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Analysis of Productive Efficiency of Soybean Production in the Mekong River Delta of Viet Nam

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Efficiency measurement is to investigate the efficiency levels of farmers got involved with agricultural activities. A major task of efficiency analysis is to identify determinants of efficiency levels. As some empirical studies mentioned, farmers in developing countries are unsuccessful in taking advantage of fully the potential of technology making inefficient decisions. Therefore, this paper makes an effort to estimate technical, allocative and economic efficiency of soybean farmers in the Mekong River Delta of Viet Nam and identify its determinants. The analysis shows average levels of technical, allocative and economic efficiency are equal to 74 percent, 51 percent and 38 percent, respectively.

INTRODUCTION

Vietnam has a population of 84 million people, 80 percent of whom live in the rural areas and nearly 68 percent of them are working in the agricultural sector. Since 1986 Vietnam moved to the market economy led by a number of reform policies. Within the agricultural sector, the Mekong River Delta (MRD) is considered the biggest agricultural production area, especially rice production, for the whole country. With the population of 17 million people, the MRD has been contributing to the country's food security policy with the diversification of agricultural production. Beside the rice production, farmers in the MRD also produce other crops to feed themselves and supply to the market such as: cassava, maize, cashew, so on and especially among of these main crops, there is soybean that is very popular with farmers in the MRD.

Although agriculture plays the most important role of economics, its contribution to gross domestic product (GDP) is annually declining. Slow agricultural growth means that the majority of the rural population earns low incomes and also the rate of savings and investment opportunities are severely limited. As a result, growth in nonagricultural sectors remains low which in turn limits employment growth and aggravates rural poverty. It is also reported that the low productivity of agriculture promotes environmental degradation, such as deforestation.

There is considerable agreement with the notion that an effective economic development strategy depends critically on promoting productivity and output growth in the agricultural sector, particularly among small–scale producers. Empirical evidence suggests that small farms are desirable not only because they provide a source of reducing unemployment, but also because they provide a more equitable distribution of income as well as an effective demand structure for other sectors of the economy (Bravo–Ureta and Evenson, 1994; Dorner, 1975). Consequently, many researchers and policymakers have focused their attention on the impact that the adoption of new technologies can have on increasing farm productivity and income (Hayami and Ruttan, 1985; Kuznets, 1966; Schultz, 1964; Seligson, 1982). However, during the last decade, major technological gains stemming from world. This suggests that attention to productivity gains from a more efficient use of existing technology is justified (Bravo–Ureta and Pinheiro, 1993; Squire and Tabor, 1991).

The presence of shortfalls in efficiency means that output can be increased without requiring additional conventional inputs and without the need for new technology. If this is the case, then empirical measures of efficiency are necessary in order to determine the magnitude of the gains that could be obtained by improving performance in agricultural production with a given technology. An important policy implication stemming from significant levels of inefficiency is that it might be more cost effective to achieve short–run increases in farm output, and thus income, by concentrating on improving efficiency rather than on the introduction of new technologies (Belbase and Grabowski, 1985; Shapiro and Muller, 1977).

The main objective of this paper is to measure the possibilities of productivity gains by enhancing the efficiency of soybean farmers in the Mekong River Delta of Viet Nam. The first step of objective is to estimate a stochastic production frontier which gives the result for measuring farm–level technical (TE), allocative (AE) and economic (EE) efficiency. After that, the second step of analysis is to calculate separate truncated equations for TE, AE and EE as a function of various attributes of the farmers in sample. This study has policy implications because it not only provides empirical

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measures of different efficiency indices, but also identifies some key variables that are correlated with these indices. In this fashion, we go beyond much of the published literature concerning efficiency because most research in this area of productivity analysis of focuses exclusively on the measurement of technical efficiency (Bravo–Ureta and Pinheiro, 1993).

SOURCE OF DATA

The analyzed numbers mainly based on the primary data collected in a field survey by interviewing farmers directly in the MRD. The process of data collection is presented as:

– In the MRD, soybean cultivation can be mainly grown in four provinces such as An Giang, Dong Thap, Can Tho, Soc Trang. Based on the location of provinces, we can divide four provinces into two different sectors. An Giang and Dong Thap represent the upper MRD; Can Tho and Soc Trang represent the lower MRD.

– Because of the limitation of survey cost, time and depending on the convenience in organizing the field trip, An Giang that represents the upper Mekong Delta region and Can Tho that represents the lower Mekong Delta region were chosen to collect primary data. In An Giang and Can Tho, we took surveys randomly. Total samples are 113 farmers. In which, 56 farmers in Can Tho and 55 farmers in An Giang were interviewed directly.

