Technical Efficiency Analysis of the Milkfish (C*hanos chanos*) Production in Taiwan - An Application of the Stochastic Frontier Production Function

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Abstract

Milkfish has been farmed in Taiwan for over 300 years. Faced with a limited land resource, the industry is looking at the problem of how to maintain a sustainable and efficient production. This study specified a stochastic production frontier function to estimate potential milkfish farm output and efficiency by using 1997-99 data from a survey of 443 aquaculture milkfish farms. Both Translog and Cobb-Douglas frontier production models are estimated using the maximum likelihood estimation method. Hypothesis testing results shows that the Translog stochastic production function model fits the data better and the milkfish farming in Taiwan already exhibits diminishing return to scale. Especially, the managerial manager's ability and the pond production conditions, which indicated by the type of mono/multi-species cultured, water source, location, education, and years of experience statistically significant capture the inefficiency effects which represent about 90.5% of the production variation. A comparison of the estimated maximum potential milkfish production per hectare under various pond conditions provide managers how to switch in input resources could boost efficiency.

Keywords: Milkfish, Technical Efficiency, Stochastic Frontier Production Function, Translog Production Function, Cobb-Douglas Production Function, Diminishing Return to Scale

1. Introduction

Milkfish (C*hanos chanos*) is Taiwan's number two inland aquaculture species. Production has grown significantly over the years and in 2001 reached a level of 59,356 M.T. or NT$2.53 billion (US$75 million). This represents 21% of total volume and 11% of total value of inland aquaculture production (Taiwan Fisheries Yearbook, 2002). Milkfish in Taiwan is produced on about 9,880 hectares scattered over 11 of the 23 counties. 17% of inland aquaculture land is in milkfish production.

Taiwan has a long history of milkfish farming and production practices have advanced significantly over time. Milkfish have been grown in Taiwan for over 300 years. Through trial and error, farming practices have evolved that mitigate the challenges imposed by typhoons in summer, severe temperature in winter and water fluctuations, and geographic limitations. In recent years, Taiwanese government has funded much research and worked with scholars and industry to improve production techniques. In 1978 deep-water pond's culture was fully developed. Successful artificial fertilization tripled productivity in 1979. Inventing an automated floating feeding system in 1983 brought significant labor savings and greater profitability to the industry. In 1984, a major breakthrough in artificially raising fish fry overcame a production bottleneck. In fact this technology enabled Taiwan to become a surplus exporter of fish fry by 1989. All these production advances have propelled Taiwan's milkfish aquaculture industry to a highly developed level.

However, challenges remain. Milkfish farming in Taiwan is easily affected by temperature drops. They cannot sustain temperatures below 10^0 C and will die. To cope, milkfish farmers sometimes hedge their risk by growing multiple types of fish together. Water constraints also affect production. In adapting, farmers produce milkfish both under freshwater and brackish water conditions. Growing season limitations have been addressed by some farmers specializing in only rearing fish fry, others focusing on growing out the fry, and others doing the entire production cycle. Land availability constraints are severe in Taiwan which has a population of 619 people/sq km. The individual milkfish farmer's management ability also leads to different production efficiencies. All these constraints will be considered to evaluate where further efficiency gains are possible.

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This study looks at the factors of milkfish production in Taiwan and estimates a stochastic frontier production function to estimate the maximum potential milkfish output and efficiency. This study uses aggregate production information from the Fisheries Yearbook, and a Field Survey Database (1997-1999) with information on individual milkfish pond culture. We then compute technical efficiency estimates for each milkfish farm. Whether the areas of efficiency gains that could boost industry output and increase profitability to Taiwanese milkfish farmers?

2. Research Methodology

2.1. ***The Farrell's Frontier Production Model***

According to the Neo-Classical economic theory, all firms are assumed to be fully efficient in their use of technology so that input and output prices are the only factors that decide output level. Farrell (1957) proposed a provocative idea to explain the variability of firms' output levels. He defined the output of the most efficient firm as the production frontier for all firms. From this reference point, Farrell defined two types of efficiencies, an allocative efficiency which represents price effects and a technical efficiency which represents management effects.

The frontier production function (FPF) defines the "most efficient" potential output level under a fixed amount of factors input. Technical efficiency means using given production methods at optimal or less than optimal levels. Aiger and Chu (1968) used linear programming, Timmer (1971) applied probability programming, and Greene (1980) utilized a revised least square method to define a deterministic FPF. If one assumes that all firms have the same technical information, then they should exhibit a common FPF, which implies that any discrepancy in output level relative to the most efficient firm represents a management inefficiency by that firm.

The assumption under the deterministic FPF, that all firms should have the same output from the same amount of inputs is often criticized as unreasonable. Firms may encounter various uncontrollable exogenous factors, such as performance of various machines, weather conditions, uncertainty of input supplies, etc. To remedy this, a stochastic frontier production function (SFPF) was independently proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). Their specification, which is for cross-sectional data, has an error term with two components, one to account for random effects and another to account for managerial technical inefficiency.

2.2. ***Managerial Technical Inefficiency Model Specification***

A number of empirical studies (e.g. Pitt and Lee, 1981) have estimated stochastic frontiers and predicted firm-level efficiencies using these estimated functions, and then regressed the predicted efficiencies upon firm-specific variables (such as managerial experience, ownership characteristics, etc) in an attempt to identify some of the reasons for differences in predicted efficiencies between firms in an industry. This two-stage estimation procedure has long been recognised as a useful exercise. However, it is inconsistent in it's assumptions regarding the independence of the inefficiency effects in the two estimation stages. The two-stage estimation procedure is unlikely to provide estimates, which are as efficient as those that could be obtained using a single-stage estimation procedure.

