80, \cdots, 85$) dummies to captur region and time effects. The region effects are important because the regional differences in the culture of paddy cultivation, irrigation water availability, and occurrence of floods during monsoon affect the level of production at the regional level. For example, the occurrence of monsoon floods, which overlaps the paddy cultivation season, is quite common in Region I compared to that of Region II and III. Unless the severity of floods is high their impact on the production level is not very severe. The year dummies are included to take account of time effects, like flood and / or drought or pest problems. These two sets of dummies affect the intercept of the production function. The region dummies are again interacted with

[13] In this model quality differences have not been introduced. Information about this aspect can not be obtained from the data set.

land variable (denoted as LReg) to account for the differences in soil fertility across regions. This specification allows the slope coefficients on land to differ across regions. The model specification with region, year, and the land-region interaction dummies was tested against to model without such specification. A log likelihood ratio test accept the hypothesis of differences in region and year effects across region. So, in our final model estimation, all three types of dummies have been used.

The data set shows that large farms on average have land holdings twice the size of small farms. Per acre productivity of larg farms is higher compared to that of small farms. Large farms receive higher price for their produce and pay lower prices for their inputs (except for manure).[14]

Three separate models have been estimated. The log likelihood ratio test rejects the hypothesis of single production function for both groups [small farms (Model A) and large farms (Model B)].[15] Thus the use of a single production function (Model C) seems to be inappropriate; however, for comparison, parameter estimates of all three models are reported in table 1. Both region Reg_k and year Yr_h dummies are found to be statistically significant. So also the land-region interaction dummies($LReg_k$).

From the policy point of view, the impact of inefficiencies on the level of cost and output is important. These are reported for both groups of farms in table 2. Both small and large farms, in our sample, are found to be technically inefficient. This is consistent with the findings of Kalirajan (1981, 1982), Bagi (1982), Battese, Coelli, and Colby (1989), and Kalirajan and Shand (1989). The estimate of potential output loss due to technical inefficiency, YL_T, indicates that large farms are technically more efficient than their smaller counterparts. This result contradicts the result obtained by Huang and Bagi (1984), who found no significant difference in technical inefficiency between large and small farms. However, the regions covered and the definition of large and small farms used in their study

[14] The mean size of land holding by the small farm is 4.1 acre and 9.59 for large. Large farm on average produces 71.28 quintal while the same figure for the small farm is 28.4 quintal. Small farm receive Rs. 142.02 per quintal for their produce, the same figure for the large farm is Rs. 145.44. Small farm on average pay Rs. 5.50 per kilogram of fertilizer, Rs.6.88 per 100 kilogram of manurè, Rs. 10.09, and Rs. 8.89 per day for human and bullock labor, respectively. The same figure for large farms are Rs. 5.23, Rs. 7.27, Rs. 9.05, and Rs. 8.67, respectively.

[15] 15 The test statistic in the case of large and small farms respectively, $-2(L_U - L_R) = 924.92$ and 240.64 which are greater than x^2 with 37 degrees of freedom for any reasonable significance level.

are different from the definitions used in the present study.

Results indicate that small farms could have increased their output level by 28% at existing level of input use. On the other hand, large farms could have, similarly, increased their output by 9.07%. Thus, our estimates indicate that the large farms on average are 18.93% technically more efficient relative to their smaller counterparts. The output loss due to scale inefficiency, YL_{ξ_0}, for small farms shows that on average they undersupply 9.37% compared to their optimum level, while their large counterparts undersupply by 16.54%. This indicates that small farms are 7.17% less scale inefficient compared to large farms. The alternative measure based on the actual cost, Y_{ξ_a}, shows that while small farms undersupply output by 21% on average, their ounterpart, large farms undersupply by 46.48%. The cost of production of small farms on average has increased by 7.03% due to allocative inefficiency, while the same figure for large farms is 24.36%. The alternative measure of allocative inefficiency, CA_π, suggests that small farms incur 17.22% additional cost due to allocative inefficiency while for the larger farm similar measure is 31.59%.

