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# MEASUREMENT OF ECONOMIC EFFICIENCY IN THE PRODUCTION OF RICE IN BANGLADESH - A TRANSLOG STOCHASTIC COST FRONTIER ANALYSIS

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## ABSTRACT

A Translog stochastic cost frontier has been estimated simultaneously with the economic inefficiency effect model using maximum likelihood for different rice crops. To estimate farm-specific economic efficiencies, single estimation of Translog cost frontier has also been done. Different cost components and their interactions are found to have different impacts on the stochastic cost frontier for different rice crops. The study reveals that there are significant economic inefficiency effect in the production of all rice crops and extension contact has negative impact on the economic inefficiency effect for all rice crops whereas experience has negative impact on the economic inefficiency effect for *Boro* and *Aman* rice. For Aus rice, education has positive impact on the economic inefficiency effect. The mean economic efficiencies estimated from Translog cost frontiers for *Boro, Aus,* and *Aman* rice are respectively 80%, 60% and 74%. The study also reveals that without change of output the production cost of *Boro, Aus* and *Ainan* can be reduced by 20%, 40% and 26%, respectively.

## I. INTRODUCTION

The measurement of the productive efficiency of a farm relative to other farms or to the "best practice" in an industry has long been of interest to agricultural economists. Efficiency measurement has received considerable attention from both theoretical and applied economists. From a theoretical point of view, there has been a spirited exchange about the relative importance of various components of firm efficiency (Leibenstein 1966,1977; Comanor and Leibenstein 1969; Stigler 1976). From an applied perspective, measuring efficiency is important because this is the first step in a process that might lead to substantial resource savings. These resource savings have important implications for both policy formulation and firm management (Bravo-Ureta and Rieger 1991)

In the policy arena, there is a continuing controversy regarding the connection between farm size, efficiency and the structure of agricultural production. For individual farms, gains in efficiency are particularly important in periods of financial stress. Efficient farms are more likely to generate higher incomes and thus stand a better chance of surviving and prospering.

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Economic development in Bangladesh mainly depends on the progresses to be made in the agricultural sector, but agricultural development is dependent on appropriate policies relating to augmenting productivity and efficiency of agricultural crops. Increase of productivity and efficiency are based on some socio-economic and demographic variables. Proper policies can be formulated only after the empirical measurement of the core variables. The accuracy of the identification of the impact of different variables depends on the functional form of the production technology (whether Cobb-Douglas or Translog or CES), the nature of the random error component (whether stochastic or deterministic), the distribution of the inefficiency component (whether it is half normal or truncated normal or cyamma or beta), the nature of the production function (whether primal or dual) etc.

When one talks about the efficiency of a firm, one usually means its success in producing as large as possible an output from a given set of inputs. Economic efficiency is generally defined as the ability of a production organisation or any other entity, for instance, a farm to produce a well-specified output at the minimum cost. Farrell (1957) proposed that economic or overall efficiency of a firm consists of two components: technical efficiency, which reflects the ability of a firm to obtain maximal output from a given set of inputs under certain production technology, and allocative efficiency, which reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices. In fact, economic efficiency is the product of technical and allocative efficiencies. If a firm has achieved both technically efficient and allocatively efficient levels of production, then the firm is economically efficient.

Economic relationships based on optimisation behaviour define efficient frontiers of minimum (e.g. cost) or maximum (e.g. production) attainment. Traditional econometric methods for estimating stochastic economic relationships have implicitly assumed that all economic agents are successful in reaching the efficient frontier. If, however, the economic agents are not equally efficient, then the average relationships estimated by ordinary least squares methods might not reflect the frontier relationships (Stevenson, 1980).

Numerous studies have been devoted to the re-specification of empirical production and cost models to make them more compatible with the underlying theory, and to the derivation of appropriate estimators. In some cases, this has amounted to minor modifications of least squares results. The remaining estimators are based on two distinct specifications. The very recent work on composite disturbances has relaxed somewhat the orthodox interpretation of the underlying function as a strict frontier with all observations lying on one side of it, and has produced well behaved maximum likelihood estimators with all of the usual desirable properties (Greene, 1980). There is a large class of disturbance distributions, which may be specified, which make the maximum likelihood frontier estimator regular and well behaved. A method of point estimation with some stronger theoretical properties than the method of OLS is the method of maximum likelihood (ML). The method of maximum likelihood, as the name indicates, consists in estimating the unknown parameters in such a manner that the probability of observing the given outputs is as high (or maximum) as possible. For any kind of distributions of the disturbances (error terms), the maximum likelihood estimators (MLEs) of parameter coefficients of the stochastic frontier function are unbiased and consistent as OLS (ordinary least square) estimators, only variances of estimated coefficients are biased downward in small samples but these variances are also asymptotically (i.e., in very large sample) unbiased.

The objectives of this paper, therefore, are: (i) to develop a specification and estimation for a Translog stochastic cost frontier model; (ii) to estimate farm-specific economic efficiencies for individual sample farmers; and (iii) to identify the factors causing variations in economic inefficiency effects (or economic efficiencies) among the sample farmers.

