STOCHASTIC PROFIT FRONTIER AND PANEL DATA: MEASURING ECONOMIC EFFICIENCY ON WETLAND RICE FARMS IN WEST JAVA

Erwidodo*)

ABSTRAK

Fungsi keuntungan, sebagai pendekatan **dual**, sering dipergunakan untuk mengukur tingkat efisiensi produksi. Pengukuran tingkat efisiensi produksi, baik efisiensi teknis maupun alokatif, dengan menggunakan fungsi keuntungan yang umum dilakukan hanya bersifat ukuran relatif. Konsep fungsi keuntungan frontier memungkinkan tingkat efisiensi diukur secara absolut. Dalam tulisan ini dikemukakan konsep dan penerapan fungsi keuntungan frontier untuk mengestimasi tingkat inefisiensi ekonomis usahatani padi sawah di wilayah DAS Cimanuk, Jawa Barat. Analisa didasarkan atas data **panel** (1976 - 1983) tingkat petani di wilayah tersebut. Dari hasil analisa diketahui bahwa tingkat inefisiensi ekonomis (profit) berkisar antara 6.9 persen to 28.9 persen, atau rata-rata antara 13.8 persen dari keuntungan frontier. Dengan mempergunakan asumsi tertentu, secara kasar dapat diestimasi kehilangan keuntungan (*profit losses*) per hektar dan total kehilangan keuntungan dalam usahatani padi sawah di Jawa Barat. Hasil analisa memperlihatkan bahwa kehilangan keuntungan usahatani padi sawah di Jawa Barat sebesar Rp 78 milyard setiap tahunnya. Dengan demikian upaya untuk mendorong petani meningkatkan efisiensi memberikan manfaat potensial yang sangat besar.

INTRODUCTION

Profit function, as a dual approach, has been widely used for estimating production, supply and demand parameter as well as production efficiency. This function, however, is commonly estimated as an "average" function. Recently, estimation of frontier function is becoming more populer following the works of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), who independently worked on the estimation of production frontiers. This paper, using this frontier approach, attempts to estimate the level of inefficiency on the rice farms in West Java. Instead of estimating technical and allocative efficiency separately, this paper estimate the so called economic efficiency, or more specifically in this paper referred to as a profit efficiency.

*) Researcher, Center for Socio Agroeconomic Research (CASER), Agency for Agricultural Research and Development (AARD).

ANALYTICAL FRAMEWORK

Stochastic Profit Frontier and Profit Efficiency

The restricted profit function of Yotopoulos and Lau (1973; 1979) implies that the underlying production function is an "average" function which is not consistent with the neoclassical notion of a firm-specific production function. Furthermore, the Yotopoulos and Lou's profit function approach can be used to analyze productivity differences between group of firms only in relative terms, assuming egual efficiencies within each group. Individual specific efficiency, however, cannot be guantified. Kalirajan (1985), following the frontier production model of Aigner, Lovell and Schmidt (1977), developed a stochastic restricted profit frontier and implemented the model on micro-level data for Indian farm production.

The derivation of the stochastic profit frontier is straightforward and follows directly the steps of the derivation of the non-frontier profit function outlined above. The only difference is that the error terms of the production function as formulated by Aigner *et al.* (1977) are taken into account in the derivation process to keep track the primal-dual error relationship. Once again, for convenience and for theoretical purpose, we use a Cobb-Douglas type of function since it is not possible to assess dual-primal relationship by using more flexible functional, such as translog.

Following Kalirajan (1985), consider the Cobb-Douglas production function as formulated by Aigner *et al.* (1977)

$$Y_i = a_o \Pi_k X_{ik}^{ak} \Pi_h Z_{ih}^{bh} e^{-ui + vi} \qquad (E.1)$$

where X_{ik}'s are the guantities of the variable inputs ($k = 1,\dots K$) and the Z_{ih}'s are the guantities of the fixed inputs ($h = 1,\dots .H$), a_k is production elasticity of the k^{th} variable input, b_h is production elasticity of h^{th} fixed input. The error component v_i captures random variation in input due to factors beyond the control of the i^{th} firm, such as weather and luck, and is assumed to be distributed as N $(0, \sigma_v^2)$, while u_i is non-negative disturbance capturing randomness under the control of the i^{th} firm, that is technical inefficiency, and it is assumed to be distributed either with a "half normal" density or with an exponential density, both with mode at $u = 0$.

The (expected) normalized restricted profit function, that is profit over variable cost normalized by price of output, is defined as:

$$\pi_i = Y_i - \Sigma_k C_{ik} X_{ik} \qquad (E.2)$$

where π_i and C_{ik} is normalized profit and input price (normalized by price of output), respectively. Let assume that firm is technically inefficient but allocatively efficient. For simplicity let us omit the i subscript. The profit miximizing condition, assuming firm is maximizing anticipated (expected) profit as in Hoch (1962), is

$$X_k = (a_k/C_k)\ Y \tag{E.3}$$

Substituting (E.3) into eguation (E.1) yields:

$$Y = a_o^{1/(1-r)}\ \Pi_k\ a_k^{ak/(1-r)}\ \Pi_k\ C_k^{-ak/(1-r)}\ \Pi_h\ Z_h^{bh/(1-r)}\ e^{(-u\ +\ v)/(1-r)} \tag{E.4}$$

where $r = \Sigma_k\ a_k < 1$. Substituting eguation (E.3) and (E.4) into eguation (E.2) yields the normalized restricted stochastic profit frontier as:

$$\pi = a_o^{1/(1-r)}\ (1-r)\ \Pi_k\ a_k^{ak/(1-r)}\ \Pi_k\ C_k^{-ak/(1-r)}\ \Pi_h Z_h^{bh/(1-r)}\ e^{(-u\ +\ v)/(1-r)} \tag{E.5}$$

Note that the profit eguation (E.5) is bounded by the stochastic profit frontier as:

$$\pi = a_o^{1/(1-r)}\ (1-r)\ \Pi_k\ a_k^{ak/(1-r)}\ \Pi_k\ c_k^{-ak/(1-r)}\ \Pi_h\ Z_h^{bh/(1-r)}\ e^{-u/(1-r)} \tag{E.6}$$

This represents the maximum possible profit for a given normalized price and amount of fixed input. The profit frontier is stochastic, as is the production frontier, because of the randomness of the v which reflects any shocks beyond the control of the firm. The term -u/ (1-r) represents the percent by which actual profit is less than the profit frontier. In other words it measures the profit forgone of producing below the production frontier due to technical inefficiency.