This issue was addressed by Kumbhakar, Ghosh, and McGuckin (1991) and Reifschneider and Stevenson (1991) who propose stochastic frontier models in which the inefficiency effects (u_i) are expressed as an explicit function of a vector of firm-specific variables and a random error. Battese and Coelli (1995) propose a model, which is equivalent to the Kumbhakar, Ghosh, and McGuckin (1991) specification, with the exceptions that allocative efficiency is imposed, the first-order profit maximizing conditions removed, and panel data is permitted. The Battese and Coelli (1995) model specification may be expressed as:

$$Y_i = \exp(X_i\beta + \varepsilon_i) = \exp(X_i\beta + y_i - u_i) \quad \varepsilon_i = v_i - u_i, \quad i = 1,..., N \qquad (1)$$

where Y_i is the production (or the logarithm of production[1]) of the i^{th} firm; X_i is a $k\times1$ vector of input quantities of the i^{th} firm; $\beta(1 \times k)$ is a vector of unknown parameters; the v_i's are assumed to be identical independently distributed (i.i.d.) random errors with $N(0, \sigma_v^2)$ and are independently distributed of the u_i's; the u_i's are assumed to be non-negative random variables, associated with technical inefficiency of production, which are often assumed to be independently distributed so that u_i's are obtained by truncating (at zero) the normal or

[1] For example, if Y_i is the log of output and x_i contains the logs of the input quantities, then the Cobb-Douglas production function is obtained.

exponential distribution with mean, m_i , and variance, σ_u^2 .

The managerial technical inefficiency effect in the stochastic frontier model (1) can be specified as follows,

$$u_i = z_i\delta + w_i \tag{2}$$

where z_i is a $p\times1$ vector of variables which may influence the efficiency of the i^{th} firm; and δ is an $1\times p$ vector of parameters to be estimated. Note that the distribution range of the random errors v_i is $[-\infty,+\infty]$, the distribution range of the random inefficiency factor u_i is $[0,+\infty]$, and w_i is a truncated random error $(\geq -z_i\delta)$.

This original specification has been used in a vast number of empirical applications over the past two decades. The specification has also been altered and extended in a number of ways. These extensions include the specification of more general distributional assumptions for u_i, such as the one-sided distributed truncated normal distribution.

Aigner, Lovell, and Schmidt (1977) expressed the likelihood function in terms of two variance parameters, $\sigma^2 \equiv \sigma_u^2 + \sigma_v^2$ and $\lambda \equiv \sigma_u / \sigma_v$. If λ is greater than 1, the variance of the specified firm inefficiency effect (u_i) is greater than the stochastic error. We utilize the parameterization of Battese and Corra (1977) who replaced σ_v^2 and σ_u^2 with $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 /(\sigma_v^2 + \sigma_u^2)$, because γ must lie between zero and one, whereas the λ -parameter could be any non-negative value. γ values of zero indicate that the deviations from the frontier are due entirely to noise, while γ values of one would indicate that all deviations are due to technical inefficiencies. The parameter values for γ must lie between 0 and 1; thus searching this range can provide a good starting value for an iterative maximization process such as the Davidon-Fletcher-Powell (DFP) algorithm. The log-likelihood function of this model is presented in the appendix in Battese and Coelli (1992).

The probability density function of v_i and u_i under $v_i \neq 0$ and $u_i \neq 0$ are as follows,

$$g(v_i|\sigma_v^2) = \frac{1}{(2\pi)^{1/2}\cdot\sigma_v}\exp\left[-\frac{1}{2}\left(\frac{v_i}{\sigma_v}\right)^2\right] \tag{3}$$

$$h(u_i|\sigma_u^2) = \begin{cases} \frac{1}{(2\pi)^{1/2}\cdot\sigma_u}\exp\left[-\frac{1}{2}\left(\frac{u_i}{\sigma_u}\right)^2\right] & \text{if} \quad u_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

By assuming v_i and u_i are mutually independent, the joint PDF of ε_i is as follows (Weinstein, 1964),

$$f(\varepsilon_i|\sigma^2,\lambda) = \frac{2}{\sigma}\phi\left(\frac{\varepsilon_i}{\sigma}\right)\left[1-\Phi\left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right] \tag{5}$$

where $\Phi(.)$ and $\phi(.)$ are the cumulative density function and probability density function of the standard normal random variable.

λ -parameterization has advantages in seeking to obtain the ML estimates because the parameter space for γ can be searched for a suitable starting value in the iterative maximization algorithm. Battese and Corra (1977) showed that the log-likelihood function, in terms of this parameterization, is equal to

$$\ln L = -\frac{N}{2}\ln\frac{\pi}{2} - \frac{\pi}{2}\log(\sigma^2) + \sum_{i=1}^{N}\ln[1-\Phi(S_i)] - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(\ln Y_i - X_i\beta)^2 \tag{6}$$

where $s_i = \frac{(\ln Y_i - X_i\beta)}{\sigma}\sqrt{\frac{\gamma}{1-\gamma}} = \frac{\varepsilon_i\lambda}{\sigma}$. The ML estimates of β , σ_s^2 and γ are obtained by finding the maximum value of the log-likelihood function, defined in equation (6). The ML estimators are consistent and asymptotically efficient (Aigner, Lovell, and Schmidt (1977), p.28). The computer program, FRONTIER Version 4.1, can be used to obtain the ML estimates for the parameters of this model. This program uses the three-step estimation procedure that is specified in Welli, Rao, and Battese (1998, p.188-189). Battese and Coelli (1992) propose a stochastic frontier production function for (unbalanced) panel data, which has firm effects to be distributed as truncated normal random variables, that are also permitted to vary systematically over time.

