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by

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Analysis of Technical Efficiency in a Rainfed Lowland Rice Environment in Central Luzon Philippines Using a Stochastic Frontier Production Function with a Heteroskedastic Error Structure

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Abstract

There have been many previous studies of technical inefficiency in rice production in the Philippines, but none has focused simultaneously on production risk and technical inefficiency at the farm level. In this study, we analyse technical inefficiency in a rainfed lowland rice environment in Central Luzon using a stochastic frontier production function with a heteroskedastic error structure.

Key Words: heteroskedastic error structure; Philippines; stochastic frontier production function; technical inefficiency

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1. Introduction

We estimate a stochastic frontier production function with heteroskedasticity based on a panel data set of small-scale farmers in a rainfed lowland rice environment in the Philippines. The function is then used to estimate technical efficiency scores and identify factors associated with technical inefficiency. Partial output elasticity estimates are presented for two flexible functional specifications with the same data set and retaining the same assumptions about the underlying technology and structure of farm efficiencies.

This paper is organised as follows. In the next section, we review relevant literature on efficiency studies in rice farming. This is followed in section 3 by an outline of the stochastic frontier model and specification of the functional forms. The empirical results are presented in section 4 and some conclusions are drawn in section 5.

2. Review of Efficiency Studies on Rice Farming

Rice production has been the focus of attention of a number of studies of technical inefficiency in developing country agriculture, reflecting the importance of rice in rural development in many developing countries. Most of these studies have been reviewed by Battese (1992), Bravo-Ureta and Pinheiro (1993) and Coelli (1995).

Frontier methodologies can be usefully classified into parametric and non-parametric approaches (although the distinction between these two approaches is becoming increasingly blurred). A summary of selected empirical (predominantly parametric) studies of production on Philippine rice farms is presented in Table 1. The following discussion focuses first on these studies and then on a similar set of efficiency studies on rice production conducted in other Asian countries. In a concluding paragraph, we summarise the major issues raised in the empirical studies.

2.1 Efficiency studies of rice production in the Philippines

Some of the early studies in rice farming applying frontier methods are in the Philippines. They include Kalirajan and Flinn (1983), Lingard, Castillo and Jayasuria (1983), Kalirajan (1984), Färe, Grabowski and Grosskopf (1985), and Dawson and Lingard (1989).

Kalirajan and Flinn (1983) applied the methodology proposed by Jondrow, Lovell, Materov and Schmidt (1982) to data for 79 rice farmers in the Bicol region. They estimated the parameters of their model using the maximum-likelihood method. The Cobb-Douglas model was found to be an inadequate representation of the farm-level data, and so a translog stochastic frontier production function was estimated to explain variations in rice output in terms of several inputs. The estimated technical efficiencies ranged from 0.38 to 0.91. Kalirajan and Flinn then regressed the predicted technical efficiencies on several farm-level variables and farm-specific characteristics to determine which factors are associated with estimated technical efficiency scores. Several variables, including the practice of transplanting rice seedlings, the incidence of fertilisation, years of farming and number of extension contacts, were found to have significant relationships.

Lingard, Castillo and Jayasuriya (1983) measured farm-specific technical efficiencies of rice farmers in Central Luzon using the "Loop Survey" data from the International Rice Research Institute (IRRI). They estimated a production function for 32 farmers from panel data for 1970, 1974 and 1979 using covariance analysis. Measures of technical efficiency were calculated from the farm-specific dummy variables. The results showed that the least efficient farm achieved only 29 per cent of the maximum possible output for given input levels.

Dawson and Lingard (1989) extended the analysis of Lingard, Castillo and Jayasuriya (1983) and estimated farm-specific technical efficiencies from a stochastic frontier production function using data for 1970, 1974, 1979 and 1982. For each year, a stochastic frontier production function was estimated applying the composed error model of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). Dawson and Lingard calculated technical efficiencies for each farm in each year by using the methodology of Jondrow et al. (1982) and assuming a Cobb-Douglas functional form. The results showed a fairly uniform distribution of estimated efficiencies across a range that was greater than that reported by Lingard, Castillo and Jayasuriya (1983). The mean technical efficiency for the four years ranged between 0.60 and 0.70.

Table 1: Selected efficiency studies in rice farming in the Philippines

Author(s)	Year of publication	Location	Model
Kalirajan and Flinn	1983	Bicol	Stochastic
Lingard, Castillo and Jayasuriya	1983	Central Luzon	Covariance Analysis
Färe, Grabowski and Grosskopf	1985	Philippines	Deterministic
Dawson and Lingard	1989	Central Luzon	Stochastic
Dawson, Lingard and Woodford	1991	Central Luzon	Stochastic-panel
Rola and Quintana-Alejandrino	1993	Selected regions	Stochastic
Larson and Plessman	2002	Bicol	Stochastic
Gragasin, Maruyama and Kikuchi	2002	Mindoro and Cavite	Stochastic
Umetsu, Lekprichakul and Chakravorty	2003	All regions	Malmquist index

Dawson, Lingard and Woodford (1991) used a Cobb-Douglas stochastic frontier production function to estimate the technical inefficiency of rice farmers in Central Luzon. The data used in this study were similar to those of Dawson and Lingard (1989), with the addition of data for 1984. Because they used a panel-data approach, the data for only 22 farmers were available. The stochastic frontier production function method was used to calculate a single measure of technical efficiency for each farm over the whole 15-year period (1970-1985). The results showed a narrow range of efficiency estimates across the 22 farms, between 0.84 and 0.95, from which Dawson, Lingard and Woodford (1991) implied that increases in rice production in the future must come from further technological progress.