Now we allow for the possibility that the firm may also be allocatively inefficient. Allocative inefficiency is modelled by permitting the profit maximizing (cost minimizing) condition to fail to hold exactly. Let us assume further that a firm makes systematic errors in seeking to equate the marginal value with marginal factor cost for any particular input. These assumptions yield the first-order profit maximizing conditions as follows:

$$X_k = (a_k\ Y/C_k)\ e^{wk} \tag{E.7}$$

where $w = (w_1, \ldots w_k)$ has a multivariate normal distribution with mean W and variance-covariance matrix Σ. Substituting equation (E.7) into the production frontier equation and simplifying, gives:

$$Y = a_o^{1/(1-r)}\Pi_k\ a_k^{ak/(1-r)}\Pi_k\ c_k^{-ak/(1-r)}\ \Pi_h\ Z_h^{bh/(1-r)}\ e^{(-u\ +\ v)/(1-r)}\ e^{-\Sigma k(ak\ wk)/(1-r)} \tag{E.8}$$

Substituting equation (E.7) and (E.8) into equation (E.2), gives

$$\pi = a_o^{1/(1-r)}\ (1\ -\ \Sigma_k a_k\ e^{-wk})\ \Pi_k\ a_k^{ak/(1-r)}\ \Pi_k\ c_k^{-ak/(1-r)}\ \Pi_h\ Z_h^{bh/(1-r)}\ e^{(-u\ +\ v)/(1-r)}\ e^{-\Sigma k(ak\ wk)/(1-r)} \tag{E.9}$$

This can be simplified asa:

$$\pi = \alpha_o\ \Pi_k\ c_k^{\alpha k}\ \Pi_h\ Z_h^{\beta h}\ e^{u^* + v^* + s^*} \tag{E.10}$$

where:

$\alpha_o = a_o^{1/(1-r)} (1 - \Sigma_k a_k e^{-wk})' \Pi_k a_k^{ak/(1-r)}$

$\alpha_k = - a_k / (1-r)$

$\beta_h = b_h / (1-r)$

$u^* = -u/(1-r)$

$v^* = v/(1-r)$

$s^* = -\Sigma_k (a_k w_k)/(1-r)$

Taking logarithms on both sides of equation (E.10), yields the following stochastic profit frontier:

$$\ln \pi = \ln \alpha_o + \Sigma_k \alpha_k \ln c_k + \Sigma_h \beta_h \ln Z_h + u^* + s^* + v^* \qquad \text{(E.11)}$$

Kalirajan (1985) estimated equation (E.11) by using the method of maximum likelihood, assuming the density functions for u*, v*, and s* as specified above. If we are not interested in separate estimates of u* and s*, we can simply combine them together and define this combined error component as an economic or profit inefficiency measure. The model can then be viewed as a generalization of stochastic production function previously described. This approach was used by Ali and Flinn (1989) for measuring farm-level profit efficiency among the Basmati rice producers (Pakistan Punjab) using cross-sectional data.

Panel Data and Stochastic Frontiers

There are great potential advantages for modifying existing frontier models to allow the use of panel data. Schmidt and Sickles (1984) pointed out three difficulties in applying stochastic production frontier models using cross section data. First, one can estimate technical inefficiency of each firm but not consistently. Second, separation of inefficiency measure from statistical noise depends on specific assumptions about the distribution of technical inefficiency. Third, the assumption that inefficiency is independent of regressors is not valid if a firm knows its level of technical inefficiency. These difficulties will analogously be found in using cross-section stochastic profit frontiers.

With the availability of panel data these problems can be avoided. First, if there are T observations on each firm, then the technical inefficiency of a particular firm can be estimated consistenly consistently as T tends to infinity. Second, any distribution of technical inefficiency need not be assumed if these are treated as firm-specific effects. Third, no assumption is needed regarding the independence of technical inefficiency and the regressors.

This section is drawn heavily from Schmidt and Sickles (1984) article, with some modification in notation. Consider a production function as:

$$Y_{it} = a_o + x_{it}\, a + v_{it} - u_i \qquad \text{(E.12)}$$

Here, i = 1,2...N indexes firms and t = 1,2...T indexes time period. The value y_{it} is output of the i^{th} farm at time t, whereas X_{it} is a vector of K inputs. As described previously, the v_{it} are assumed uncorrelated with regressors and distributed iid N (0, σ_v^2). The u_i represent technical inefficiency and $u_i \geqslant 0$ for all i. It is also assumed that u_i is iid with mean U and variance σ_u^2 and is independent of the v_{it}.

For T = 1 (a single cross section) the model is the stochastic frontier of Aigner, Lovell and Schmidt (1977). For T >1, it is a straight forward generalization of that model, and it fits the usual framework in the panel-data literature with individual effects but no time effects. The only difference from the standard panel data model is that individual effects are one-sided.