This paper has been organised in four sections. In section 2 data and specification of stochastic cost frontier and economic inefficiency effect model are described. Section 3 contains empirical results and discussions. Some conclusions are made in the final section.

## II. DATA AND SAMPLING TECHNIQUE

Data:

The three regions, that is, **Brahmanbaria, Mymensingh** and **Dinajpur** were selected purposively considering the relative importance of these regions in producing rice. These three areat regions (old district) produce about 16 percent of total rice in Bangladesh (BBS 1998). Considering their contribution to the total output, the selection of these regions was appropriate for a study on the efficiency of rice production. Moreover, the soil texture of these regions represents a good cross section of the soil texture of the country. Farmers of these regions are familiar with new inputs of production such as HYV* seeds, artificial irrigation, chemical fertiliser etc. for several years and in these regions there are the requisite number of households with different farm sizes. The regions are also relatively easily accessible and well communicated. Since **Dinajpur** is the north-west district of the country, **Mymensingh** is the middle district and **Brahmanbaria** is the south-east district, the selection of these areas was uniform on the spatial context.

To collect the primary data from the farmers of Bangladesh, probability sampling technique was adopted. At first a sampling frame of farmers was constructed with the help of village leaders and some other relevant persons. The villages were selected with simple random sampling technique but the farmers were selected with stratified random sampling with arbitrary allocation. The data were collected for the crop year July 1998 to June 1999. The sample was composed of small (below 1.00 hectare), medium (1.00 - 3.00 hectares) and large (above 3.00 hectares) farms. Within the sample, 50 percent were small, 30 percent were medium and 20 percent were large farmers. Five hundred farmers in total were interviewed in this study. Of the five hundred sampled farmers, 300 farmers had direct contact with extension workers and were selected 100 from each region to ascertain the importance of extension service in Bangladesh. Another 200 farmers who had no relationship with the extension workers were selected, 100 from each region except Mymensingh region. For the region **Mymensingh,** only a sample of 100 farmers with access to the extension service was selected but no sample of non-extension farmers was selected because there is one agricultural university known as **Bangladesh Agricultural University** and from this university every year several extension programmes are carried out in this region side by side with government extension programmes. Thus most of the farmers in this region are connected to extension programmes. To compare the productivities and efficiencies between farmers with extension services and farmers without extension services, these two types of data are very useful.

## III. SPECIFICATION OF TRANSLOG STOCHASTIC COST FRONTIER AND ECONOMIC INEFFICIENCY EFFECT MODEL AND THEIR ESTIMATION

### Model Specification

For this study a Translog stochastic cost frontier was estimated simultaneously with the economic inefficiency effect model using maximum likelihood for different rice crops. To estimate farm-specific economic efficiencies, single estimations of Translog cost frontier was also done. The Cobb-Douglas form of the production or cost function imposes certain limitations, such as, the elasticity coefficients are constant, implying constant shares regardless of the input level or input cost, and the elasticity of substitution among inputs is unity, whereas the Translog production or cost function does not impose these restrictions upon the production or cost structure and it is a flexible functional form. Another advantage of Translog stochastic frontier function is that with the help of this function we can estimate the effects of interactions of different complementary variables along with the individual effect of each variable on output or cost. Nevertheless, it has certain problems also. It is more difficult to mathematically manipulate and it can suffer from degrees of freedom and multicollinearity problems.

The model has been estimated for three different rice crops, *Boro*, *Aus* and *Aman*, and for all regions. The data used in this model are cross-sectional data and sample sizes for *Boro*, *Aus* and *Aman* rice are 490, 82 and 460, respectively.

An explicit form of Translog Stochastic Frontier Cost Function (TSFCF) including farm-specific variables specified for *Boro* rice is presented below:

$$\ln (C/P_f) = \alpha_0 + \alpha_1 \ln(W/P_f) + \alpha_2 \ln(P_s/P_f) + \alpha_3 \ln(P_b/P_f) + \alpha_4 \ln(C_i/P_f) + \alpha_5 \ln(R_l/P_f) + \alpha_6 \ln Q + \tfrac{1}{2} \beta_{11}\{\ln(W/P_f)\}^2 + \beta_{12} \ln(W/P_f) \times \ln(P_s/P_f) + \beta_{13} \ln(W/P_f) \times \ln(P_b/P_f) + \beta_{14} \ln(W/P_f) \times \ln(C_i/P_f) + \beta_{15} \ln(W/P_f) \times \ln(R_l/P_f) + \beta_{16} \ln(W/P_f) \times \ln Q + \tfrac{1}{2} \beta_{22} \{\ln(P_s/P_f)\}^2 + \beta_{23} \ln (P_s/P_f) \times \ln(P_b/P_f) + \beta_{24} \ln(P_s/P_f) \times \ln(C_i/P_f) + \beta_{25} \ln(P_s/P_f) \times \ln(R_l/P_f) + \beta_{26} \ln(P_s/P_f) \times \ln Q + \tfrac{1}{2} \beta_{33} \{\ln(P_b/P_f)\}^2 + \beta_{34} \ln(P_b/P_f) \times \ln(C_i/P_f) + \beta_{35} \ln(P_b/P_f) \times \ln(R_l/P_f) + \beta_{36} \ln(P_b/P_f) \times \ln Q + \tfrac{1}{2} \beta_{44} \{\ln(C_i/P_f)\}^2 + \beta_{45} \ln(C_i/P_f) \times \ln(R_l/P_f) + \beta_{46} \ln(C_i/P_f) \times \ln Q + \tfrac{1}{2} \beta_{55}\{\ln(R_l/P_f)\}^2 + \beta_{56} \ln(R_l/P_f) \times \ln Q + \tfrac{1}{2} \beta_{66} (\ln Q)^2 + \beta_7 \, EDU + \beta_8 \, EXT + \beta_9 \ln(AGE) + \beta_{10} \ln(EXPERIENCE) + V+U \quad (1).$$