Rola and Quintana-Alejandrino (1993) used a stochastic frontier production function to estimate the technical efficiencies of rice farmers in different rice environments in selected regions of the Philippines. The study used a Cobb-Douglas production frontier and estimated the model by the maximum-likelihood method. Input variables in the production frontier included farm size, fertiliser (nitrogen), insecticide, herbicide and labour. In addition, variables such as education of the household head, tenurial status and water source were used in the production function. Input-output data and other demographic information were gathered from farmers in the irrigated, rainfed and upland environments of five rice-producing regions in the Philippines. The data were collected for 1987 in Central Luzon, Western Visayas and Central Mindanao, 1988 in Bicol and 1990 in the Cagayan Valley. Rola and Quintana-Alejandrino (1993) estimated mean technical efficiencies of 0.72, 0.65 and 0.57 for irrigated, rainfed and upland environments, respectively, indicating high variability in the technical efficiency estimates between the different rice environments. Education, access to capital and tenurial status were some factors that affected the levels of technical efficiencies of farmers in the different environments.

Larson and Plessman (2002) used data collected in the Bicol region in the years 1978, 1983 and 1994 to construct a balanced panel data set comprising 144 observations. They estimated a translog stochastic frontier production function that included the inputs of irrigated area, rainfed area, upland area, fertiliser and labour. A model that takes into account the factors associated with technical inefficiency was also estimated. Larson and Plessman (2002) found that diversification and technology choices affected efficiency outcomes among Bicol rice farmers, although these effects were not dominant. Other factors associated with efficiency were accumulated wealth, education, favourable market conditions and weather.

One factor that was considered in the early literature on efficiency analysis in rice farming in the Philippines was the proportion of irrigated land under rice production. In some cases, the availability of irrigation facilities such as tubewells and water pumps was included in both the production function and inefficiency model. In the same vein, some analysts examined the effect of institutional organisation or association. Recently, Gragasin, Maruyama and Kikuchi (2002) attempted to determine whether the existence of an association for irrigators increased the technical efficiency of rice farmers in the Philippines. The data used in their study were collected from Oriental Mindoro and Naic, Cavite. The estimation of stochastic frontier production functions for groups of rice farmers with and without membership of an association for irrigators revealed that the mean level of technical efficiencies of farmers who were members of an association were on average higher than those of farmers who were not.

More recently, Umetsu, Lekprichakul and Chakravorty (2003) examined regional differences in total factor productivity, efficiency and technological change in the Philippine rice sector in the post-Green Revolution era. Malmquist indices were constructed for 1971-1990 and were decomposed into efficiency and technological change. The factors affecting productivity, efficiency and technological change were analysed by second-stage regression analyses. The factors considered were irrigation infrastructure, population, technology variables (higher education, modern variety), an institutional variable (landlord share), factor price variables (land/fertiliser price, labour/machinery price), factor-intensity variables (fertiliser/land, hand tractor/land), exogenous macro-variables (weather, disaster, oil shock, currency crisis) and geographical location (Luzon and Mindanao). It was found that the regions of Central Luzon, Western Visayas, Southern Tagalog and Northern Mindanao had higher rates of technological change than other regions because of higher investment in infrastructure and education, increased adoption of tractors and a better agroclimatic environment. This study was conducted on a regional basis, which provided a good macro-level analysis of the changes in efficiency, productivity and technological change. However, the input and output variables were aggregated while information on farm-specific characteristics was used.

2.2 Efficiency studies of rice production in other developing countries

Efficiency measurement in rice farming has also been the focus of many studies in other developing countries. A summary of selected studies is presented in Table 2. Most of these studies involved the estimation of a single-equation production frontier using cross-sectional or panel data. Stochastic frontier models have been widely applied, estimated using the maximum likelihood method. Almost all of these studies assumed that Cobb-Douglas or translog production frontiers were appropriate in the analysis of farm-level data on rice production.

The source of efficiency differentials that were observed among rice farmers was an issue of overriding concern. Most of these studies examined factors that explain why some farmers are more efficient than others. Studies of the sources of technical inefficiency in rice farming concentrated on characteristics of the farms and farmers. The efficiency variables were related to managerial and socio-economic characteristics.

Table 2: Selected efficiency studies of efficiency in rice farming in Asian countries other than the Philippines

Author(s)	Year of Publication	Location	Model
Kalirajan	1981	Tamil Nadu, India	Stochastic
Ekayanake	1987	Sri Lanka	Stochastic
Ali and Flinn	1989	Punjab, Pakistan	Stochastic
Kalirajan and Shand	1989	South India	Stochastic-panel
Erwidodo	1990	Java, Indonesia	Stochastic-panel
Squires and Tabor	1991	Java, Indonesia	Stochastic
Battese and Coelli	1992	India	Stochastic-panel
Battese and Coelli	1995	India	Stochastic-panel
Dev and Hossain	1995	Bangladesh	Stochastic
Trewin et al.	1995	Java, Indonesia	Stochastic-panel
Xu and Jeffrey	1998	Jiangsu, China	Stochastic
Ahmad, Rafiq and Ali	1999	Pakistan	Stochastic
Mythili and Shanmugam	2000	India	Stochastic-panel
Shanmugam	2000	India	Stochastic
Tian	2000	China	Stochastic-panel
Ajibefun, Battese and Kada	2002	Japan	Stochastic-panel
Coelli, Rahman and Thirtle	2002	Bangladesh	Non-parametric
Tian and Wan	2002	China	Stochastic-panel

Source: Adapted from Coelli (1995), plus authors' own literature search.