The equation (E.12) can be rewritten in two ways. First, let $E(u_i) = \underline{u} > 0$, and define

$$a_o^* = a_o - \underline{u} \text{ and } u_i^* = u_i - \underline{u}$$

so that u_i^* are iid with mean 0. Equation (3.12) than can be rewritten as

$$y_{it} = a_o^* + X_{it}'a + v_{it} - u_i^* \qquad \text{(E.13)}$$

with the error terms v_{it} and u_i^* have zero mean. Most of the results of panel data literature can be applied directly, except those hat hinge on normality.

Secondly, define

$$a_{oi} = a_o - \underline{u} = a_o^* - u_i^*$$

and then rewrite the model into

$$Y_{it} = a_{oi} + X_{it}'a + v_{it} \qquad \text{(E.14)}$$

This is exactly a variable intercept model of the panel data framework. The variable intercept model can be estimated using either a dummy variable estimator or Generalized Least Square (GLS) estimator.

Fixed Effect : Dummy Variable Estimator

This estimator treats the u_i as fixed, that is, estimates a separate intercept for every individual farm. This can be done by suppressing the constant term and adding a dummy variable for each of the N farms or, equivalently, by keeping the constant term and adding (N-1) dummies. Another equivalent procedure is to apply the Within transformation, that is, to apply OLS after transforming the data in terms of deviations from the farm means (Judge *et al.*, 1982).

The advantage of the within estimator is that its consistency does not hinge on uncorrelatedness of the regressors and the effects. It also does not depend on the distribution of the effects, since in treating them as fixed it simply proceeds conditionally from whatever their realizations are. The estimates of a is consistent as either N or T tends to infinity. Consistency of the individual estimated intercept reguires $T \rightarrow \infty$

A considerable disadvantage of the within estimator is that it is impossible to include in the specification the time invariant regressors even though they vary across farms. In this case the estimated individual effects will include the effects of all variables that are fixed within the sample at the farm level, possibly including some that are not in any sense a representation of inefficiency (Schmidt and Sickles, 1984).

In the case of the frontier function, if N is large, we can use the fact that $u_i \geqslant 0$ to appropriately normalize the individual effects (u_i) and the overall constant (a_o). If N estimated intercepts are $\hat{a}_{o1}$, $\hat{a}_{o2}, \ldots\ldots$ $\hat{a}_{oN}$, simply define

$$\hat{a}_o = \max (\hat{a}_{oi}) \qquad (E.15)$$

$$\hat{u}_i = \hat{a}_o - \hat{a}_{oi} \qquad (E.16)$$

This difinition amounts to counting the most efficient firm in the sample as 100 percent efficient. The estimates $\hat{a}_o$ and $\hat{u}_i$ are consistent as N and T go to infinity.

Random Effects : GLS Estimator

With σ_v^2 and σ_u^2 known, the Genelized Least Square (GLS) estimator of a_o^* and a of equation (E.13) is consistent as either N or T approaches infinity. It is more efficient than the within estimator in the case of $N \rightarrow \infty$ and T fixed, but this difference in efficiencies disappears as $T \rightarrow \infty$. When σ_v^2 and σ_u^2 are not known, their consistent estimates need to be estimated. Consistent estimation of σ_u^2 requires $N \rightarrow \infty$. Thus the strongest case for GLS is when N large and T is small. If the opposite is true the GLS is useless, unless σ_u^2 were known *apriori.*

Given estimates $\hat{a}$, we can recover estimates of the individual frim intercepts ($\hat{a}_{oi}$) from the residuals, that is, mean (over time) of the residuals of each individual firms.

$$\hat{a}_{oi} = 1/T \, \Sigma_t \, \hat{e}_{it} \qquad (E.17)$$

These estimates are consistent as $T \rightarrow \infty$, provided that estimates of a are consistent. Note that $\hat{a}_{oi}$ can be decomposed into $\hat{a}_o$ and u_i, for which consistency reguires $N \rightarrow \infty$ and consistency of the $\hat{a}_{oi}$. Another way to estimate the individual effects (inefficiency) is by using Battese and Coelli (1986) method, which is actually a generalization of the method suggested by Jondrow *et. al* (1982). The Battese and Coelli method is presented in a slightly different notation as follows:

$$\hat{u}_i = 1 - \frac{[1 - F(\sigma^* - m_i/\sigma^*)]}{[1 - F(-m_i/\sigma^*)]} \exp(-m_i + \sigma^{*2}/2) \qquad (E.18)$$

where

$\sigma^* = \sigma_u^2 \sigma_v^2 (\sigma_v^2 + T\sigma_u^2)^{-1}$

$m_i = -(\sigma_u^2 \underline{e}_i)(\sigma_u^2 + \sigma_v^2/T)^{-1}$

$\underline{e}_i = \hat{a}_{oi} - \underline{u}$

where F is a symbol for standard normal cumulative distribution function (cdf).

The important advantage of GLS estimator relative to within estimator in the present context is not efficiency, but rather the ability to include the time invariant regressors. In cases where time-invariant regressors are relevant, this is important so that their effects do not contaminate measured efficiency.

The problem with Fixed Effect (FE) model is that if there are any time invariant variables that are excluded, the firm dummies will reflect this influence. This would make inefficiency comparisons difficult unless the excluded time-invariant variables affect all firms equally. Since this is not always the case, inefficiency measures relative to the best firm (which has to be assumed 100% efficient in FE model) might give misleading results. Thus, even though FE models have the advantage of allowing correlation among inefficiency and the regressors and no distributional assumption on inefficiency is required, the results should be interpreted carefully. Khumbakar (1986), in his study of the U.S Class 1 railroads, found that the estimates of inefficiency in the FE models are much bigger than those of random effect (RE) models. On the other hand, all the production function parameters in the FE model are much lower than those in the RE model.