2.3. *Estimation of Mean Technical Efficiency*

The mathematical expectation (mean) of technical efficiency, $TE_i = \exp(-u_i)$, can be calculated, given certain distributional assumptions. It can be shown that, if the u_is are i.i.d. half-normal random variables, as assumed above, then

$$E[\exp(-u_i)] = 2[1 - \Phi(\sigma\sqrt{\gamma})]\exp(-\gamma\sigma^2 / 2) \qquad (7)$$

By revising the concept of $E(u_i|\varepsilon_i)$ proposed by Jondrow, Lovell, Materov and Schmidt (1982), Battese and Coelli (1988) point out that the best prediction of $\exp(-u_i)$ is obtained by using

$$E[\exp(-u_i|\varepsilon_i)] = \frac{1 - \Phi(\sigma_A + \frac{\gamma\varepsilon_i}{\sigma_A})}{1 - \Phi(\frac{\gamma\varepsilon_i}{\sigma_A})}\exp(\gamma\varepsilon_i + \frac{\sigma^2{}_A}{2}) \qquad (8)$$

Where $\sigma_A = \gamma(1 - \gamma)\sigma^2$, $\varepsilon_i = \ln(y_i) - x_i\beta$. The ratio of the observed output for the i^{th} firm, relative to the potential output, defined by the frontier function, $Y^* = \exp(X_i\beta + v_i)$, given the input vector, x_i, is used to define the technical efficiency of the ith firm:

$$TE_i = Y / Y^* = Y / \exp(X_i\beta + v_i) = \exp(-u_i) = \exp(-z_i\delta - w_i) \qquad (9)$$

2.4. *Hypothesis Tests*

Because we have adopted the Battese and Corra (1977) parameterization, all hypotheses involving γ need to be considered here. For the Wald test, the ratio of the γ estimate over its estimated standard error is calculated. If $H_0 : \gamma = 0$ is true, this test statistic is asymptotically distributed as a standard normal random variable. However, the test must be performed as a one-sided test because γ cannot take negative values.

Under the null hypothesis, $H_0 : \gamma = 0$, the model is equivalent to the traditional average response function, without the technical inefficiency effect u_i. The test statistic is,

$$LR = -2\{\ln\{L(H_0)/L(H_1)\}\} = -2\{\ln[L(H_0)] - \ln[L(H_1)]\} \sim \chi^2_k \qquad (10)$$

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 number of restrictions involved (in this instance one). However, difficulties arise in testing $H_0 : \gamma = 0$ because $\gamma = 0$ lies on the boundary of the parameter space for γ. In this case, if $H_0 : \gamma = 0$ is true, the generalized likelihood-ratio statistic, LR, has an asymptotic distribution which is a mixture of two chi-square distributions, namely $\frac{1}{2}\chi^2_0 + \frac{1}{2}\chi^2_1$, (Coelli, 1995)[2].

According to Kodde and Plam (1986), the significance level of the critical value of a mixture of χ^2 distributions is defined as follows,

$$\alpha = \frac{1}{2}\Pr[\chi^2(df - 1) \geq c] + \Pr[\chi^2(df) \geq c] \qquad (11)$$

where c is a constant and df are the degrees of freedom. The calculation of the critical value for this one-sided generalized likelihood-ratio test of $H_0 : \gamma = 0$ versus $H_1 : \gamma > 0$ is quite simple. The critical value for a test of size α is equal to the value of $\chi^2_1(2\alpha)$, where this is the value which is exceeded by the χ^2_1 random variable with probability equal to 2α. Thus the one-sided generalized likelihood-ratio test of size α is "Reject $H_0 : \gamma = 0$ in favors of $H_1 : \gamma > 0$ if LR exceeds $\chi^2_1(2\alpha)$. The critical value for a test of size, $\alpha = 0.05$, is 2.71 rather than 3.84.[3]

The following hypotheses need to be tested with generalized likelihood-ratio tests to ensure that inefficiency effects are absent form the model.

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[2] Note that χ^2_0 is the unit mass at zero.

[3] The regular (two-sided) generalized likelihood-ratio test was included in the Monte Carlo experiment in Coelli (1995) and shown to have incorrect size (too small) as expected.

(1) $H_0 : \mu = 0$, where the null hypothesis specifies that a simpler half-normal distribution is an adequate representation of the data, given the specifications of the generalized truncated-normal model. Suppose the distribution of the inefficiency random factor u_i is obtained and it is truncation at zero with a normal distribution with mean μ and variance σ_u^2. The one-sided generalized likelihood-ratio test, to test the null hypothesis that there are no technical inefficiency effects in the half-normal hypothesis, can be extended for use in the truncated-normal model.

(2) $H_0 : \gamma = \delta_0 = \delta_1 = ... = \delta_p = 0$, the null hypothesis specifies that inefficiency effects are absent from the model at every level;

(3) $H_0 : \gamma = 0$, the null hypothesis specifies that the inefficiency effects are not stochastic; and

(4) $H_0 : \delta_1 = \delta_2 = ... = \delta_p = 0$, the null hypothesis specifies that the inefficiency effects are not a linear function of each of the inefficiency factors.