By definition, managerial variables are concerned with the ability of the farmer to choose farm output mixes and patterns, for example, seed type and rates, the application of fertilisers and chemicals (rate, types and timing), and planting and harvesting techniques. From the literature, the most common socio-economic variables were farm size, the education, age and experience of the farmers, and their access to extension services and credit. Education was found to be one of the significant factors associated with the technical efficiency of farmers (Ali and Flinn 1989; Kalirajan and Shand 1989; Xu and

Jeffrey 1998), implying that human capital is an important factor in carrying out production and managerial tasks on rice farms.

3. The Empirical Stochastic Frontier Production Model

In this study, we estimate the farm-level technical efficiencies of rainfed rice farmers based on a stochastic frontier production function with an additive heteroskedastic error structure. In light of the above review of selected efficiency studies on rice production, we also identify factors that are associated with the technical inefficiency of farmers. A distinct feature of this study is that it uses farm-level panel data collected purely from a rainfed environment. Previous studies on technical inefficiency in rainfed environments are based on regional or aggregate data. In this section, the model is estimated and the functional forms and variables are defined. The empirical results and tests of hypotheses are presented in the following section.

3.1 The basic model

A stochastic frontier production function is applied to panel data to model rainfed rice production in Tarlac, Central Luzon, Philippines. The model of Battese and Coelli (1993, 1995) is used in accordance with the original models of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). It has the general form:

$$Y_{it} = f(X_{it}, \alpha)\exp(\varepsilon_{it}) \tag{1}$$

where Y_{it} is the output of farm i (i = 1, 2, …, N) in year t (t = 1, 2, …, T); X_{it} is the corresponding matrix of inputs; α is the vector of parameters to be estimated; and ε_{it} is the error term that is composed of two independent elements, V_{it} and U_{it}, such that $\varepsilon_{it} \equiv V_{it} - U_{it}$. The V_{it}s are assumed to be symmetric identically and independently distributed errors that represent random variations in output due to factors outside the control of the farmers as well as the effects of measurement error in the output variable, left-out explanatory variables from the model and statistical noise. They are assumed to be normally distributed with mean zero and variance, σ_V^2.

Following Battese and Coelli (1995), the U_{it}s are non-negative random variables that represent the stochastic shortfall of outputs from the most efficient production. It is assumed that U_{it} is defined by truncation of the normal distribution with mean, $\mu_{it} = \delta_0 + \sum_{j=1}^{J} \delta_j Z_{jit}$, and variance, σ^2 , where Z_{jit} is value of the j-th explanatory variable associated with the technical inefficiency effect of farm i in year t; and δ_0 and δ_j are unknown parameters to be estimated.

The parameters of both the stochastic frontier model and the inefficiency effects model can be consistently estimated by the maximum-likelihood method. The variance parameters of the likelihood function are estimated in terms of $\sigma_S^2 \equiv \sigma_V^2 + \sigma^2$ and $\gamma \equiv \sigma^2 / \sigma_S^2$.

Few empirical studies have attempted to analyse production risk and technical efficiency in a single framework. Kumbhakar (1993) demonstrated a method to estimate production risk and technical efficiency using a flexible production function to represent the production technology. The model was estimated using panel data, and the risk function appears multiplicatively to accommodate negative and positive marginal risks with respect to output. Individual technical efficiencies were also estimated.

Battese, Rambaldi and Wan (1997) specified a stochastic frontier production function with an additive heteroskedastic error structure that is adopted in this study. Following Kumbhakar (1993), their model permits negative or positive marginal effects of inputs on production risk, consistent with the Just and Pope (1978) framework. The error specification in equation (1) takes the form:

$$\varepsilon_i = g(X_i;\beta)[V_i - U_i] \tag{2}$$

where the $U_i s$ are non-negative random variables associated with the technical inefficiency of the farmers, and are assumed to be independent and identically distributed truncations of the half-normal distribution, $|N(0, \sigma_U^2)|$, independently distributed of the $V_i s$.

By using the specification in equation (2) and rewriting equation (1), we obtain:

$$Y_i = f(X_i;\alpha) + g(X_i;\beta)[V_i - U_i]\,. \tag{3}$$

Equation (3) is the specification of the stochastic frontier production function with flexible risk properties that Battese, Rambaldi and Wan (1997 p. 270) used. We follow their exposition by specifying the mean and variance of output for the *i*-th farmer, given the values of the inputs and the technical inefficiency effect, U_i, as:

$$E(Y_i \mid X_i, U_i) = f(X_i;\alpha) - g(X_i;\beta)U_i\,. \tag{4}$$

The risk function is defined as:

$$Var(Y_i \mid X_i, U_i) = g^2(X_i;\beta)\,. \tag{5}$$

The marginal production risk with respect to the *j*-th input is defined to be the partial derivative of the variance of production with respect to X_j, which can be either positive or negative:

$$\frac{\partial Var(Y_i | X_i, U_i)}{\partial X_{ij}} > 0 \text{ or } < 0\,. \tag{6}$$