Fixed Effects or Random Effects

The choice between these two has nothing to do with the frontier model as such. The only problem with the FE framework in the context of a production or cost (profit) frontier is that the firm-specific effects pick up the effect of variables that differ across firms but are invariant over time. These effects are not in any sense a representation of inefficiency. This might be one of the reasons why estimated inefficiencies in the FE models are much greater than in the RE models.

One way to decide whether to use a fixed effects or random effects model is to test the null hypothesis that there is no correlation between the individual effects and the included explanatory variables against the alternative hypothesis that such correlation exists. For this purpose, we can use either Hausman test (1978) or an asymptotically equivalent test suggested by Mundlak (1978). If the null hypothesis holds we use the random-effects model, otherwise we use the fixed-effect model. There is a strong justification for performing this test when dealing with the estimation of the production function by single eguation methods, since input might be correlated with technical inefficiency. In the case of profit (cost) functions, however, inefficiencies can be assumed with greater confidence to be uncorrelated with input prices.

DATA SET AND MODEL SPECIFICATION

Data Set

The data set used in this study was collected by the Agro Economic Survey, as part of the Rural Dynamic Study in the rice production area of the Cimanuk. River Basin, West Java, and obtained from the Center for Agro Economic Research, Ministry of Agriculture, Indonesia.

The survey area, which is the rice production area in the Cimanuk river basin, is characterized by irrigated rice firms and an almost uniform agroclimate. It covers six **desa** (villages) lacated in five **kabupaten** (the administrative unit between district and province level), namely: desa Wargabinangun in kabupaten Cirebon, desa Lanjan in kabupaten Indramayu, desa Gunung Wangi and Malausma in kabupaten Majalengka, desa Sukaambit in kabupaten Sumedang and desa Ciwangi in kabupaten Garut.

In 1977, the survey was conducted twice, that is at the beginning and the end of the year. The first survey gathered information on farming practices in the wet season of 1975/1976 and the dry-season of 1976. The second survey covered farm household activities in the wet season of 1976/1977. A similar survey was undertaken in 1978 to cover farm management activities in the dry season of 1977. The resurvey of 1983 to the same areas and same farmers was conducted with a different emphasis on labor utilization, asset holding, and land tenure arrangements.

The Panel Nature of the Data

The data set generated by the survey is commonly referred to as a panel data set, since the individual farmer was odserved over time. This data set will be used in its advantage manner, that is in the framework of panel data analysis discussed in the next chapter. To date, several studies have used thase data. However, these studies, Sugianto (1982), Hutabarat (1986) and Gunawan (1987) among others, analyzed these data using separate crosssectional analysis or by simply pooling the data.

The analysis of this study uses the so called balance design, where individuals are observed for the same lengths of time. Using the individual identification number to check and match individual respondents, only 171 respondents were found to have been continuously recorded for six seasons (Table 1). Some respondents, for various reasons, were replaced by the new ones in the next survey, while others were not recorded in a particular planting season since they were absent. All these respondents were excluded from the analysis. Some respondents were also excluded from the analysis because of incomplete information associated with them. It is possible, of course, to analyze panel data where individuals are observed for different lengths of time, that is $t = 1, 2 \ldots T_i$, where i is individual's subscript, which commonly referred to as imbalance design (Judge *et al.*, 1982). Due to its potential computational difficulties, however, this study does not use this approach.

Table 1. Number of respondents in each Sample Village

Desa (Village)	Kabupaten (Regency)	Number of Observation
Wargabinangun	Cirebon	19
Lanjan	Indramayu	24
Gunung Wangi	Majalengka	37
Malausma	Majalengka	33
Sukaambit	Sumedang	22
Ciwangi	Garut	36
Total Observations		171

Model Specification and Functional Form

In this analysis, we make the following specification. To produce rice, each farmer must first decide how many hectares to plant. The farmer can then determine the amount of seed, fertilizer and labor to use for his land. Thus, the planning horizon for the farmer is a short-run period covering only one season of rice production. This palanning and production process is assumed to be repeated for each planting season. In this case we can therefore treat hectareage of land (farm size) as fixed input, while seed, fertilizers and labor as variable inputs.

Farmers are assumed to maximize restricted profit, that is profit over variable costs, subject to a production function; thus, variable factor prices, quantities of fixed factors, and price of output are concidered as exogenous, but not output. This is consistent with the Zellner, Kmenta and Dreze (1966) approach of maximizing expected profit, assuming that prices and quantities of fixed factors of production are exogenous variables (Kalirajan, 1985).

The Cobb-Douglas and translog functional forms will be used in this analysis, to determine if individual level of profit inefficiency is insensitive to the functional form. In this analysis, the translog specification only applies to the prices and fixed inputs, not to the categorical variables.

Cobb-Douglas Type of Profit Frontier

In its notation, the specification of the Cobb-Douglas restricted profit function is the same as the production function. The difference is in the independent variables involved in the model. In the logarithmic form, the Cobb-Douglas restricted profit function to be estimated is

$$\begin{aligned}\ln \pi_{it} = {} & \ln a_o + \Sigma_k a_k \ln C_{kit} + a_4 \ln Z + a_4 \ln Z + a_5 DP_{it} + a_6 DV1_{it} \\ & + a_7 DV2_{it} + a_8 DSS + a_9 DSIZE + a_{10} DR1 + a_{11} DR2 \\ & + a_{12} DR3 + a_{13} DR4 + a_{14} DR5 + v_{it} - u_i \end{aligned} \qquad (E.19)$$

where:

i = 1,2,......171 subscript for individual observations

t = 1,2,.......6 subscript for time

k = 1,2,3 is subscript for variable input prices.

v = the error component represents random noise, and is assumed to be distributed normally with zero mean and variance of σ_v^2.

u = the non-negative error component representing profit inefficiency.