For *Boro* rice, cost function was normalised with fertiliser price ($P_f$) and for *Aus* and *Aman* rice cost functions were normalised with seed price ($P_s$). We used to normalise the cost function to make it compatible with the theory of cost function. Since the Cobb-Douglas cost function is linearly homogeneous in input prices, we have to normalise it before its estimation. It makes no difference, economically or statistically, which price is used to normalise the cost function, of course (Schmidt and Lovell 1979). Translog cost frontier is not normally linearly homogeneous but under certain conditions this cost frontier is linearly homogeneous in input prices. The share equations or minimum cost factor demand frontiers derived from it with the help of Shephard's Lemma are linear in input prices. These minimum cost factor demand frontiers are used along with Translog cost frontier to estimate allocative efficiency, which is a component of cost or economic efficiency. Kopp and Diewert (1982) showed that for decomposing cost function deviations into technical and allocative components are most applicable to flexible function forms such as the Translog. Since all farmers used fertiliser to produce *Boro* rice, we used fertiliser price to normalise the cost function in case of *Boro* rice. But for producing *Aus* and *Aman* rice all farmers did not use fertiliser as a factor of production

**Table 1. Descriptions of different variables of translog stochastic frontier cost function in tabular form.**

| Name of the variables | Symbols used | Parameters |
|---|---|---|
| Constant | | $\alpha_0$ |
| Normalised human labour price | $(W/P_f)$ | $\alpha_1$ |
| Normalised seed price | $(P_s/P_f)$ | $\alpha_2$ |
| Normalised bullock power price | $(P_b/P_f)$ | $\alpha_3$ |
| Normalised per hectare irrigation cost | $(C_i/P_f)$ | $\alpha_4$ |
| Normalised per hectare rent | $(R_l/P_f)$ | $\alpha_5$ |
| Output | Q | $\alpha_6$ |
| Normalised h. labour price x normalised h. labour price | $(W/P_f) \times (W/P_f)$ | $\beta_{11}$ |
| Normalised h. labour price x normalised seed price | $(W/P_f) \times (P_s/P_f)$ | $\beta_{12}$ |
| Normalised h. labour price x normalised bullock power price | $(W/P_f) \times (P_b/P_f)$ | $\beta_{13}$ |
| Normalised h. labour price x p. h. normalised irrigation cost | $(W/P_f) \times (C_i/P_f)$ | $\beta_{14}$ |
| Normalised h. labour price x p. h. normalised rent | $(W/P_f) \times (R_l/P_f)$ | $\beta_{15}$ |
| Normalised h. labour price x output | $(W/P_f) \times Q$ | $\beta_{16}$ |
| Normalised seed price x normalised seed price | $(P_s/P_f) \times (P_s/P_f)$ | $\beta_{22}$ |
| Normalised seed price x normalised bullock power price | $(P_s/P_f) \times (P_b/P_f)$ | $\beta_{23}$ |
| Normalised seed price x p. h. normalised irrigation cost | $(P_s/P_f) \times (C_i/P_f)$ | $\beta_{24}$ |
| Normalised seed price x p. h. normalised rent | $(P_s/P_f) \times (R_l/P_f)$ | $\beta_{25}$ |
| Normalised seed price x output | $(P_s/P_f) \times Q$ | $\beta_{26}$ |
| Normalised b. power price x normalised b. power price | $(P_b/P_f) \times (P_b/P_f)$ | $\beta_{33}$ |
| Normalised b. power price x p. h. normalised irrigation cost | $(P_b/P_f) \times (C_i/P_f)$ | $\beta_{34}$ |
| Normalised b. power price x p. h. normalised rent | $(P_b/P_f) \times (R_l/P_f)$ | $\beta_{35}$ |
| Normalised b. power price x output | $(P_b/P_f) \times Q$ | $\beta_{36}$ |
| P. h. normalised irrigation cost x p. h. normalised irrigation cost | $(C_i/P_f) \times (C_i/P_f)$ | $\beta_{44}$ |
| P. h. normalised irrigation cost x P. h. normalised rent | $(C_i/P_f) \times (R_l/P_f)$ | $\beta_{45}$ |
| P. h. normalised irrigation cost x output | $(C_i/P_f) \times Q$ | $\beta_{46}$ |
| P. h. normalised rent x P. h. normalised rent | $(R_l/P_f) \times (R_l/P_f)$ | $\beta_{55}$ |
| P. h. normalised rent x output | $(R_l/P_f) \times Q$ | $\beta_{56}$ |
| Output x output | Q x Q | $\beta_{66}$ |
| Education of farm operator | EDU | $\beta_7$ |
| Extension service | EXT | $\beta_8$ |
| Age of farm operator | AGE | $\beta_9$ |
| Experience of farm operator | EXPERIENCE | $\beta_{10}$ |