3. Empirical Model Specification

3.1. *Data Source and Variable Definition*

The 1997-1999 Economic Survey database of 433 Offshore and Aquaculture Fishermen in Taiwan is used in this study. The input cost and output revenue data for the various classes of milkfish farming ponds in four different counties in the southern Taiwan were obtained from the database released by the *Annual Economic Survey of Offshore Fisheries and Aquaculture* (Taiwan Fisheries Bureau, 1998-2000). For the purpose of this study, milkfish fishermen are defined as those who derive at least 60% of their income from the sale of milkfish. Milkfish production occurs primarily in Chiayi, Tainan, and Kaohsiung counties. The average input costs for the industry fall roughly into these categories: fry 17%, feed 51%, water, electricity and fuel 13%, and other miscellaneous cost 20%.

This study specifies the Translog SFPF for Taiwan's milkfish industry as follows,

$$\ln Y_i = \beta_0 + \sum_{j=1}^{5} \beta_j \ln X_{ji} + \sum_{j \le k}^{5} \sum_{k=1}^{5} \beta_{jk} \ln X_{ji} \ln X_{ki} + v_i - u_i \qquad (12)$$

where, i represent the i[th] milkfish farmer for i = 1, 2, …, 443 and X_{ji} represents the amount of input j used by the i[th] milkfish farmer. See Table 1 for input definitions. If the $\beta_{jk} = 0$ in equation (12), then the model reduces to the Cobb-Douglas (C-D) SFPF model with constant returns to scale as follows,

$$\ln Y_i = \beta_0 + \sum_{j=1}^{5} \beta_j \ln X_{ji} + v_i - u_i \qquad (13)$$

The estimated parameters $\beta_1, \beta_2, ..., \beta_5$ in the above equation (13) represent the output elasticities of the corresponding inputs, and the sum of these parameters equals the estimated output elasticity. Output elasticity, which measures returns to scale, is defined as the percentage change of output for a 1% increase in all input factors. For the output elasticity greater than one, there are increasing returns to scale for the industry.

Suppose the technical inefficiency of each milkfish farmer depends on the manager's ability and the pond production conditions and the managerial technical inefficiency u_i for each individual milkfish farm is specified in equation (14) as follows,

$$u_i = \delta_0 + \delta_1 Y98_i + \delta_2 Y99_i + \delta_3 MONO_i + \delta_4 FRESH_i + \delta_5 CHIAYI_i + \delta_6 TAINAN1_i$$
$$+ \delta_7 SCALE\_1_i + \delta_8 SCALE\_3_i + \delta_9 EDUMONO_i + \delta_{10} EDUHIGH_i + \delta_{11} EXP_i + \delta_{12} LABOR_i \qquad (14)$$

The milkfish farmer's education and the years of production experience are used to represent the management ability. Pond size, monoculture status, water source, county dummies, number of employees, and two yearly dummy variables, which are all used to represent the pond production conditions, are also included to account for differences in efficiency across various milkfish farmers in different years.

3.2. *Production Elasticity, Substitution Elasticity, and Return to Scale*

For each input factor X_j (j = 1, 2, ..., 5), there is a corresponding output elasticity, which is defined as the percentage change of i[th] milkfish farm's output for a 1% increase in the j[th] input factors which is defined as EX_{ji}

and is defined as follows,

$$EX_{ji} = \beta_j + 2\beta_{jj} \ln X_{ji} + \sum_{k \neq j} \beta_{jk} \ln X_{ji} \quad (15)$$

Under the Translog SFPF specification, the output elasticity for each input of various milkfish farms actually dependents on the relative input levels used by various milkfish farmers. If $\beta_{jk} = 0$, the SFPF reduces to a C-D SFPF, the output elasticity for the jth input is defined as β_j, represent the output elasticities of the corresponding inputs, and the sum of these parameters equals the estimated returns to scale. Suppose the input-output relationships of Taiwan's milkfish industry are measured under financially profitable conditions, then all output elasticities for each of the input factors should be positive.

Hick's eleasticity of complementarity (HEC) under the Translog SFPF for each milkfish farm can be defined as follows,

$$H_{jji} = (\beta_{jj} + EX_{ji}^2 - EX_{ji}) / EX_{ji}^2 \quad (16)$$

The cross substitution elasticity for factors j and k is defined as follows,

$$H_{jki} = (\beta_{jk} + EX_{ji} \times EX_{ki}) / (EX_{ji} \times EX_{ki}) \quad (17)$$

Since EX_{ji} is different for each milkfish farmer, this study replaces EX_{ji} with the sample mean for the industry $\overline{EX}_{ji}$. A positive HEC value now implies that the factors j and k are jointly complementary.

4. Estimation Results

4.1. *Parameter Estimates*

Table 2 shows the SFPF estimation results for Taiwan's milkfish industry, using a C-D production model. The highest output elasticity is for feed, 0.39, implying that a 1% increase of feed input will increase production by 0.39%. The other output elasticities are 0.16% for Acreage, 0.14% for Water and Electricity, 0.11% for Fry cost, and 0.09% for Other Costs. The sum of all output elasticities is 0.9, indicating that on average the industry has diminishing returns to scale. Put another way, if the industry increases all factor inputs by 1%, milkfish output would increase by only 0.9%, which is clearly not a sensible economic decision.