$\ln \pi$ = ln PLRO: restricted profit, that is profit over variable cost, normalized by per kg price of rough rice

$\ln C_1$ = lnLPS: per kg price of seed normalized by per kg price of riçe

$\ln C_2$ = lnLPF: per kg price of fertilizer by per kg price of rice

$\ln C_3$ = lnLWG: per hour labor wage normalized by per kg price of rice

lnZ = LnHA: farm size, as a fixed factor, in hectare.

DP : dummy variable of pesticide use, equals 1 if farmer uses pesticides and equals 0 otherwise

DV1 : dummy HYV variety, equals 1 if HYV, zero otherwise

DV2 : dummy of Mixed Varietas (MV), equals 1 if mixed varieties are used, zero otherwise Note: traditional variety (TV) is the control

Note = Traditional variety (TV) is the control

DSS : dummy variable of season, equals 1 if wet season, zero otherwise

DSIZE : dummy variable of farm size, equals 1 if farm size greater than 0.5 ha, zero otherwise

DR1 : dummy village, equals 1 if desa Lanjan kabupaten Indramayu, zero otherwise

DR2 : dummy village, equals 1 if deda Gunung Wangi kabupaten Majalengka, zero otherwise

DR3 : dummy village, equals 1 if desa Malausma kabupaten Majalengka, zero otherwise

DR4 : dummy village, equals 1 if desa Sukambit kabupaten Sumedang, zero otherwise.

DR5 : dummy village, equals 1 if desa Ciwangi kabupaten Garut, zero otherwise.

Note : Wargabinangun (kabupaten Cirebon) is the control village

Translog Profit Frontier

The specification of the translog profit function used in this analysis is as follows:

$$
\begin{aligned}
\ln \pi_{it} = {} & \ln a_o + \Sigma_k a_k \ln C_{kit} + 1/2\ \Sigma_k \Sigma_l a_{k.l} \ln C_{kit} * \ln C_{lit} \\
& + a_4 \ln Z + 1/2\ a_{4.4} \ln Z * \ln Z + \Sigma_k a_{k.4} \ln C_{kit} * \ln Z \\
& + a_5 DP_{it} + a_6 DV1_{it} + a_7 DV2_{it} + a_8 DSS + a_9 DSIZE \\
& + a_{10} DR1 + a_{11} DR2 + a_{12} DR3 + a_{13} DR4 + \\
& + a_{14} DR5 + v_{it} - u_i \qquad \text{(E.20)}
\end{aligned}
$$

The symmetry restriction will be imposed **a priori,** that is $a_{k.l} = a_{l.k}$ for all k and l. This implies that the coefficient of (1/2) will occur only if l = k. The definition of variables is the same as previously described.

Estimation Methods

Two estimators, i.e., the within and EGLS estimators, are used in this study. In addition to these two estimators, the simple OLS estimator will also be presented for comparison purposes. The Hausman test and Mundlak test are used to decide whether to use the within estimator estimator or the EGLS estimator. The individual level of profit inefficiency is measured using the Battese and Coelli (1986) method as described in eguation E.17.

RESULTS AND DISCUSSION

Statistical tests for both the FE specification (standard F test) and the RE specification (LM test) confirm the existence of individual specific effects representing individual levels of inefficiencies. The third test, the Mundlak test, justifies the use of RE specification, since the test could not reject the null hypothesis that no correlation exints between the individual effects and the included exogenous variables. This test, therefore, insures that the EGLS estimator is more efficient than the within estimator.

Cobb-Douglas Profit Frontier

The parameter estimates of the Cobb-Douglas normalized profit frontier are presented in appendix 1. The EGLS estimator provides a best fit compared to other estimators, with R^2 = 0.9825, compared to 0.6755 for OLS and 0.4458 for the within estimator. The parameter estimates of these three estimators are close enough to each other both in sign and magnitude, indicating the random effect specification is valid. In the situation where the assumption of random effect is correct, the EGLS is more efficient than the within estimator. The following discussion will focus only on the EGLS estimator, although some comparisons to the others will also be made.

Except for labor wage, the coefficient estimates of the variable input prices have negative signs as expected, and are statistically significant at the 0.01 level for fertilizer price and at the 0.10 level for seed price. The regression coefficient of the normalized labor wage has a positive sign, which is unexpected, and is significant at the 0.10 significance level.

The profit elasticity with respect to the normalized seed price is -0.1331, meaning that a one percent increase in normalized (real) seed price will reduce the normalized profit by 0.13 percent. This relatively small elasticity is reasonable since seed input, in terms of its value, accounts for a very small percenta ge of the total value of output.

The profit elasticity with respect to the normalized fertilizer price is -0.3596, which indicates that a one percent increase in normalized price of fertilizer results in 0.36 percent reduction in normalized profit. Again the relatively low elasticity is due to the fact that the total value of fertilizer is only a minor percentage of the total profit or total value of output.

The sign of the labor wage coefficient is unexpected, and is rather difficult to interpret. However, the magnitude of the coefficient is very small, that is 0.1937 and significant at the 0.10 level. This can be interpreted that the variation of the normalized profit is weakly associated with the variation of the normalized labor wage. The explanation of this finding could be as follows. Labor is a dominant production input in Indonesia rice farming in general, and particularly in densely populated areas such as West Java. No substitutes are available for this input. In addition, economic considerations are not the only driving factor in hiring labor, and there may be many other factors which are more relevant in the rural sitution. For example, it is very common for farm households to hire and to be hired by other households. Since money wage is only part of the total wage, (in some places like Wargabinangun it is only small part), this labor exchange situation occurs regardless the level of wage rate. This may explain why farmers are not so responsive to wage levels in their farm activities. Gunawan

(1988), using the same data and cost function model, also found an unexpected (negative) sign for the labor wage coefficient.