Accordingly, the technical efficiency of the *i*-th farmer, denoted by TE_i, is defined by the ratio of the mean production for the *i*-th farmer, given the values of the inputs, X_i, and its technical inefficiency effect, U_i, to the corresponding mean production if there were no technical inefficiency of production (Battese and Coelli 1988, p. 389). It is specified as:

$$TE_i = \frac{E(Y_i \mid X_i, U_i)}{E(Y_i \mid X_i, U_i = 0)} = 1 - TI_i \tag{7}$$

where TI_i is technical inefficiency, defined as potential output loss and represented as:

$$TI_i = \frac{U_i \cdot g(X_i, \beta)}{E(Y_i \mid X_i, U_i = 0)} = \frac{U_i \cdot g(X_i;\beta)}{f(X_i;\alpha)}\,. \tag{8}$$

If the parameters of the stochastic frontier production function were known, then the best predictor of U_i would be the conditional expectation of TE_i, given the realised values of the random variable $E_i = V_i - U_i$ (Jondrow et al. 1982). It can be shown that $U_i|(V_i - U_i)$ is distributed as $N(\mu_i^*, \sigma_*^2)$, where μ* and σ_*^2 are defined by:

$$\mu_i^* = \frac{-(V_i - U_i)\sigma_U^2}{(1+\sigma_U^2)} \tag{9}$$

$$\sigma_*^2 = \frac{\sigma_U^2}{(1+\sigma_U^2)}. \tag{10}$$

It can also be shown that $E[U_i|(V_i\text{-}U_i)]$, denoted by $\hat{U}_i$, is given as:

$$\hat{U}_i = \mu_i^* + \sigma_*\left[\frac{\phi(\mu_i^*/\sigma_*)}{\Phi(\mu_i^*/\sigma_*)}\right] \tag{11}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ represent the density and distribution functions of the standard normal random variable. Equation (11) can be estimated by using the corresponding predictors for the random variable, E_i, given by:

$$\hat{E}_i = \frac{Y_i - f(X_i;\hat{\alpha})}{g(X_i;\hat{\beta})}. \tag{12}$$

After equation (11) is estimated, equation (8) can be estimated as:

$$TI_i = \frac{\hat{U}_i \cdot g(X_i;\hat{\beta})}{f(X_i;\hat{\alpha})}. \tag{13}$$

The technical efficiency of the i-th farmer is predicted by $\widehat{TE}_i = 1 - \widehat{TI}_i$.

3.2 Functional forms and variables

The Cobb-Douglas form of the stochastic frontier production in this study is:

$$\ln Y_{it} = \alpha_0 + \sum_{j=1}^{4}\alpha_j \ln X_{it} + \alpha_5 X_5 + \varphi_1 D_{1it} + V_{it} - U_{it} \tag{14}$$

where Y represents the quantity of freshly threshed rice paddy (in tonnes)[1]; X_1 is the total area planted to rice (in hectares); X_2 is the fertiliser (as nitrogen, phosphorus and potassium, or NPK) (in kilograms); X_3 is the herbicide applied (in grams of active ingredients)[2]; X_4 is the total labour input (person-days) by family, exchanged and hired labourers in the growing, harvesting and threshing of rice;[3] X_5 denotes the year in which the observation on rice production is obtained; D_1 is the dummy variable for herbicide, with a value of 1 if $X_3 > 0$ and 0 if $X_3 = 0$; the subscripts, j, i and t refer to the j-th input (j =1,2…5), i-th farmer (i=1,2,..,46) and t-th year (t =1,2,…,8), respectively; and the αs and φs are unknown parameters to be estimated.

The second specification is the translog model, which is given by:

$$\begin{aligned}\ln Y_{it} = \alpha_0 + \sum_{j=1}^{4}\alpha_j \ln X_{jit} + 0.5\sum_{j\leq}^{4}\sum_{k}^{4}\alpha_{jk} \ln X_{jit} \ln X_{kit} + \alpha_5 X_{5it} \\ +0.5\sum_{j\leq}^{4}\sum_{k}^{4}\alpha_{jk} \ln X_{jit} X_{5it} + \varphi_1 D_{1it} + V_{it} - U_{it}\end{aligned} \tag{15}$$

where the variables are as previously defined. The translog function is the most frequently used flexible functional form in production studies.

As a special case of the translog function, the Cobb-Douglas functional form imposes severe restrictions on the technology by restricting the production elasticities to be constant and the elasticities of input substitution to be unity. We tested the Cobb-Douglas against the translog function to determine whether it was an adequate representation of the data, and found conclusive evidence that it was not. We have therefore excluded this model from further consideration.

The third specification of the stochastic frontier model is the quadratic form, which is defined as:

$$\mathrm{Y}_{it} = \alpha_0 + \sum_{j=1}^{5}\alpha_j X_{jit} + 0.5\sum_{j\leq}^{5}\sum_{k}^{5}\alpha_{jk} X_{jit} X_{kit} + V_{it} - U_{it}\,. \tag{16}$$

[1] Traditionally, farmers measure their harvest in *cavans*. One cavan is approximately 46 kilograms.

[2] This implies that the logarithm of the herbicide applied is taken only if it is positive, otherwise the herbicide variable is zero, as proposed by Battese (1997).

In the next section, we present empirical results for two specifications, the translog and quadratic functional forms, and examine the corresponding results.