and that is why we used seed price to normalise the cost functions in case of *Aus* and *Aman* rice. U is a non-negative cost (or economic) inefficiency effect, which is assumed to have a half-normal distribution, and V is a random variable, which is assumed to be independently and normally distributed with 0 mean and constant variance $\sigma^2_v$.

We may note that the inefficiency effect, U, is added in the cost frontier, instead of being subtracted, as in the case of the production frontier. This is because the cost function represents minimum cost, whereas the production function represents maximum output. The U provides information on the level of the cost efficiency or overall economic efficiency (EE).

The model for the economic inefficiency effects in the stochastic frontier of equation (1) is defined by

$$U_i = \delta_0 + \delta_1 \text{ AGE}_i + \delta_2 \text{ EDU}_i + \delta_3 \text{ EXPERIENCE}_i + \delta_4 \text{ CONTACT}_i + \delta_5 \text{ FARMSZ}_i + W_i \quad (2)$$

Where AGE, EDU and EXPERIENCE are defined as earlier;
CONTACT represents extension contact by the extension agents to the farmers;
FARMSZ represents farm size; and
the $W_i$ are unobservable random variables, which are assumed to be independently distributed with a positive half normal distribution.
The β- and δ- coefficients are unknown parameters to be estimated, together with the variance parameters which are expressed in terms of

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \quad (3)$$

and

$$\gamma = \sigma_u^2/\sigma^2 \quad (4)$$

where the γ-parameter has a value between zero and one. The parameters of the Translog stochastic frontier cost function model are estimated by the maximum likelihood method, using the computer program, FRONTIER Version 4.1.

The expected signs on the δ-parameters in the inefficiency effect model, defined by equation (2), are not clear in all cases. The age of the farmers could be expected to have a positive or a negative effect upon the size of the inefficiency effects. The older farmers are likely to have had more farming experience and hence have less inefficiency. However, they are also likely to be more conservative and thus be less willing to adopt new practices, thereby perhaps having greater inefficiencies in agricultural production.

Education of farmers is expected to have a negative effect upon the inefficiency effects. That is, we expect that greater levels of formal education will be associated with smaller values for the inefficiency effects. It may also happen that if the farmers with more formal education have alternative sources of income, or if they are not attentive to farming practices and rely more on fixed labourer who are not educated, may have positive effect upon the inefficiency effects.

Experiences of farmers are expected to have a negative impact upon the inefficiency effects and it is generally assumed that farmers with more experiences of farming practices are more efficient than farmers with less experiences.

Contact of extension agents with the farmers is expected to have a negative impact upon the inefficiency effects. That is, farmers with more contacts with the extension agents are likely to be more efficient than farmers with less extension contacts.

The sign of the coefficient of the land or farm size variable in the model for the inefficiency effect is expected to be negative. This expectation is partially based upon the likelihood that the farmers with smaller operations may have alternative income sources, which are more important and hence put less effort into their farming operations compared with the larger farmers (Coelli and Battese 1996; Rahman, Schmitz and Wronka 1999).

It is important to note that the model for the inefficiency effects (2) can only be estimated if the inefficiency effects are stochastic and have a particular distributional specification. Hence there is interest to test the null hypotheses that the inefficiency effects are not present, $H_0$: $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$; the inefficiency effects are not stochastic, $H_0$: $\gamma = 0$; and the coefficients of the variables in the model for the inefficiency effects are zero, $H_0$: $\delta_1 = \delta_2 = \ldots = \delta_5 = 0$. These and other null hypotheses of interest are tested using the generalised likelihood-ratio test and t-test. The generalised likelihood-ratio test is a one-sided test since $\gamma$ can not take negative values. The generalised likelihood-ratio test requires the estimation of the model under both the null and alternative hypotheses. Under the null hypothesis, $H_0$: $\gamma = 0$, the model is equivalent to the traditional average response function, without the economic inefficiency effect, $U_i$. The test statistic is calculated as

$$LR = -2\{\ln[L(H_0)/L(H_1)]\} = -2\{\ln[L(H_0)] - \ln[L(H_1)]\} \quad (5)$$

where $L(H_0)$ and $L(H_1)$ are the values of the likelihood function under the null and alternative hypotheses, $H_0$ and $H_1$, respectively.

If $H_0$ is true, this test statistic is usually assumed to be asymptotically distributed as a chi-square random variable with degrees of freedom equal to the number of restrictions involved. However, difficulties arise in testing $H_0$: $\gamma = 0$ because $\gamma = 0$ lies on the boundary of the parameter space for $\gamma$. In this case, if $H_0$: $\gamma = 0$ is true, the generalised likelihood-ratio statistic LR, has asymptotic distribution which is a mixture of chi-square distributions, namely $\frac{1}{2}\chi_0^2 + \frac{1}{2}\chi_1^2$, (Coelli 1995a).