The profit elasticity with respect to land is positive and statistically significant at the 0.01 significance level. The magnitude of 0.9794 of this coefficient tells us that one percent increase in farm size will result in 0.9794 percent increase in profit. In our case, this coefficient directly represents the returns to scale coefficient of the underlying production function. The within estimator of this coefficient is smaller, that is 0.9194, and is significant at the 0.01 significance level.

The coefficient estimates of the dummy variables for pesticide and rice variety are all significant with positive signs, indicating that the use of pesticide and HYV increase the profit. The equestion is then why large numbers of farmers are not using HYV. It is very likely that economic factors are not the only ones farmesr use to make decisions regarding the use of HYV. In Gunung Wangi (kabupaten Majalengka), for example, efforts to increase adoption of HYV have been unsuccessful, and almost all respondents in this village grew TV. Preference for growing TV could also be explained by the fact that most of the rice produced is for own-consumption, and since villagers find TVs taste better than HYV they prefer growing TV.

The dummy variable for season is not significantly different from zero, indicating that season is not an explanatory variable for the profit variation. Profit is a function of price and total product. Price in the dry season sometimes is higher than in the wet season due to inelastic nature of rice supply function. The relatively higher price in the dry season may offset the reduction of total product, resulting in a non-significant difference between the wet and dry seasons profits.

Dummy variables for regions all have positive signs, although only three of them are significantly different from zero, indicating that, compared to Wargabinangun (as a control) the restricted profit earned by farmers in the other villages is higher. In light of individual village's accessibility factors, this finding is reasonable, since these three villages have better product marketing channels due to better transportation facilities. The higher the price received, the higher the profit earned.

Profit Efficiency

Let us now examine the level profit inefficiency. The individual level of profit inefficiency and its individual rank are not presented in this paper. The frequency distribution of farms based on technical inefficiency level is shown in Table 2. The computation, as in the case of technical inefficiency, follows the equation of Battese and Coelli (1986). The level of profit inefficiency ranges from 6.9 percent to 28.9 percent with the mean 13.8 percent. The average ineffi-

Table 2. Frequency, distribution of farmers based on the level of profit inefficiency from Cobb-Douglas profit frontier.

Level of profit inefficiency	% from farms with		% from total farms
	≤ 0.5 ha	> 0.5 ha	
≤ 5%	0.0	0.0	0.0
5% < u ≤ 10%	11.8	6.8	10.5
10% < u ≤ 15%	58.3	63.6	59.6
15% < u ≤ 20%	24.4	20.5	23.4
20% < u ≤ 25%	3.9	6.8	4.7
25% < u ≤ 30%	1.6	2.3	1.8
> 30%	0.0	0.0	0.0
Total %	100	100	100
Total Farms	127	44	171

ciency is 18.4 percent. This indicates that on the average rice farmers are 13.8 percent profit inefficient. This percentage can also be interpreted as a percentage of profit loss. Table 2 also shows, as in the case of production function, that the level of profit inefficiency does not have any association function, that the level of profit inefficiency does not havy any association with the farm size, meaning that small farms may or may not be move efficient than large farms. Therefore, as in the case of production frontier discussed above, it seems reasonable to interpret the mean of profit ineffisiency level (13.8%), as a perhectare profit loss due to inefficiency. Alternativelly, we can restimate a per hectare profit frontier to get the same measure of profit inefficiency.

Assuming that the estimated profit frontier represents existing wetland rice production technology in West Java, one could then roughly estimate the total annual profit losses due to inefficiency. This is very roughly estimate the total intended and mainly intended as an illustration. Given a figure of profit per hectare and the annual hervested area of rice farms in West Java (1.74 million hectare), we can approximate the annual profit loss due to inefficiency (both technical and allocative inefficiencies). Using per-hectare profit figure in the dry season 1983 (Rp 326,000/ha) the per-hectare profit loss amounts to about Rp 45,000, and the total profit loss in rice farms in West Java amounts to about 78 billion Rupiahs annually (US$ 81 million, using exchange rate Rp 970/US$ in 1983). Thus the benefits of promoting increased efficiency in rice farm in Indonesia, particularly in West Java, appear to be extremely attractive.

Translog Profit Frontier

The estimated translog profit frontier suffers from multicollinearity problem. While most coefficient estimates have correct signs, many are not statistically significant. There is no attempt to interpret the coefficient estimates individually, since they do not provide valuable information. Apart from the fact that some of them are not significant, the profit elasticities with respect to variable input prices are not constant in the case of translog profit function. The coefficient of the dummy variables can be interpreted individually as before. The coeficient of the dummy varieties have the same signs and relatively the same magnitude compared to the Cobb-Douglas functional form. Similarly the coefficients of the dummy regions do not change in signs, the only difference being the coefficient of DR4 which previously was not significant now is highly significant.

The individual level of profit inefficiency (not presented in this paper) is very close to the level obtained from Cobb-Douglas functional form. This is not surprising, and indeed it is expected. The level of profit inefficiency should be invariant from the functional form. The frequency distribution of farms based on the profit inefficiency level is described in Table 3.