Given the functional specifications presented above, the estimated technical inefficiency model is the specification of Battese and Coelli (1995), which is defined as:

$$\mu_{it} = \delta_0 + \sum_{j=1}^{4} \delta_j Z_{jit} + \sum_{k=5}^{11} \delta_k D_{kit} \tag{17}$$

where the δ_js (j = 0,1,…11) are unknown parameters; Z_1 is the age of the household head; Z_2 is the years of education completed by the household head; Z_3 represents the ratio of adults to the total household size; Z_4 is the total income from non-farm activities (in thousands of US dollars); and D_k (k = 5,..11) denote the dummy variables for the last seven years of the data set.

3.3 Descriptive statistics

Descriptive statistics of the variables included in the stochastic frontier production function for the eight-year study period, 1990-1997, are presented in Table 3. The average production of rice was approximately 6.5 tonnes per household, which translates to a mean yield of about 3.1 tonnes per hectare. Rice production was highly variable, ranging from 92 kilograms to a maximum of 31.1 tonnes per household. Average fertiliser use was 187 kilograms per household, which was equivalent to approximately 89 kilograms per hectare. The average labour use was approximately 51 person-days per hectare.

The ages of farmers varied from 25 years to 81 years and almost 80 per cent of the household members were adults. While rice was the dominant source of household income, income from non-farm activities accounted for almost 20 per cent, which was about US$280 per household.

[3] Because the data are not disaggregated by gender, this is the total amount of labour used regardless of the gender of the farm labourers.

Table 3: Descriptive statistics of the variables in the stochastic frontier production models and inefficiency models

Variable name	Mean	Standard deviation	Minimum	Maximum
Rice harvested (t)	6.5	5.1	0.09	31.1
Area (ha)	2.1	1.5	0.20	7.00
Fertiliser (kg)	187.0	168.8	3.36	1030.9
Herbicide (grams)	0.39	0.62	0	4.41
Labour (person-days)	107.0	76.8	7.8	436.9
Age (years)	49.7	11.0	25	81
Education (years)	7.2	1.9	6	14
Adult ratio (%)	0.79	0.22	0.28	1
Non-farm income (US$000)	0.28	0.61	0	4.34

3.4 Inefficiency effects

The sign on the coefficient of the *age of the household head* could be negative or positive. If older farmers were not willing to adopt better practices while younger farmers were more motivated to embrace better agricultural production practices that reduce technical inefficiency effects, then the coefficient would be positive (greater technical inefficiency). However, if older farmers have more experience and knowledge of the production activities and are more reliable in performing production tasks, then the coefficient would be negative.

The coefficient of *education* is expected to have a negative sign because a higher level of educational attainment would result in lower inefficiency. The educational attainment of the farm manager is a proxy for human capital.

The coefficient associated with *the ratio of adult members of the household* is expected to have a negative sign. More adult members in the household mean more quality labour is available for carrying out farming activities in a timely fashion, thus making the production process more efficient.

The *non-farm income* variable is expected to have a negative effect on efficiency and so its coefficient is expected to have a positive value. Non-farm activities can affect the timing of farming activities. Obtaining additional income for the household might result in neglect of the farm activities and thereby increase the inefficiency of the production system. However, extra non-farm income could assist in the timely purchase of inputs and increase efficiency.

The coefficients of *year of observation* in the stochastic frontier production functions allow the frontier to change over time to capture any technological changes. In the case of the translog and quadratic models, more than one parameter is associated with technical change (year) effects. Hence, the change is measured as the first derivative of the frontier function with respect to variable year (X_5). Incorporating year-specific dummy variables in the inefficiency model captures changes in the inefficiency effects over time.[4]

The technical efficiency of production for the *i*-th farm in the *t*-th year is defined by

$$TE_{it} = \exp(-U_{it}) \quad (18)$$

The prediction of the technical efficiencies is based on its conditional expectation, given the observable value of (V_{it}-U_{it}) (Jondrow et al. 1982; Battese and Coelli 1988). The technical efficiency index is equal to one if the farm has an inefficiency effect equal to zero and it is less than one otherwise.

3.5 Estimation procedure

The stochastic frontier production functions, defined by equations (2) to (4), and the technical inefficiency models, defined by equation (5), are jointly estimated by the maximum-likelihood method using FRONTIER 4.1 (Coelli 1996).[5]

[4] A time trend was initially included in the inefficiency model, implying that the inefficiency effects change by a constant value each year. This assumption is unlikely to hold in the rainfed rice environment where farmers have to contend with erratic rainfall, causing inefficiency to vary between years. The sign of the coefficient on the trend variable was positive but insignificant.

[5] The FRONTIER software uses a three-step estimation method to obtain the final maximum-likelihood estimates. First, estimates of the α-parameters are obtained by OLS. A two-phase grid search for γ is conducted in the second step with α-estimates set to the OLS values and other parameters set to zero. The third step involves an iterative procedure, using the Davidon-Fletcher-Powell Quasi-Newton method to obtain final maximum-likelihood estimates with the values selected in the grid search as starting values.