The estimation results of the Translog production function are also reported in Table 2. The output elasticity is again highest for Food (- 0.51%). Output elasticities of Water and Electricity, Acreage, Fry Cost, and Other miscellaneous inputs, are 0.13%, 0.12%, 0.12%, and 0.03% respectively, so that the return to scale is 0.92. Comparing the output elasticities between the C-D and Translog specifications, there appears little difference except that the output elasticity of the Feed cost. Under both specifications the sum of all output elasticities is around 0.90, which indicates diminishing returns to scale.

Under the Translog SFPF specification, the error term for the technical efficiency $\lambda \equiv \sigma_u / \sigma_V$ is 3.093, which shows that the variance of the firm specific error term is bigger than the variance of the stochastic error term. More specifically, since $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2) = 0.905$, our estimation shows that 90.5% of the production variation from the SFPF is due to managerial inefficiency. Furthermore, the results from both models show that the managerial technical inefficiency (σ_u^2) is greater than the inefficiency caused by stochastic factors (σ_v^2).

4.2. *Testing for Model Specification*

A likelihood ratio test was conducted to test the null hypothesis that the Translog SFPF can be reduced to a C-D SFPF. The test result statistic, as shown in Table 3: $H_0 : \beta_{jk} = 0, H_1 : \beta_{jk} \neq 0$, has a likelihood ratio value of 89.8, which implies a rejection of the null hypothesis at the 5% significance level, i.e., the Translog SFPF is more suitable to the milkfish farm survey data and the substitution elasticities for the various input factors are statistically different. Olson, Schmidt, and Waldman (1980), and Huang and Bagi (1984) found that estimates of technical efficiency depend on the specified functional form. For example, both Kopp and Smith (1980) and Schmidt (1986) found the estimates of technical efficiency under a stochastic Translog functional form are much higher than the estimates of technical efficiency under a stochastic C-D functional form. Consequently the remainder of this paper uses the Translog SFPF specification to derive conclusions from.

4.3. *Testing Managerial Technical Inefficiency Assumptions*

(1) The first technical assumption to be tested is that the inefficiency factor error term u_i has a semi-normal

distribution with $\mu = -1.12$. The test statistic for $H_0 : \mu = 0$ is 9.7 which leads to a rejection of the null hypothesis and implies that μ has a truncated normal distribution.

(2) The next hypothesis tests the existence of the inefficiency factor. If $H_0 : \gamma = \delta_0 = \delta_1 = ... = \delta_{12} = 0$ is accepted then there is no inefficiency in the industry. However, a significant likelihood ration test value of 66 rejects H_o and implies the existence of inefficiency across the milkfish industry. Conceptually, there exists stochastic managerial inefficiency, i.e., wrong allocation amount of resources.

(3) The next hypothesis tests for the presence of stochastic inefficiency. The null hypothesis is that $H_0 : \gamma = 0$, i.e., the stochastic inefficiency (σ_u^2) is not exist. The test result rejects H_o, implying that the traditional average response function if not an adequate representation of the data.

(4) The last hypothesis test establishes if the existence of inefficiency significantly affected technical efficiency. The null hypothesis $H_0 : \delta_1 = \delta_2 = ... = \delta_{12} = 0$ is rejected with a test value of 46. Rejection of the null hypothesis implies that stochastic frontier model is significantly different from the deterministic frontier model with no random error significant technical inefficiency exists.

The lower half of Table 2 shows the managerial inefficiencies where the negative parameter values indicating greater efficiency. The statistically significant variables of the Translog SFPF affecting efficiency are Year (Y98, Y99), mono/multi-species cultured type (MONO), Water Source (FRESH), County (CHIAYI, TAINAN), Education (EDUNONE, EDUHIGH), Years of Experience (EXP) and Fixed Labor (LABOR). Positive parameter estimates indicate relative technical inefficiency while negative parameter estimates point out relative technical efficiency. The more the estimated value differs from zero, the stronger this efficiency/inefficiency.

Considering each of the parameter estimates provides some interesting insights. Efficiency appears to vary from year to year. In 1998 $(\delta_1 = -1.195)$ fishermen's technical efficiency was greater than during the base year 1997. However, in 1999 when Y99 had a parameter value of δ_2 is 0.441, production was less efficient than in 1997. It is interesting to know that the milkfish production facing a bottleneck of improving its efficiency in 1999.

The MONO variable which measures if there is only one fish species or if there are multiple species raised on each milkfish farm, has a parameter value of $\delta_3 = -1.491$. This implies that specialized milkfish farms tend to be more efficient than milkfish farms growing several types of fish. Note that MONO has the greatest parameter estimate, indicating that the criteria whether to farm one or more types of fish has a greater impact on efficiency than any other input factor.

The type of water used in production is also statistically significant. FRESH has a parameter value of $\delta_4 = 0.355$ and suggests that the milkfish farms operated in brackish water shows a better technology than the milkfish farms operated in fresh water. The county in which production occurs is another significant variable. CHIAYI and TAINAN have parameter estimates of $\delta_5 = 0.399$ and $\delta_6 = 1.292$ to indicate that milkfish farmer in KOAHSIUNG are relatively more efficient. The area under production tends not to impact efficiency. However, education affects efficiency with the least educated milkfish farmers being more efficient which implies more educated milkfish farmers may not are efficient than those less educated milkfish farmers.

Similarly odd is that more experienced milkfish farmers/managers are less efficient than farmers with fewer years in production. The new farmers with progressive production practices may enter the industry and implementing efficient changes in production practices and some of the older farmers stay in production even though they are inefficient because they are nearing retirement and have few alternative employment options. Also interesting is that farms with more labor are less efficient. This suggests that small owner operators are more motivated than their hired employees.