Table 3. Percentage of farmers based on the level of profit inefficiency (Translog Profit Funcion)

Level of profit inefficiency	% From farms with		% From total farms
	$\leq$ 0.5 ha	$>$0.5 ha	
$\leq$5%	0.0	0.0	0.0
5% $<$ u $\leq$ 10%	7.1	4.5	6.4
10% $<$ u $\leq$ 15%	53.5	54.6	53.8
15% $<$ u $\leq$ 20%	28.4	25.0	27.5
20% $<$ u $\leq$ 25%	8.7	9.1	8.8
25% $<$ u $\leq$ 30%	1.6	6.8	2.9
$>$ 30%	0.8	0.0	0.6
Total %	100	100	100
Total Farms	127	44	171

CONCLUSION

This paper has demonstrated the advantages of stochastic profit frontier for estimating profit efficiency in absolute term. With the availability of panel data the problem of inconsistency in the parameter estimates can be potentially solved. The analysis in this paper can be summarized as follows:

1. The profit elasticity with respect to the normalized seed price, fertilizer price and size of land is -0.1331, -03596 and 0.9794, respectively. These elasticities are all statistically significant at the 0.01 significance level. The profit elasticity with respect to normalized labor wage has a positive sign, so that inconsistent with theoretical expectation. This parameter, however, can be neglected since its magnitude is relatively small and is not strongly significant.
2. The dummy variables for varieties, HYV and MV, of the profit function all have positive signs and are statistically significant. indicating that HYV and MV farmers are making more profits than the TV farmers. Interestingly, the majority of farmers in the study area were still using TV rice. Preference for growing TV could be justified given that (i) consumers prefer the taste of TV over HYV, and (ii) most of the rice produced is for own-consumption.
3. The dummy variable for season is not significantly different from zero. The relatively higher rice price in the dry season (due to inelastic nature of rice supply function) may offset the reduction of total output, resulting in a non-significant difference between profit in the dry season and the wet season.
4. The dummy variables for regions all have positive signs, although only three of them are statistically significant, indicating that, compared to Wargabinangun (as a control), the profit earned by farmers in other regions is significantly higher. This finding is reasonable, since the other villages have relatively better product marketing channels due to better transportation facilities. The higher the price received, the higher the profit earned.
5. The individual profit inefficiency ranges from 6.9 percent to 28.9 percent with the mean 13.8 percent, indicating that on the average rice farms are 13.8 percent profit inefficient or 86.2 percent profit efficient. Thus, on the average, 13.8 percent of profits are foregone due to inefficiency. The results also show that individual level of profit inefficiency does not have any association with individual farm size, meaning that large farms may or may not be more profit efficient than small farms, Using a per-hectare profit figure in the dry season 1983 (Rp 326,000/ha) and the total harvested areas in West Java per year (1.74 million hectare), a roughly estimate of per-hectare profit loss amounts to about Rp 45,000, while the total profit loss in West Java rice farms amounts to about Rp 78 billion annually, or about US$ 81 million at the 1983 exchange rate (Rp 970/US$). Thus, the benefits of promoting increased efficiency in rice farms in Indonesia appear to be very attractive.

BIBLIOGRAPHY

Aigner, D.J, C.A.K. Lovell, and P. Schmidt. 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. Journal of Econometrics 6: 21-37.

Ali, M. and J.C. Flinn. 1989. Profit Efficiency Among Basmati Rice Producers in Pakistan Punjab. American Journal of Agricultural Economics. Vol.2, No.2: 303-310.

Battese, G.E. and T.J. Coelli. 1988. Prediction of Firm-Level Technical Efficiencies With A Generalized Frontier Production Function and Panel Data. Journal of Econometrics, 38: 387-399.

Gunawan, M. 1988. Adoption and Bias of New Agricultural Innovation in Jawa Barat, Indonesia. Unpublished Ph.D thesis, Univ. of Minnesota, st. paul Minnesota.

Hausman, J.A. 1978. Specification test in Econometrics. Econometrica, 46: 1251-1272.

Hoch, I. 1962. Estimation of Production Function Parameters Combining Time-Series and Cross-Section Data. Econometrica, Vol.30, no 1: 34-53.

Hutabarat, B. 1985. An Assessment of Farm-Level Input Demands and Production Under Risk on Rice Farms in Cimanuk River Basin, Jawa Barat, Indonesia. Unpublished Ph.D thesis, Iowa State Univ. Ames, Iowa.

Jondrow, J, C.A.K. Lowell, I.S. Materov, and P.Schmidt. 1982. On The Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model. Journal of Econometrics, 19: 233-238.

Judge, G.E, R.C. Hill, W.E. Griffiths, H. Lutkepohl, and T-C Lee. 1982. Introduction to the Theory and Practice of Econometrics. John wiley and Sns, N.Y, USA.

Kalirajan, K. 1985. On Measuring Absolute Technical and Allocative Efficiencies. The Indian Journal of Statistics, vol.47, series B, pt.3: 385-400.

Khumbakar, S.C. 1987. Production Frontiers and Data: An Application to U.S. Class I Railroads. Journal of Business and Economic Statistics, vol.5, no.2: 249-255.

Meeusen, W. and J van den Broeck. 1977. Efficiency Estimation From Cobb-Douglas Production Functions With Composed Error. International Economic Review, vol.18, no.2: 435-444.

Mundlak, Y. 1978. On the Pooling of Time Series and Cross Section Data. Econometrica, 46: 69-85.

Schmidt, P. and C.A. Knox Lovell. 1979. Estimating Technical and Allocative Inefficiency Relative to Stochastic Production and Cost Frontiers. Journal of Econometrics, 9: 343-366

Schmidt, P. and R.C. Sickles. 1984. Production Frontiers. and Panel Data. Journal of Business and Economic Statistics, vol.2, no.4: 367-374.

Sugianto, T. 1982. The Relative Economic Efficiency of Irrigated Rice Farms, West Java, Indonesia. Unpublished Ph. D thesis, Univ. of Illinois. Urbana-Champaign, Illinois.

Yotopoulos, P.A. and L. J. Lau. 1973. A Test for Relative Economic Efficiency: Some Further Results. Amer. Econ. Rev., vol.63, no.1: 214-223.