Various tests of null hypotheses for the parameters in the frontier production functions and in the inefficiency models are performed using the generalised likelihood-ratio test statistic defined by:

$$\lambda = -2 \{\log [L(H_0) - \log [L(H_1)]\}. \tag{19}$$

where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and alternative (H_1) hypotheses, respectively. If the null hypothesis is true, the test statistic has approximately a chi-square or a mixed chi-square distribution with degrees of freedom equal to the difference between the parameters involved in the null and alternative hypotheses. If the inefficiency effects are absent from the model, as specified by the null hypothesis, H_0: $\gamma=\delta_0=\delta_1=\delta_2=\ldots\delta_{11}=0$, then λ is approximately distributed according to a mixed chi-square distribution with 13 degrees of freedom. In this case, critical values for the generalised likelihood-ratio test are obtained from Table 1 of Kodde and Palm (1986).

4. Empirical Results

4.1 Production frontier estimates

The maximum-likelihood estimates of the parameters of the translog and quadratic stochastic frontier production functions given by equations (2) to (5) are presented in Table 4.[6] The maximum-likelihood estimates of the parameters of the inefficiency model for the two functions are presented in Table 5. The values of the explanatory variables in the translog stochastic frontier model were mean-corrected by subtracting the means of the variables so that their averages were zero. This approach dictates that the first-order parameters are estimates of output elasticities for the individual inputs at the mean values.

Table 4: Maximum-likelihood estimates for parameters of the stochastic frontier production models for rainfed lowland rice production in Tarlac

		Translog		Quadratic	
Variable	Parameter	Coefficient	Standard error	Coefficient	Standard error
Constant	α_0	1.713 [a]	0.067	0.34	0.67
Area	α_1	0.510 [a]	0.062	0.02	0.75
Fertiliser	α_2	0.240 [a]	0.035	0.0240 [a]	0.0049
Herbicide	α_3	0.025	0.024	0.016	0.015
Labour	α_4	0.210 [a]	0.063	0.12	0.84
Year	α_5	0.106 [a]	0.047	0.22	0.27
(Area) ^{2}	α_{11}	-0.56 [a]	0.22	-0.67	0.55
(Area) (Fertiliser)	α_{12}	0.05	0.13	-0.0054 [a]	0.0025
(Area) (Herbicide)	α_{13}	-0.059	0.045	0.0309 [a]	0.0074
(Area) (Labour)	α_{14}	0.75 [a]	0.19	-1.32 [a]	0.42
(Area) (Year)	α_{15}	0.042	0.090	0.238 [a]	0.095
(Fertiliser)^2	α_{22}	0.207 [a]	0.047	-0.000012	0.000011
(Fertiliser) (Herbicide)	α_{23}	0.036 [b]	0.032	0.000021	0.000046
(Fertiliser) (Labour)	α_{24}	-0.35	0.13	0.0086 [a]	0.0029
(Fertiliser) (Year)	α_{25}	-0.119 [b]	0.068	-0.00114	0.00072
(Herbicide)^2	α_{33}	-0.016	0.026	-0.00058 [a]	0.00015
(Herbicide) (Labour)	α_{34}	0.043	0.053	0.0073	0.0070
(Herbicide) (Year)	α_{35}	0.008	0.099	-0.0017	0.0017
(Labour)^2	α_{44}	-0.51 [b]	0.29	0.20	0.87
(Labour) (Year)	α_{45}	0.044	0.022	0.10	0.13
(Year)^2	α_{55}	0.35	0.11	-0.033	0.056
Dummy variable for herbicide	φ_1	0.025	0.052		
Variance parameters	σ^2	0.29 [a]	0.13	7.62 [a]	1.65
	γ	0.89 [a]	0.050	0.768 [a]	0.064
Log-likelihood function		-44.08		-685.41	

[a] denotes significance at the one per cent level, [b] denotes significance at the five per cent level and [c] denotes significance at the ten per cent level.

Table 5: **Maximum-likelihood estimates for parameters of the inefficiency effects model of the translog and quadratic production functions for rainfed lowland rice production in Tarlac**

		Translog		Quadratic	
Variable	**Parameter**	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Constant	δ_0	-0.05	0.61	-14.1 [a]	6.3
Age	δ_1	0.0076	0.0057	-0.003	0.021
Education	δ_2	-0.038	0.039	0.46 [a]	0.18
Adult Ratio	δ_3	-0.49 [c]	0.30	1.1	1.2
Non-farm Income	δ_4	0.00044 [c]	0.00022	0.00008	0.00049
Year 2 (1991)	δ_5	-0.49 [c]	0.31	6.27 [a]	3.1
Year 3 (1992)	δ_6	-2.5	2.5	-8.76 [a]	2.6
Year 4 (1993)	δ_7	-0.98 [c]	0.55	7.46 [a]	3.4
Year 5 (1994)	δ_8	-0.13	0.24	10.48 [a]	3.8
Year 6 (1995)	δ_9	-0.83	0.57	7.23 [a]	3.2
Year 7 (1996)	δ_{10}	0.45	0.32	11.9 [a]	4.1
Year 8 (1997)	δ_{11}	-0.63 [c]	0.35	2.78	1.9

[a] denotes significance at the one per cent level, [b] denotes significance at the five per cent level and [c] denotes significance at the ten per cent level.

All estimated first-order coefficients in the translog model fall between zero and one, satisfying the monotonicity condition that all marginal products are positive and diminishing at the mean of inputs. Except for herbicide, all estimated first-order coefficients are significant at the five per cent level in the translog model. In the case of the quadratic functional specification, only the coefficients of fertiliser and the interaction between area and other inputs are significant.