Table 4 breaks down technical efficiency by county, type of water supply, mono/multi-species cultured and water depth. All of the monoculture production is more efficient than spreading resources over several species. The highest technical efficiency is found for the deep brackish water monoculture ponds in Kaohsiung (0.92), followed by Chiayi (0.91) and then Tainan (0.89). Again the technical efficiency in the deep freshwater monoculture pond in Kaohsiung (0.91) is also higher than Chiayi (0.86) and Tainan (0.69). The result is the same as shown in Table 2 for both Chiayi and Tainan are inefficient than Kaohsiung.

Hicks' complementary elasticity estimates for milkfish farms using a Translog SFPF are shown in Table 5. Negative complementary elasticity estimates, such as for Acreage-Fry Cost, Acreage-Other Costs, Fry Cost-Feed

Cost, Fry Cost-Other Costs, Feed Cost-Water & Electricity, and Water & Electricity-Other Costs imply that these two input categories need to be raised or lowered together. For example, if production increases are to be achieved by increasing Acreage, then the Fry Cost and Other Costs will also increase. Likewise, if a rise in production is to be achieved by stocking the ponds with more Fry then Feed costs and Other Costs will also increase.

Positive complementary elasticities imply that a given output can be maintained by switching inputs between the two resources. For example, if Acreage is increased, Feed Costs would drop while total output and the other variables remain constant.

4.4. *Estimates of Technical Efficiency*

A scatter diagram (Figure 1) shows the relationship between estimated potential output Y_i* and the actual output Y_i. Let technical efficiency be defined as $TE_i = Y_i/Y_i^*$, and any point along the 45^0 diagonal is perfectly efficient. The more distant a point (farm) from the diagonal, the less efficient the farm. The 20-50 M.T. group has 4 bad outliers but the rest of the group seems to be closer to the diagonal than the biggest produces. Technical inefficiency seems to be more apparent for these 4 bad milkfish farms with output levels between 20 to 50 M.T.

Using the Translog SFPF TE across all milkfish farms is estimated to be at 0.84. The most efficient milkfish farm has a TE of 0.96 while the less efficient milkfish farm has TE of 0.10. The median TE is 0.88. The best 36% of milkfish farms have TE's between 0.9-1.0, another 43% of milkfish farms have TE's between 0.8-0.9, 11% have TE's between 0.7-0.8 and 10% have TE's below 0.7.

4.5. *Estimates of Maximum Potential Output*

Farmers and government officials may find it useful to compare milkfish aquaculture farms by potential output. Since the locations where the milkfish farm set-up dictate certain constraints, farms are separated by these and other input factors in Table 6. Notice that the average maximum potential milkfish output for the period 1997-99 is estimated at 9.8 M.T., which compares to an actual output of 8.3 M.T. The maximum potential output is 18% above actual production.

Output under a monoculture regime output could possibly increase to 10.8 M.T./ha or 11%, while output on farms that produce a variety of species could potentially increase to 8.6 M.T./ha or by 29%. Clearly such dramatic increases can only be achieved if the production logistics are feasible. Milkfish farms using fresh and brackish water should be able to increase their output to 12 M.T. and 8.5 M.T. or by 15% and 20% respectively. Production gains should be greater in Kaoshiung county and greatest for the largest milkfish farms.

5. Concluding Remarks

Faced with a limited land resource, Taiwanese milkfish farmers need to be looking at increasing efficiency to raise their production levels. This study specifies a stochastic translog frontier production function to estimate potential milkfish farm output and production efficiency. Using data from 433 milkfish farms gathered between 1997-99, this study details how to determine possible potential yields for the industry and under different production constraints. Especially, the managerial manager's ability and the pond production conditions, which indicated by the type of mono/multi-species cultured, water source, location, education, and years of experience statistically significant capture the inefficiency effects which represent about 90.5% of the production variation, i.e., the managerial technical inefficiency actually hampers production.

Hypothesis testing results shows that the translog stochastic frontier production function model fits the data better and the milkfish farming in Taiwan already exhibits diminishing returns to scale, i.e. the output wouldn't increase as much as we increase the major input factors. Hence, this study also documents the cross-elasticity estimates to provide guidance where milkfish farmers should shift input resources to achieve production gains. The estimates of maximum potential yield indicate that about 80% of all milkfish farms reach a technical efficiency level of 0.8. Average technical efficiency is 0.82. By eliminating the technical inefficiency, the production per hectare could increase by 18% or the maximum output could reach 9.8 M.T. per hectare in average. In addition, a comparison of the estimated maximum potential milkfish production per hectare under various pond conditions could provide managers about how to switch in input resources could boost efficiency.