The calculation of the critical value for this one-sided generalised likelihood-ratio test of $H_0$: $\gamma = 0$ versus $H_1$: $\gamma > 0$ is quite simple. The critical value for a test of size $\alpha$ is equal to the value, $\chi_1^2\,(2\alpha)$, where this is the value which is exceeded by the $\chi_1^2$ random variable with probability equal to $2\alpha$. Thus the one-sided generalised likelihood-ratio test of size $\alpha$ is:"Reject $H_0$: $\gamma = 0$ in favour of $H_1$: $\gamma > 0$ if LR exceeds $\chi_1^2\,(2\alpha)$". Thus the critical value for a test of size, $\alpha = 0.05$, is 2.71 rather than 3.84 for degree of freedom one.

The economic efficiency of a farmer at a given period of time is defined as the ratio of the frontier minimum cost (in which the inefficiency effect is zero) to the observed cost. Given the specifications of the stochastic frontier model (1) – (2), the economic efficiency of the i-th farmer can be shown to be equal to

$$\begin{aligned} EE_i &= \exp(-U_i) \\ &= \exp\{-E(U_i/\varepsilon_i)\} \\ &= 1 - E(U_i/\varepsilon_i) \end{aligned} \tag{6}$$

Thus the economic efficiency of a farmer is between zero and one and is inversely related to the inefficiency effect. The farm-specific efficiencies are predicted using the predictor that is based on the conditional expectation of $U_i$ given composed error $\varepsilon_i = (V_i + U_i)$.

Firm-specific or observation-specific estimates of economic inefficiency, U (subscripts can safely be omitted here), can be obtained by using the expectation of the inefficiency term conditional on the estimate of the entire composed error term, as suggested by Jondrow, Lovell, Materov, and Schmidt (1982) and Kalirajan and Flinn (1983). One can use either the expected value or the mode of this conditional distribution as an estimate of U:

$$E(U/\varepsilon) = \sigma_*[\ E(U/\varepsilon) = \sigma_*\left[\frac{f\left(\varepsilon\lambda/\sigma\right)}{1-F\left(\varepsilon\lambda/\sigma\right)} - \left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \tag{7}$$

where f and $F$ are, respectively, the standard normal density and distribution functions, evaluated at $\varepsilon\lambda/\sigma$, $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$, $\lambda = \sigma_u/\sigma_v$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$.

Aigner, Lovell and Schmidt (1977), Jondrow et al. (1982), Bravo-Ureta and Rieger (1991) and others expressed the likelihood function in terms of the two variance parameters, $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u/\sigma_v$. But they interpreted $\lambda$ to be an indicator of the relative variability of the two sources of the random error that distinguish firms from one another. Here $\lambda = \sigma_u/\sigma_v$ is the ratio of the standard deviation of the non-negative error term $U_i$ to the standard deviation of the two-sided symmetric error term $V_i$. If $\lambda$ approaches 0 then it implies $\sigma_v$ very large or $\sigma_u$ is close to zero, i.e. the symmetric error dominates in the determination of $\varepsilon$ and the density function of $\varepsilon$ becomes the density of a N $(0,\sigma^2)$ random variable. In other words, the discrepancy between the observed and the frontier output or cost is dominated by random factors beyond the control of the farmer. Similarly, when $\sigma_v$ is close to zero (i.e. $\sigma_v \to 0$), $\lambda$ becomes very large (i.e. $\lambda \to \alpha$) and the one-sided error becomes the dominant source of random variation in the model and hence the production process is characterised by inefficiency, where density of $\varepsilon$ takes on the form of a negative half-normal. Some other authors (Battese and Corra 1977; Battese and Coelli 1992; Coelli and Battese 1996; Kalirajan 1981, 1984; Kalirajan and Flinn 1983; Kalirajan and Shand 1985) have used different parameter $\gamma = \sigma_u^2/\sigma^2$ to explain the discrepancy between the frontier output level or cost and the actual output or cost. Battese and Corra (1977) suggested that the parameter, $\gamma = \sigma_u^2/\sigma^2$, be used because it has a value between zero and one, whereas the $\lambda$-parameter could be any non-negative value. They also suggested that the γ-parameterisation has advantages in seeking to obtain the ML estimates because the parameter space for γ can be searched for a suitable starting value for the iterative maximisation algorithm involved.

The mean economic efficiency or the mathematical expectation of the farm-specific economic efficiencies can be calculated for given distributional assumptions for the economic inefficiency effects. The mean economic efficiency can be defined by

$$\text{Mean E.E.} = E[\exp\{-E(U_i/\varepsilon_i)\}] = E\{1 - E(U_i/\varepsilon_i)\} \tag{8}$$

Because the individual economic efficiencies of sample farms can be predicted, an alternative estimator for the mean economic efficiency is the arithmetic average of the predictors for the individual economic efficiencies of the sample farms. This is what is calculated by FRONTIER (Version 4.1c) Package. With the help of the FRONTIER programme the parameters of the stochastic frontier cost function (1) are estimated, together with farm-specific economic efficiencies and mean economic efficiency for the farms involved. However, the arithmetic mean may not be the best estimator when the sample farms have significantly different sizes of operations or are not obtained by a simple random sampling from the population of the farms.