The results of several tests of hypotheses performed on the estimated coefficients are summarised in Table 6. If the first null hypothesis, H_0: $\alpha_{ij}=0$, is true, given the specifications of the inefficiency effects model and a translog stochastic frontier model, equation (3) is identical to the Cobb-Douglas functional form. Given a quadratic functional form, the model becomes an ordinary linear model if this null hypothesis is true. At the five per cent level of significance, both hypotheses are rejected. As indicated above, the Cobb-Douglas functional form is rejected and the following analysis excludes results for this model.

Table 6: Tests of null hypotheses for parameters in the stochastic frontier production functions and the inefficiency effects models

Hypothesis	Translog			Quadratic		
	λ	Critical value	Decision	λ	Critical value	Decision
1. H_0: $\alpha_{ij} = 0$	72.5	25.7	Reject H_0	63.1	25.7	Reject H_0
2. H_0: $\alpha_5 = (\alpha_{i5}) = 0$	25.4	11.9	Reject H_0	8.6	11.9	Accept H_0
3. H_0: $\gamma=\delta_0=\delta_1=\ldots=\delta_{11}=0$	56.8	21.7	Reject H_0	57.8	21.7	Reject H_0
4. H_0: $\delta_1=\ldots=\delta_{11}=0$	51.6	19.0	Reject H_0	43.8	19.0	Reject H_0
5. H_0: $\delta_1=\delta_2=\delta_3=\delta_4=0$	16.2	8.8	Reject H_0	41.9	8.8	Reject H_0
6. H_0: $\delta_5=\delta_6=...=\delta_{11}=0$	40.8	13.4	Reject H_0	4.3	13.4	Accept H_0

The second null hypothesis is that there was no technical change in the eight-year study period. For the translog model, the null hypothesis, H_0: $\alpha_5 = \alpha_{i5} = 0$, i=1,2,.., 5, is rejected indicating that the *Year* variable should not be excluded from the model. However, this variable was found not to be significant in the model with the quadratic functional form.

The γ-parameters associated with the variance of the technical inefficiency effects in the stochastic frontiers are estimated to be 0.89 for the translog model and 0.77 for the quadratic model. These results indicate that the technical inefficiency effects are a significant component of the total variability of rice output in the rainfed rice environments. This result is supported by the third hypothesis test in which the null hypothesis, H_0: $\gamma=\delta_0=\delta_1=\ldots=\delta_{11}=0$, indicates that the inefficiency effects in the frontier model are not present. If γ=0 and all the δ-coefficients are zero, the stochastic frontier production function is the same as the mean production function that does not account for the inefficiency effects. From Table 6, it can be seen that this null hypothesis is rejected at the five per cent level of significance for both models**.** This rejection indicates that the traditional production function is not an adequate representation of the data.

The coefficients of the explanatory variables in the inefficiency model are found to have the expected signs for the translog model. The *age* variable has a significant positive association, indicating that older farmers tend to be more inefficient. The coefficient of the e*ducation* variable has a negative sign, which implies that more educational training acquired by farm operators is associated with higher technical efficiency of rice production. On the other hand, the *income from non-farm activities* accruing to the household has a positive relationship with inefficiency. However, this was only found to be significant in the case of the translog model. This result suggests that the more household members engage in non-farm activities and earn off-farm income, the more the farming operations become inefficient.

The proportion of adults in the household has a significant negative association with technical inefficiency. This result implies that the higher the ratio of adults to children the less inefficient the rice production in the rainfed environment.

The coefficients of the *year* dummy variables show negative signs for 1992, 1993, 1995 and 1997. The negative signs for the effects of year on the inefficiency values imply that the level of technical efficiency of farmers tended to be greater than in the first year, 1990. The positive coefficient on the year 7 dummy (1996) can be attributed to drought periods in late 1995 and 1996 that are likely to have affected the effort farmers put into their input allocation decisions and production tasks.

The fourth null hypothesis, H_0: $\delta_0=\delta_1=\delta_2=\ldots.\delta_{11}=0$, specifies that all parameters in the technical inefficiency model have a value of zero (technical inefficiency effects have half-normal distribution). This hypothesis is also rejected in all three cases at the five per cent level of significance. The null hypothesis, H_0: $\delta_1=\delta_2=\ldots=\delta_{11}=0$, means that all the coefficients of the explanatory variables of the inefficiency model are zero and therefore the technical inefficiency effects have a truncated normal distribution.

The test of the fifth null hypothesis, that the variables *age*, *education*, *adult* and *non-farm incomes* do not have any effects on inefficiency, was rejected. Finally, a test on the significance of the year-to-year dummy variables (that the inefficiency effects do not vary over time) was rejected for the translog model but not rejected for the quadratic model.

4.2 Elasticities and returns to scale

The estimates of the elasticities of output with respect to inputs of production are presented in Table 7. The figures in parenthesis are standard errors. Because the variables of the translog model were mean-corrected to zero, the first-order coefficients are the estimates of elasticities at the mean input levels. The elasticities for the quadratic model are evaluated at the mean input and output levels using the following expression:

$$\frac{\partial f(\hat{\alpha}, X_i)}{\partial X_i} \times \frac{\overline{X}_i}{\overline{Y}}. \tag{20}$$

Table 7: Output elasticity estimates for inputs in the stochastic frontier production functions

Input	**Translog**	**Quadratic**
Area	0.510 (0.062)	0.477 (0.077)
Fertiliser	0.240 (0.035)	0.323 (0.002)
Herbicide	0.0253 (0.024)	0.0147 (0.157)
Labour	0.210 (0.063)	0.284 (0.067)
Returns to scale	0.985 (0.075)	1.10 (0.27)

The parameters of the two frontier models indicate that the elasticity of output is highest with respect to the area planted to rice (0.51 at the mean input values for the translog function and 0.48 for the quadratic function). These elasticities are about double the estimated fertiliser output elasticities (0.24 for the translog function and 0.32 for the quadratic function) and labour output elasticities (0.21 for the translog function and 0.28 for the quadratic function). The estimated herbicide output elasticities are small and not significant.