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Table 1. Variable Definitions and Measurement Units for the Empirical Model

Variable	Definitions	Unit
Y	Milkfish production quantity of the i^{th} farm.	M.T.
X_1	Pond hectares of the i^{th} farm, representing the level of capital investment.	Hectares
X_2	Fry cost of the i^{th} farm.	NT$1,000
X_3	Feed cost of the i^{th} farm.	NT$1,000
X_4	Water, electricity and oil costs of the i^{th} farm.	NT$1,000
X_5	Other miscellaneous costs, including part-time labor, medicine, pond maintenance fee, equipment maintenance fee, rent, insurance, transportation cost.	NT$1,000
X_6	Multiculture ratio of the milkfish production value.	
Y98	Y98 = 1, for farm survey data collected in 1998; otherwise Y98 = 0.	
Y99	Y99 = 1 for farm survey data collected in 1999; otherwise Y99 = 0.	
MONO	MONO = 1 if the farm is a monoculture farm; MONO=0 if more than one species is produced.	
FRESH	FRESH = 1 if the water source of the pond is fresh water, otherwise FRESH=0.	
CHIAYI	CHIAYI = 1 if the i^{th} milkfish farm is located in Chiayi county; otherwise CHIAYI=0.	
TAINAN	TAINAN = 1 if the i^{th} milkfish farm is located in Tainan county; otherwise TAINAN=0.	
SCALE_1	SCALE_1 = 1 if the i^{th} milkfish farm's pond size is under one hectare; otherwise SCALE_1=0.	
SCALE_3	SCALE_3 = 1 if the i^{th} milkfish farm's pond size is 1 to 3 hectare; otherwise SCALE_3=0.	
EDUNONE	EDUNONE = 1 if the manager is not able to read; otherwise EDUNONE=0.	
EDUHIGH	EDUHIGH = 1 if the manager's education is above senior high school level; otherwise EDUHIGH =0.	
EXP	Years of experience	Years
LABOR	Number of hired employees, including family members.	Persons

Table 2. Estimation Results Output Elasticities and Technical Inefficiencies

Item	Cobb-Douglas Production function			Translog Production Function		
	Parameter		t Value	Parameter		t Value
Output Elasticity						
Acreage (X_1)	EX_1	0.16—	5.09	EX_1	0.12	
Fry Cost (X_2)	EX_2	0.11—	5.90	EX_2	0.12	
Feed Cost (X_3)	EX_3	0.39—	10.67	EX_3	0.51	
Water & Electr._X_4_	EX_4	0.14—	5.60	EX_4	0.13	
Other Costs (X_5)	EX_5	0.09—	3.57	EX_5	0.03	
Return to Scale	RTS	0.90		RTS SSS	0.92	
Technical Inefficiency factors						
Y98	δ_1	-0.72—	-2.73	δ_1	-1.19—	-7.83
Y99	δ_2	-0.03	-0.22	δ_2	0.44–	2.54
MONO	δ_3	-0.89—	-3.64	δ_3	-1.49—	-5.33
FRESH	δ_4	0.04	0.39	δ_4	0.36—	3.40
CHIAYI	δ_5	0.60—	3.15	δ_5	0.40-	1.93
TAINAN	δ_6	0.76—	3.46	δ_6	1.29—	3.49
SCALE_1	δ_7	-0.67	-1.54	δ_7	-0.40	-0.73
SCALE_3	δ_8	0.16	1.51	δ_8	0.06	0.38
EDUNONE	δ_9	-0.17	-0.97	δ_9	-0.48–	-2.55
EDUHIGH	δ_{10}	0.23-	1.76	δ_{10}	0.53—	3.73
EXP	δ_{11}	0.25–	2.09	δ_{11}	0.34—	3.36
LABOR	δ_{12}	0.39–	2.41	δ_{12}	0.84—	2.71
	σ^2	0.24—	5.59	σ^2	0.49–	5.20
	γ	0.73—	13.92	γ	0.91—	40.79
	σ_v^2	0.07		σ_v^2	0.05	
	σ_u^2	0.17		σ_u^2	0.45	
	λ	1.63		λ	3.09	

Note: t-values are in the parentheses. ***, **, and * represents significance at the 1%, 5%, and 10% level respectively.

Table 3. Hypothesis Tests for Model Specification and Statistical Assumptions

Item and H_0	Likelihood Value of the Reduced Model	Likelihood Value of the Full Model	Likelihood Ratio Test (LR)	Mixture $\chi^{2*}_{0.05}$ Critical Value	Degrees of Freedom	Conclusion
(1) $H_0: \beta_{jk} = 0$ $H_1: \beta_{jk} = 0$	-106.0	-61.1	89.8	32.1	21	Reject H_0
(2) $H_0: \mu = 0$	-132.5	-127.7	9.7	2.7	1	Reject H_0
(3) $H_0: \gamma = \delta_0 = \delta_1 = \ldots = \delta_{12} = 0$	-103.0	-69.9	66.2	23.1	14	Reject H_0
(4) $H_0: \gamma = 0$	-135.8	-132.5	6.5	2.7	1	Reject H_0
(5) $H_0: \delta_1 = \delta_2 = \ldots = \delta_{12} = 0$	-124.6	-101.7	46.0	20.4	12	Reject H_0

$-\chi^2_{0.05}$ is obtained from David A. Kodde and Franz C. Plam, *Econometrica*, Vol. 54, No.5, p.1246.