If we estimate the technical efficiency effects frontier by the FRONTIER 4.1 package, we can simultaneously estimate the stochastic frontier and economic inefficiency effect model.

## IV. RESULTS AND DISCUSSIONS

Table (2) presents simultaneous estimation of Translog Stochastic Cost Frontiers and Economic Inefficiency Effect Models for *Boro*, *Aus* and *Aman* rice. Although the simultaneous estimation procedure has simultaneous-equation bias, it is also important to identify the factors, which influence the technical or economic inefficiency of farmers. Kumbhakar, Ghosh and McGuckin (1991), Reifschneider and Stevenson (1991), Huang and Lui (1994) and Battese and Coelli (1995) specify stochastic frontiers and models for the technical inefficiency effects and simultaneously estimate all the parameters involved. This one-stage approach is less objectionable from a statistical point of view and is expected to lead to more efficient inference with respect to the parameters involved. But most of the researchers used two-stage approach to explain the differences in technical efficiencies of farmers. The first stage involves the estimation of a stochastic frontier production function and the prediction of farm-level technical inefficiency effects (or technical efficiencies). In the second stage, these predicted technical inefficiency effects (or technical efficiencies) are related to farmer-specific factors using Ordinary Least Squares (OLS) regression (Kalirajan 1981; Parikh and Shah 1994). This two-stage approach is more objectionable from a statistical point of view. Estimation procedure of economic efficiency is the same as that of technical efficiency where the former is estimated from the cost frontier and the latter is estimated from the production frontier. Table (2) reveals that the coefficients of square of normalised human labour price, square of normalised seed price, interactions of normalised human labour and bullock power prices, normalised human labour price and per hectare normalised irrigation cost, normalised human labour price and output, normalised seed and bullock power prices, normalised seed price and per hectare normalised irrigation cost, and per hectare normalised irrigation cost and output are found to be positive and significant in the Translog stochastic cost frontier for *Boro* rice. But the coefficients of normalised human labour price, interactions of normalised seed price and output, and normalised bullock power price and output are negative and significant in the cost frontier for *Boro*. The mean economic efficiency estimated from the model is 80% (Table 3).

In the economic inefficiency effect model, the coefficients of experience and extension contact are found to be negative and significant. The generalised likelihood-ratio (LR) test statistic calculated from the model is 27.02*, which is significant. That is, there is significant economic inefficiency effect in the production of *Boro* rice. The significant value of $\gamma$ shows the same phenomenon.

For *Aus* rice, the coefficients of normalised human labour price and normalised bullock power price are significantly negative whereas the coefficients of extension service (dummy) and age of farm operator are found to be significantly positive in the stochastic cost frontier. The mean economic efficiency estimated from the model is 60% (Table 3). In the economic inefficiency effect model, the coefficient of education is significantly positive whereas the coefficient of extension contact is significantly negative. The generalised likelihood-ratio (LR) test statistic derived from the model for *Aus* rice is 27.18*, which is significant. That is, there is also economic inefficiency effect in the production of *Aus* rice.

For *Aman* rice, the coefficients of the interactions of normalised human labour and bullock power prices, normalised human labour price and output, square of normalised bullock power price, coefficients of extension service and age of farm operator are found to be positive and significant whereas only coefficient of normalised human labour price is

**Table 2. Maximum likelihood (ML) estimation of translog stochastic cost frontiers and economic inefficiency effect models for *Boro*, *Aus* and *Aman* rice.**

| Variables | Parameters | Crops | | |
|---|---|---|---|---|
| | | *Boro* | *Aus* | *Aman* |
| Stochastic frontier: | | | | |
| Constant | $\alpha_0$ | -0.60825<br>(1.10783) | 2.88725**<br>(0.84495) | 0.46459<br>(0.38270) |
| Normalised human labour price | $\alpha_1$ | -0.0000096**<br>(0.00000048) | -0.00001138**<br>(0.00000110) | -0.00001018**<br>(0.00000063) |
| Normalised seed price | $\alpha_2$ | -0.47079<br>(0.66787) | - | - |
| Normalised bullock power price | $\alpha_3$ | -0.0000050<br>(0.0000070) | -1.37529*<br>(0.68270) | -0.35969<br>(0.30492) |
| Per hectare normalised irrigation cost | $\alpha_4$ | 0.19030<br>(0.14522) | - | - |
| Per hectare normalised rent | $\alpha_5$ | 0.0000020<br>(0.0000018) | -0.0000042<br>(0.0000113) | -0.0000058<br>(0.0000038) |