The estimated results are further subdivided by region to examine if inefficiency estimates vary across regions. These results are also reported in table 2. Small farms of region III are found to be technically most inefficient (29%) compared to the small farms of other two regions. On average, small farms in region III are 2% more technically inefficient. As regard the cost of allocative inefficiency, small farms in region III are found to be the most inefficient by both measures. The estimated cost of allocative inefficiency under constant output, *CA*, indicates that small farms in region III incur almost 5% higher cost compared to that of region I and II. However, the *CA* for small farms of regions I and II are found to be almost of same magnitude, 5.6% and 6.4%, respectively. The costs of allocative inefficiency under profit maximization condition (CA_π) are found to be higter than their *CA* measure for all three regions. However, the cost is least for farms of region II (14%), and maximum for farms from region III (22%). As regard scale inefficiency, ther does not exist much of a difference across region when the ξ_0 definition (net of allocative and technical inefficiency) is used. However, the small farms of region III are found to be the most scale inefficient when the alternative measure (ξ_a)is used.

The large farms in region I are found to be 3% more technically efficient than the large farms of region II. As regard cost of allocative efficiency, large farms of region II are allocatively least efficient by both measures. However, there does not exist much difference between farms of region I and III. Regarding scale inefficiency, like small farms, there does not exist much difference across regions when ξ_o measure is applied. However, large farms of region II are found to be the most scale inefficient when the alternative measure is used.

VI. Conclusion

The main purpose of this paper is to investigate technical, allocative, and scale inefficiency of paddy producers of the Indian state of West Bengal using the frontier production function approach. To bring some degree of flexibility in measuring inefficiencies, a quasi -translog stochastic production function has been introduced which takes into account the interaction between fixed and endogenous factors. This specification allows for analytical derivations of all three types inefficiencies and simultaneous estimation.

The empirical results generate at least four fundamental results. First, the small farms appear technically less efficient than their larger counterparts. Second, large farms are more scale inefficient compared to the smaller units. Third, the cost of allocative efficiency is lower for smaller farms compared to larger farms, a result which supports the results of earlier studies. Fourth, both groups of farms are characterized by undersupply of output by either measure of scale inefficiency.

Table 1. Maximum Likelihood Parameter Estimates*

Parameter	Small Farm	Large Farm	Pooled Model
	A	B	C
α_0	3.3539	2.4795	2.4926
	(1.1385)	(0.1892)	(0.2762)
α_F	1.1827	0.9197	0.9378
	(0.3539)	(0.1438)	(0.2246)
α_M	0.5680	1.4027	0.4889
	(0.3657)	(0.6178)	(0.2509)
α_H	1.7244	1.2263	1.7236
	(0.6383)	(0.4403)	(0.3885)
α_B	0.6500	0.9465	0.6364
	(0.5885)	(0.6393)	(0.3544)
β_K	2.8506	0.9846	0.1170
	(0.3167)	(0.8413)	(0.2036)
β_L	3.1013	1.1658	0.5343
	(0.4364)	(1.0937)	(0.4364)
β_E	0.7287	0.2655	0.2367
	(0.8420)	(0.4853)	(0.1297)
β_O	1.0969	-0.5079	-0.1342
	(0.1278)	(0.3107)	(0.3094)
Yr_{80}	-1.0560	-0.6989	-0.1008)
	90.1366)	(0.3945)	(0.1058)
Yr_{18}	-0.4098	-0.1209	-0.4518
	(0.0689)	(0.2683)	(0.0508)

*Asymptotic standard errors are in parentheses.

continued

Parameter	Small Farm A	Large Farm B	Pooled Model C
Yr_{82}	-0.2581	-0.4942	-0.2944
	(0.0555)	(0.4213)	(0.0391)
Yr_{83}	-0.4376	-0.0837	-0.4539
	(0.0714)	(0.3244)	(0.0520)
Yr_{84}	-0.9783	-0.3061	-0.9848
	(0.1217)	(0.3794)	(0.0953)
Reg_1	-2.4283	3.0336	-2.5162
	(0.4073)	(0.3816)	(0.2741
Reg_2	-1.1472	2.0412	-1.2426
	(0.5341)	(0.3691)	(0.1856)
LReg1	1.1317	-1.8103	1.1304
	(0.2389)	(0.4039)	(0.1371)
LRge2	0.5037	-1.2241	0.5199
	(0.1887)	(0.3974)	(0.0970)
γ_{FL}	-0.1618	1.5374	-0.0317
	(0.1760)	(0.7368)	(0.0871)
γ_{FK}	0.2688	0.2886	0.1578
	(0.1602)	(0.1824)	(0.1007)
γ_{FO}	-1.0307	-0.8102	-0.3968
	(0.1870)	(0.7223)	(0.1682)
γ_{FE}	0.6381	0.4474	0.2752
	(0.1308)	(0.1793)	(0.0640)
γ_{ML}	-0.0053	-0.0857	0.0040
	(0.2499)	(0.0618)	(0.1322)
γ_{MK}	0.1806	-0.3500	0.1539
	(0.1983)	(0.0734)	(0.1345)