Yotopoulos, P.A. and L. J. Lau. 1979. Resource Use in Agriculture: Applications of the Profit Function to Selected Countries. Food Research Institute Studies, vol.17, no.1.

Zellner, A, J. Kmenta and J. Dreze. 1966. Specification and Estimation off Cobb-Douglas Production Function Models. Econometrica, vol.34, no.4: 784-795.

Appendix 1. Estimated parameters of the Cobb-Douglas type stochastic profit frontier

Independent variables	Estimation methods		
	OLS	Within	GLS
Constant	6.9280***	–	6.9315***
	(0.1093)		(0.1184)
LPS	-0.1408*	-0.1173	-0.1331*
	(0.0845)	(0.0818)	(0.0758)
LPF	-0.3670***	-0.3394***	-0.3596***
	(0.0785)	(0.0673)	(0.0759)
LWG	0.1621	0.2817**	0.1937*
	(0.1049)	(0.1891)	(0.1021)
LHA	0.9905***	0.9194***	0.9794***
	(0.0250)	(0.0359)	(0.0272)
DP	0.1241**	0.1343**	0.1279**
	(0.0543)	(0.0563)	(0.0550)
DV1	0.2931***	0.2133***	0.2734***
	(0.0786)	(0.0778)	(0.0785)
DV2	0.1793*	0.2657***	0.2019**
	(0.1094)	(0.1071)	(0.1088)
DSS	0.0218	0.0555	0.0222
	(0.0477)	(0.0696)	(0.0569)
DR1	-0.0179	–	-0.0161
	(0.0863)	–	(0.1024)
DR2	0.2555**	–	0.2475**
	(0.1090)	–	(0.1200)
DR3	0.2109**	–	0.1940**
	(0.1058)	–	(0.1182)
DR4	0.1553	–	0.1373
	(0.1017)	–	(0.1165)
DR5	0.4336***	–	0.4212***
	(0.1046)	–	(0.1163)
σ_v^2	–	0.4278	0.4278
σ^2	–	–	0.6572
σ_u^2	–	–	0.0382
$w = \sigma_v/\sigma$	–	–	0.8068
$\theta = 1 - w$	–	–	0.1932
E[u]	–	–	0.156
F-Statistic	162.0	117.2	4053.6
R^2	0.6755	0.4458	0.9825
N (individuals)	171	171	171
T (seasons)	6	6	6

Figures in parentheses are standard deviations

*** statistically significant at $\alpha = 0.01$

** statistically significant at $\alpha = 0.05$

* statistically significant at $\alpha = 0.10$

Appendix 2. Estimated parameters of the Translog Profit Function

Independent variables	Estimation methods		
	OLS	Within	GLS
Constant	6.6701***	–	6.6905***
	(0.1208)		(0.1298)
LPS	-0.1913	-0.1802	-0.1931
	(0.1807)	(0.1744)	(0.1785)
LPF	-0.6695***	-0.6372***	-0.6564***
	(0.0785)	(0.1498)	(0.1590)
LWG	-0.2972	-0.0797	-0.2171
	(0.2228)	(0.2033)	(0.2154)
0.5*LPSLPS	0.1906	0.2635	0.2201
	(0.1849)	(0.1782)	(0.1827)
LPSLPF	-0.4571*	-0.5434**	-0.4841**
	(0.2496)	(0.2332)	(0.2437)
LPSLWG	0.2767	0.0363	0.1950
	(0.2767)	(0.3456)	(0.3617)
0.5*LPFLPF	1.0926***	1.1027***	1.0984***
	(0.2350)	(0.2108)	(0.2262)
LPFLWG	-2.1349***	-2.0544***	-2.1114***
	(0.4321)	(0.3990)	(0.4207)
0.5*LWGLWG	0.1349	0.1188	0.1300
	(0.3155)	(0.1941)	(0.3081)
LHA	1.0305***	1.0189***	1.0381***
	(0.0602)	(0.0742)	(0.0631)
0.5*LHALHA	0.0398**	0.0529***	0.0448***
	(0.0157)	(0.0189)	(0.0166)
LHALPS	0.0426	0.0600	0.0454
	(0.0744)	(0.0745)	(0.0745)
LHALPF	-0.2828***	-0.2975***	-0.2879***
	(0.0744)	(0.0696)	(0.0720)
LHALWG	-0.2078**	-0.1310	-0.1778*
	(0.1061)	(0.0981)	(0.1033)
DP	0.0656	0.0648	0.0659
	(0.0542)	(0.0571)	(0.0553)
DV1	0.2869***	0.2072***	0.2617***
	(0.0774)	(0.0765)	(0.0772)
DV2	0.1775*	0.2609***	0.2034**
	(0.1076)	(0.1052)	(0.1069)
DSS	0.0005	0.0045	0.0022
	(0.0464)	(0.0696)	(0.0578)

Appendix 2. (Continued)

DR1	-0.0702	–	-0.0726
	(0.0862)	–	(0.1052)
DR2	0.3623***	–	0.3534***
	(0.1088)	–	(0.1218)
DR3	0.2895***	–	0.2693**
	(0.1059)	–	(0.1206)
DR4	0.3455***	–	0.3275***
	(0.1058)	–	(0.1228)
DR5	0.5323***	–	0.5191***
	(0.1074)	–	(0.1210)
σ_v^2	–	0.3924	0.3924
σ^2	–	–	0.6682
σ_u^2	–	–	0.0460
$W = \sigma_v/\sigma$	–	–	0.7664
$\theta = 1 - w$	–	–	0.2336
E[u]	–	–	0.171
F-Statistic	101.5	58.6	2341.8
R^2	0.6997	0.4458	0.9825
ADJ-R^2	0.6928	0.4420	0.9821
N (individuals)	171	171	171
T (seasons)	6	6	6