| | | | | |
|---|---|---|---|---|
| Output | $\alpha_6$ | 0.13767<br>(0.13236) | 0.40264<br>(0.37722) | 0.03148<br>(0.15454) |
| Normalised h. labour price x normalised h. labour price | $\beta_{11}$ | 0.0000034*<br>(0.0000015) | 0.0000043<br>(0.0000034) | -0.0000018<br>(0.0000016) |
| Normalised h. labour price x normalised seed price | $\beta_{12}$ | 0.10451<br>(0.05835) | - | - |
| Normalised h. labour price x normalised bullock power price | $\beta_{13}$ | 0.0000023**<br>(0.00000074) | -0.01253<br>(0.07815) | 0.13389*<br>(0.05432) |
| Normalised h. labour price x p. h. normalised irrigation cost | $\beta_{14}$ | 0.13445**<br>(0.03992) | - | - |
| Normalised h. labour price x p. h. normalised rent | $\beta_{15}$ | 0.00000105<br>(0.00000076) | -0.000000183<br>(0.000001295) | 0.0000011<br>(0.00000087) |
| Normalised h. labour price x output | $\beta_{16}$ | 0.64098**<br>(0.09338) | 0.09845<br>(0.18148) | 0.58799**<br>(0.06782) |
| Normalised Seed price x normalised seed price | $\beta_{22}$ | 0.0000077**<br>(0.0000010) | - | - |
| Normalised seed price x normalised bullock power price | $\beta_{23}$ | 0.47356*<br>(0.19908) | - | - |
| Normalised seed price x p. h. normalised irrigation cost | $\beta_{24}$ | 0.0000050*<br>(0.0000022) | - | - |
| Normalised seed price x p. h. normalised rent | $\beta_{25}$ | -0.12859<br>(0.07708) | - | - |
| Normalised seed price x output | $\beta_{26}$ | -0.0000019*<br>(0.00000094) | - | - |
| Normalised b. power price x normalised b. power price | $\beta_{33}$ | -0.04821<br>(0.04925) | -0.00000089<br>(0.00000201) | 0.0000054**<br>(0.00000096) |
| Normalised b. power price x p. h. normalised irrigation cost | $\beta_{34}$ | -0.00000055<br>(0.00000067) | - | - |
| Normalised b. power price x p. h. normalised rent | $\beta_{35}$ | -0.02869<br>(0.02336) | -1.19504<br>(0.90711) | 0.21219<br>(0.15376) |
| Normalised b. power price x output | $\beta_{36}$ | -0.0000011*<br>(0.00000053) | -0.0000104<br>(0.0000089) | 0.00000092<br>(0.0000018) |
| P. h. normalised irrigation cost x p. h. normalised irrigation cost | $\beta_{44}$ | -0.01601<br>(0.01710) | - | - |
| P. h. normalised irrigation cost x p. h. normalised rent | $\beta_{45}$ | 0.000000079<br>(0.000000545) | - | - |
| P. h. normalised irrigation cost x output | $\beta_{46}$ | 0.08593*<br>(0.04108) | - | - |
| P. h. normalised rent x P. h. normalised rent | $\beta_{55}$ | 0.00000046<br>(0.00000062) | -0.25576<br>(0.15649) | 0.10809<br>(0.07551) |
| P. h. normalised rent x output | $\beta_{56}$ | 0.02508<br>(0.06605) | -0.0000026<br>(0.000025) | 0.00000049<br>(0.0000010) |
| Output x output | $\beta_{66}$ | 0.0000019<br>(0.0000015) | 0.01752<br>(0.04734) | -0.01747<br>(0.03590) |
| Education of farm operator | $\beta_7$ | -0.03688<br>(0.04571) | 0.0000019<br>(0.0000016) | -0.0000013<br>(0.00000069) |
| Extension service (dummy) | $\beta_8$ | 0.000000077<br>(0.00000066) | 0.48084**<br>(0.12875) | 0.13544**<br>(0.04825) |
| Age of farm operator | $\beta_9$ | 0.03418<br>(0.01892) | 0.0000078**<br>(0.0000019) | 0.00000152*<br>(0.00000076) |

| | | | | |
|---|---|---|---|---|
| Experience of farm operator | $\beta_{10}$ | -0.00000015 (0.00000052) | -0.08886 (0.10883) | -0.05196 (0.04932) |
| Inefficiency effect model: | | | | |
| Intercept | $\delta_0$ | -0.00000061 (0.00000052) | -0.64687 (0.36960) | -0.0000052 (0.0000043) |
| Age | $\delta_1$ | -0.0000000068 (0.0000000037 | 0.0000014 (0.0000038) | 0.0000016 (0.0000041) |
| Education (EDU) | $\delta_2$ | -0.0000015 (0.0000014) | 0.17618** (0.04131) | -0.00000011 (0.00000015) |
| Experience | $\delta_3$ | -0.00000000049* (0.00000000021) | -0.00000016 (0.00000281) | -0.0000045** (0.0000011) |
| Extension contact | $\delta_4$ | -0.000000042* (0.000000020) | -0.09106* (0.04569) | -0.00000071** (0.00000023) |
| Farm size | $\delta_5$ | -0.00000000032 (0.00000000071) | -0.0000011 (0.0000026) | 0.000000202 (0.00000045) |
| Variance parameters: | | | | |
| | $\sigma^2$ | 0.128* (0.0631) | 0.133** (0.0228) | 0.220** (0.0751) |
| | $\gamma$ | 0.720** (0.2302) | 0.988** (0.0551) | 0.790** (0.1275) |
| Log likelihood function | | -82.82 | 2.58 | -169.90 |

** and * indicate significance at 0.01 and 0.05 probability level, respectively.
Source: Own estimation.

significantly negative in the stochastic cost frontier. The mean economic efficiency estimated from the model is 74% (Table 3). The coefficients of experience and extension contact are significantly negative in the economic inefficiency effect model for *Aman* rice. The production of *Aman* rice is also characterised by significant economic inefficiency effect since the generalised likelihood-ratio (LR) test statistic derived from the model is 22.89*, which is also significant.The coefficient of education in the cost frontier is insignificant for all rice crops.