continued

Parameter	Small Farm A	Large Farm B	Pooled Model C
γ_{MO}	-0.1982	-0.6765	-0.1675
	(0.1858)	(0.1737)	(0.2227)
γ_{ME}	0.0639	0.4110	0.0559
	(0.1259)	(0.1272)	(0.0786)
γ_{HL}	-0.3366	0.6801	-0.3184
	(0.3736)	(0.8589)	(0.1787)
γ_{HK}	-0.1998	-0.5900	-0.2043
	(0.2715)	(0.1683)	(0.1667)
γ_{HO}	-0.2434	-0.3455	-0.2426
	(0.2591)	(0.2145)	(0.2660)
γ_{HE}	0.2295	0.1944	0.2536
	(0.1712)	(0.0682)	(0.0963)
γ_{BL}	0.0100	0.1292	0.0247
	(0.3804)	(0.0976)	(0.1780)
γ_{BK}	0.0620	-0.2643	0.0655
	(0.0338)	(0.3016)	(0.1785)
γ_{BO}	-0.2224	-0.2952	-0.2246
	(0.3188)	(0.3074)	(0.2909)
γ_{BE}	0.1426	0.0808	0.1545
	(0.2199)	(0.0551)	(0.1040)
σ_{τ}	0.4451	0.7715	0.8574
	(0.4593)	(0.3709)	(0.1921)
σ_{ξ}	0.3654	5.2399	4.2811
	(0.0411)	(0.54424)	(4.0535)
σ_{ϵ}	2.0235	2.0235	1.0235
	(1.0121)	(2.0235)	(0.2762)

Table 2. Mean Inefficiency Measures by Region

Parameter	Region I	Region iI	Region III	Total
Large Farms				
YL_{τ}	0.0848	0.0902	0.1160	0.0907
	(0.0770)	(0.0909)	(0.0995)	(0.0839)
$YL_{\xi 0}$	-0.1654	-0.1655	-0.1652	-0.1654
	(0.0055)	(0.0048)	(0.0398)	90.0050)
$YL_{\xi a}$	-0.4472	-0.4949	-0.4554	-0.4647
	(0.0913)	(0.1029)	(0.1709)	(0.1065)
$\hat{C}A$	0.2343	0.2610	0.2343	0.2436
	(0.0716)	(0.0818)	(0.1197)	(0.0815)
$\hat{C}A_{\Pi}$	0.2961	0.3460	0.3166	0.3159
	(0.0017)	(0.0017)	(0.0015)	(0.0016)
N	29	19	7	55
Small Farms				
YL_{τ}	0.2756	0.2944	0.2944	0.2775
	(0.1234)	(0.1671)	(0.1671)	(0.1360)
$\mathrm{YL}_{\xi 0}$	-0.0917	-0.0969	-0.0969	-0.0937
	(0.0159)	(0.0159)	(0.0159)	(0.0159)
$\mathrm{YL}_{\xi a}$	-0.2220	-0.2405	-0.2405	-0.2079
	(0.2839)	(0.1728)	(0.1728)	(0.2268)
$\hat{\mathrm{C}}\mathrm{A}$	0.0558	0.1196	0.1196	0.0703
	(0.0454)	(0.0921)	(0.0921)	(0.0712)
$\hat{\mathrm{C}}\mathrm{A}_{\Pi}$	0.1762	0.2170	0.2170	0.1722
	(0.1592)	(0.0946)	(0.0946)	(0.1318)
N	121	45	45	245

Standard deviations are in the Parentheses

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