The estimated returns-to-scale parameters, computed as the sum of estimated output elasticities of all inputs at their mean values, are 0.99 for the translog model and 1.10 for the quadratic models. These estimates suggest that scale diseconomies are unlikely to exist on the frontier.

4.3 Estimates of marginal output risk

The marginal output risk estimates of the inputs are presented in Table 8. On average, it can be seen that area, fertiliser and labour are risk-increasing while herbicide is riskdecreasing. These results imply that fertiliser and labour are estimated to increase the variance of the value of output. Given the high standard errors relative to the respective coefficients, however, they need to be treated with caution.

Table 8: Marginal production risk estimates at the mean input values

Input	Coefficient	Standard error
Area	0.03	1.9
Fertiliser	0.0038	0.0055
Labour	0.012	0.020
Herbicide	-0.02	0.75

4.4 Technical efficiency indexes

The yearly average farm-level technical efficiencies of the rainfed rice farmers were predicted for the two specifications of the stochastic frontier models. The estimates are presented in Table 9. A salient feature of these estimates is their wide range, from 10.7 per cent to 98.8 per cent. The average predicted technical efficiencies are not significantly different between the two frontier specifications (Table 9). Overall, the mean technical efficiency is about 0.79, indicating that the average farm produced only 79 per cent of the maximum attainable output for given input levels over the eight-year period of analysis. The highest estimated technical efficiencies were in 1992 and the lowest were in 1996.

The upper bound of the average technical efficiency estimates reported here is similar to those of other studies in the nearby provinces in Central Luzon. For instance, Dawson, Lingard and Woodford (1991) reported a mean efficiency of 89 per cent with the best farm over 95 per cent efficient. However, the minimum efficiency level in this study was only about 11 per cent compared with 84 per cent reported by Dawson, Lingard and Woodford (1991). The high degree of variability in our technical efficiency estimates can be attributed to the instability of farming conditions in the rainfed lowland environment. The study areas covered by Dawson, Lingard and Woodford (1991) were mostly of a favourable environment in which farming conditions were relatively stable.

In our study, about one in three sample farmers had a mean technical efficiency in the range of 0.81-0.90, one-quarter had a mean technical efficiency above 0.90, and 17 per cent had a mean technical efficiency in the range of 0.71-0.80. Farmers who fell within the 0.11 to 0.20 range were those who were badly affected by drought.

Table 9: Descriptive statistics of predicted technical efficiency indexes by production frontier model and year

Year	Translog			Quadratic		
	Mean	Minimum	Maximum	Mean	Minimum	Maximum
1990	0.719	0.379	0.927	0.884	0.631	0.984
1991	0.792	0.413	0.936	0.800	0.437	0.962
1992	0.917	0.821	0.964	0.939	0.825	0.988
1993	0.847	0.480	0.942	0.790	0.494	0.979
1994	0.759	0.378	0.934	0.671	0.332	0.976
1995	0.831	0.573	0.932	0.796	0.538	0.978
1996	0.644	0.308	0.897	0.582	0.107	0.874
1997	0.827	0.127	0.952	0.874	0.377	0.988
All years	0.792	0.127	0.964	0.792	0.107	0.988

The technical efficiency estimates for the two models were used to obtain the average values by different farm-size categories. The average estimates of technical efficiencies by farm-size categories are presented in Table 10. In general, producers on large farms are more efficient than producers on smaller farms, with a small difference in mean efficiency between producers on small and medium farms. However, there was no discernible pattern from year-to-year results.

Table 10: Average technical efficiency estimates by farm-size categories

Year	Size of farm			
	Small	Medium	Large	All farms
1990	0.794	0.780	0.831	0.802
1991	0.775	0.761	0.827	0.788
1992	0.909	0.908	0.941	0.919
1993	0.804	0.840	0.836	0.823
1994	0.695	0.717	0.765	0.723
1995	0.792	0.781	0.871	0.814
1996	0.589	0.627	0.673	0.625
1997	0.801	0.876	0.879	0.845
All years	0.770	0.786	0.828	0.792

5. Concluding Remarks

In this paper, the technical efficiencies of small rainfed rice farmers in Tarlac, Philippines, are analysed using rice production and input-use data plus information on some farm characteristics for the eight-year period, 1990-1997. These data were used to estimate stochastic frontier models with an additive heteroskedastic error structure, based on translog and quadratic production functions in which the inefficiency effects are modelled as a function of farm-specific variables and time. Our results indicate that the traditional production function model is inadequate for a farm-level analysis of rice production in the rainfed lowland environment.

The estimated output elasticities of major inputs lie within the bounds reported in previous studies. Several characteristics of farm operators, such as age and educational attainment, ratio of adults in the farm households and income from non-farm activities, were found to have significant effects on the technical inefficiency of rice production in the rainfed lowland environment. High variability was observed in frontiers and technical efficiency estimates from farmer to farmer and from year to year.

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