Table 4. Technical Efficiencies of Milkfish Farms by County, Water Type, Number of Species Produced and Water Depth

County	Deep Freshwater Pond		Brackish Water Pond			
			Deep Pond		Shallow Pond	
	Monoculture	Multiculture	Monoculture	Multiculture	Monoculture	Multiculture
Chiayi	0.86	0.82	0.91	0.88	-	0.87
Tainan	0.69	0.65	0.89	0.70	0.86	0.58
Kaohsiung	0.91	0.90	0.92	0.87	-	-

Table 5. Hicks' Complementary Elasticities for Inputs used in Milkfish Production

Item	Substitute Elasticity	
Acreage - Fry Cost	H_{12}	-2.91
Acreage - Feed Cost	H_{13}	2.46
Acreage - Water & Electricity	H_{14}	6.78
Acreage - Other Cost	H_{15}	-26.09
Fry-Cost - Feed Cost	H_{23}	-0.72
Fry-Cost - Water and Electricity	H_{24}	6.84
Fry-Cost - Other Cost	H_{25}	-12.24
Feed Cost - Water & Electricity	H_{34}	-2.85
Feed Cost - Other Cost	H_{35}	0.15
Water & Electricity - Other Cost	H_{45}	-13.70

Table 6. Percentage Incensement of Milkfish Farm Output if there were no Technical Inefficiency

Percentage of milkfish farm output in crease if there were no technical inefficiency (%)	1997	1998	1999	Total
Maximum Milkfish Farm Output per Hectare without Technical Inefficiency	(MT)	(MT)	(MT)	(MT)
All Kind of Milkfish Farms	**8.1**	**10.7**	**12.6**	**9.8**
Mono/Multi-Species Cultured Pond				
Monoculture	10.1	11.1	11.5	10.8
Multi-Species	6.0	9.8	13.7	8.6
Water Source				
Freshwater	10.4	12.7	14.3	12.0
Blackish	6.6	9.6	11.3	8.5
County				
Chiayi	4.9	7.3	8.0	6.0
Tainan	5.9	9.5	12.3	8.7
Kaohsiung	15.0	14.6	17.6	15.3
Scale				
Under 1ha.	13.9	12.4	14.8	13.2
1-3 ha.	8.0	10.9	12.5	10.0
Above 3 ha.	6.6	8.3	11.9	7.9
All Kind of Aquafarms	**20%**	**10%**	**26%**	**18%**
Monoculture	12%	9%	14%	11%
Mixed Species	32%	12%	36%	29%
Water Source				
Freshwater	13%	10%	23%	15%
Blackish	26%	10%	30%	20%
County				
Chiayi	22%	15%	13%	18%
Tainan	17%	10%	42%	22%
Kaohsiung	21%	8%	9%	14%
Scale				
Under 1ha.	12%	9%	9%	10%
1-3 ha.	14%	10%	32%	17%
Above 3 ha.	30%	12%	27%	25%

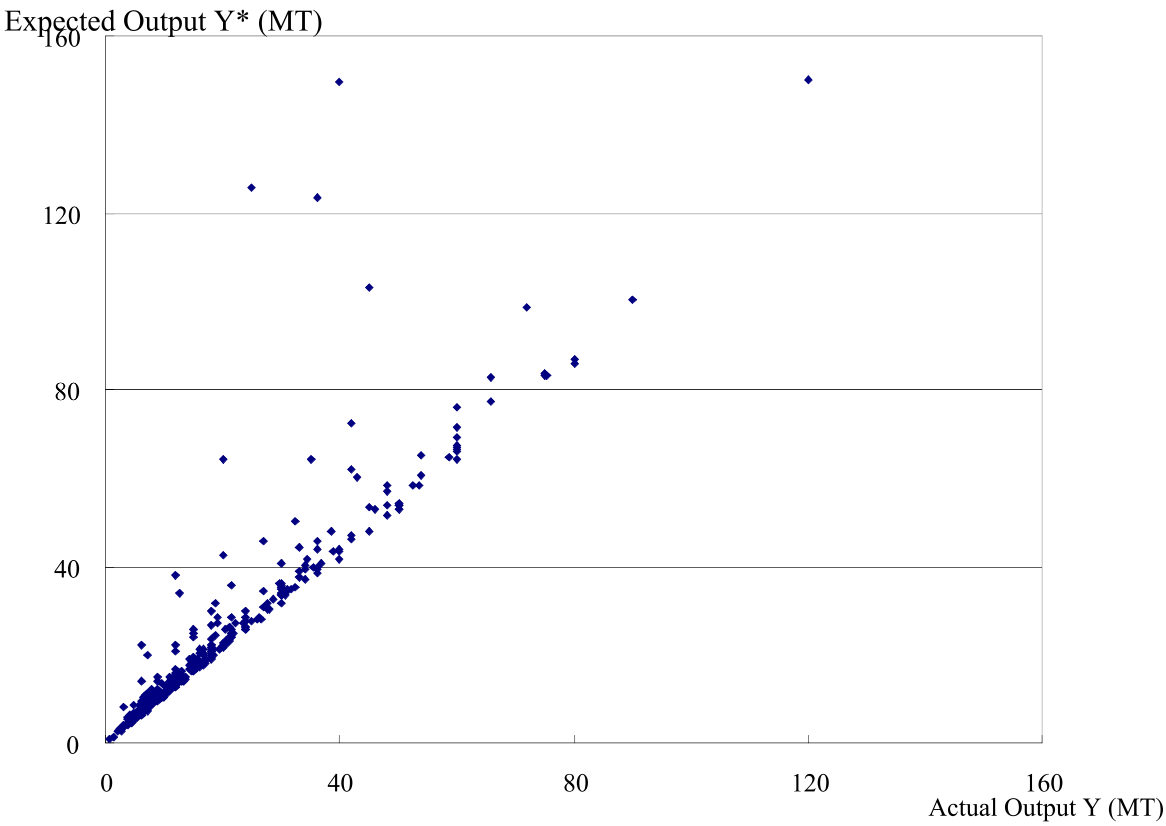

Figure 1. Scatter Diagram of the Relationship between Potential Ou
and Actual Output for all Milkfish Farmers in Taiwan (1997-199