Table 3 shows frequency distribution of farm-specific economic efficiency estimates from Translog stochastic cost frontiers for *Boro*, *Aus* and *Aman* rice. Table 3 reveals that the farm-specific economic efficiency varies from 32% to 97% for *Boro* rice, 25% to 98% for *Aus* rice, and 15% to 94% for *Aman* rice. The maximum farm-specific economic efficiency has been observed in the range 80-85% for *Boro* rice and in the range 75-80% for *Aman* rice. But for *Aus* rice, there is greater variability of farm-specific economic efficiency throughout all ranges. The mean economic efficiencies estimated from Translog cost frontiers for *Boro*, *Aus*, and *Aman* rice are respectively 80%, 60% and 74%. The study also reveals that without change of output the production cost of *Boro*, *Aus* and *Aman* can be reduced by 20%, 40% and 26%, respectively.

## V. CONCLUSIONS

A Translog stochastic normalised cost frontier was estimated simultaneously with the economic inefficiency effect model using maximum likelihood for different rice crops. To estimate farm-specific economic efficiencies, single estimation of Translog cost frontier was also done. The coefficients which have significantly positive effect on the cost of *Boro* rice are the coefficients of square of human labour price, square of seed price, interactions of human labour and bullock power prices, human labour price and per hectare irrigation cost, human labour price and output, seed and bullock power prices, seed price and per hectare irrigation cost, and per hectare irrigation cost and output. For *Aus* rice, the coefficients of extension service and age of farm operator are significantly positive in the stochastic cost frontier and for *Aman* rice, the coefficients of the interactions of human labour and bullock power prices, human labour price and output, square of bullock power price, coefficients of extension service and age of farm operator are significantly positive in the stochastic cost frontier.

**Table 3. Frequency distribution of farm-specific economic efficiency estimates from translog stochastic cost frontiers.**

| Efficiency level (%) | Crops | | |
|---|---|---|---|
| | *Boro* | *Aus* | *Aman* |
| <25 | 0 | 0 | 1 (0.22) |
| 25-30 | 0 | 3 (3.66) | 1 (0.22) |
| 30-35 | 2 (0.41) | 2 (2.44) | 1 (0.22) |
| 35-40 | 0 | 3 (3.66) | 1 (0.22) |
| 40-45 | 1 (0.20) | 2 (2.44) | 1 (0.22) |
| 45-50 | 1 (0.20) | 12 (14.63) | 1 (0.22) |
| 50-55 | 4 (0.82) | 4 (4.88) | 7 (1.52) |
| 55-60 | 1 (0.20) | 5 (6.10) | 12 (2.61) |
| 60-65 | 2 (0.41) | 3 (3.66) | 30 (6.52) |
| 65-70 | 14 (2.86) | 7 (8.54) | 52 (11.30) |
| 70-75 | 30 (6.12) | 3 (3.66) | 77 (16.74) |
| 75-80 | 117 (23.88) | 7 (8.54) | 127 (27.61) |
| 80-85 | 199 (40.61) | 7 (8.54) | 91 (19.78) |
| 85-90 | 105 (21.43) | 5 (6.10) | 52 (11.30) |
| 90-95 | 13 (2.65) | 10 (12.20) | 6 (1.30) |
| 95-100 | 1 (0.20) | 9 (10.98) | 0 |
| Total number of farm | 490 (100.00) | 82 (100.00) | 460 (100.00) |
| Mean Efficiency | 80 | 60 | 74 |
| Minimum Efficiency | 32 | 25 | 15 |
| Maximum Efficiency | 97 | 98 | 94 |

Source: Own estimation.

There are significant economic inefficiency effect in the production of all rice crops and extension contact has negative impact on the economic inefficiency effect for all rice crops whereas experience has negative impact on the economic inefficiency effect for *Boro* and *Aman* rice. That is, economic inefficiency decreases as the increase in the number of extension contact for all rice crops. Similarly, economic inefficiency decreases as the increase in experience of farm operator for *Boro* and *Aman* rice. For *Aus* rice, education has positive impact on the economic inefficiency effect.

The mean economic efficiencies estimated from Translog cost frontiers for *Boro*, *Aus*, and *Aman* rice are respectively 80%, 60% and 74%. The study also reveals that without change of output the production cost of *Boro*, *Aus* and *Aman* can be reduced by 20%, 40% and 26%, respectively.

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