METHODOLOGY

Efficiency

Productive efficiency has two components. The purely technical, or physical, component refers to the ability to avoid waste by producing as much output as input usage allows, or by using as little input as output production allows. Thus the analysis of technical efficiency can have an output augmenting orientation or an input–conserving orientation. The allocative, or price component refers to the ability to combine inputs and outputs in optimal proportions in light of prevailing prices (Lovell, 1993).

Koopmans (1951, p. 60) provided a formal definition of technical efficiency: a producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if reduction in any input requires an increase in at least one other input or a reduction in at least one output. Thus a technically inefficient producer could produce the same outputs with less of at least one input, or could use the same inputs to produce more of at least one output. The formal definition is given below.

Efficiency: A PU with input–output configuration $(x, y) \in T$ is efficient if there is no $(x', y') \in T$ for $(x', y') \neq (x, y)$ with $x' \leq x$ and $y' \geq y$.

Debreu (1951) and Farrell (1957) introduced a measure of technical efficiency. Their measure is defined as one minus the maximum equiproportionate reduction in all inputs that still allows continued production of given outputs. A score of unity indicates technical efficiency because no equiproportionate input reduction is feasible, and a score less than unity indicate technical–inefficiency.

Based on Farrell (1957), measure of technical efficiency can be obtained by using input and output quantity without introducing prices of these inputs and outputs. Technical efficiency can be decomposed into three components such as scale efficiency, congestion and pure technical efficiency.

In the Fig. 1 below, observation A utilises two input factors to produce a single output. SS' is the efficient isoquant estimated with an available technique. Now point B on the isoquant represents the efficient reference of observation A. The technical efficiency of a production unit operating at A is most commonly measured by the ratio

$$TE=OB/OA \tag{1}$$

Which is equal to one minus BA/OB. It will take a value between zero and one, and hence an indicator of the degree of technical inefficiency of the production unit. A value of one indicates the firm is fully technically efficient. For instance, the point B is technically efficient because it lies on the efficient isoquant.

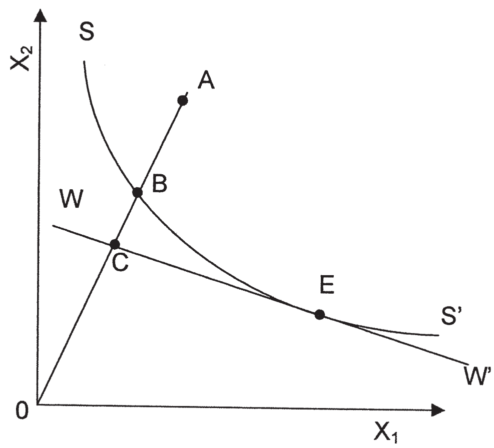

Fig. 1. Technical and Allocative Efficiencies.

If the input price ratio, represented by the slope of the isocost line, WW' in Fig. 1, is also known, allocative efficiency may also be calculated. The allocative efficiency (AE) of a PU operating at A is defined to be the ratio

$$AE=OC/OB \tag{2}$$

Since the distance CB represents the reduction in productions costs that would occur if production were to occur at the allocatively (and technically) efficient point E, instead of the at the technically efficient, but allocatively inefficient point B.

The total economic efficiency (EE) is defined to be the ratio

$$EE=OC/OA \tag{3}$$

where the distance CA can also be interpreted in terms of a cost reduction. Note that the product of technical efficiency and allocative efficiency measures provides the measure of overall economic efficiency.

Techniques of efficiency measurement

Various approaches to efficiency analysis have been used by two parallel traditions, the econometrics methods and non–parametric Data Envelopment Analysis (DEA) methods.

The econometrics approach has been motivated to develop stochastic frontier models based on the deterministic parameter frontier of Aigner and Chu (1968). The Stochastic Frontier Analysis (SFA) acknowledges the random noise around the estimated production frontier. In a simple case of a singe output and multiple inputs, the approach predicts the outputs from inputs by the functional relationships $y_1=f(x_i, \beta)+\varepsilon_i$ where i denotes the PU being evaluated and β*'s* are the parameters to be estimated. The residual ε_1 is composed by a random error v_i and an efficiency component u_i. When we assume that $v_1=0$, SFA is reduced to the Deterministic Frontier Analysis (DFA); if we further let $u_i=0$, SFA will be reduced to central tendency analysis.

The non–parametric approach or mathematical programming method has mainly focused on the development of DEA methods engaged with multiple–input and multiple–output production technologies. This approach was initiated by the seminal work of Charnes, Cooper and Rhodes (1978). The frontier model in their study is well known as the CCR model. DEA applies operational program to construct piece wise linear production frontiers. The specification of the functional form of the production frontiers is not required in this method. DEA studies producers' behavior by the efficient frontier and the distance between a PU and the frontier. The basic DEA models are deterministic and more recently they have been extended to incorporate stochastic characteristics.

The two approaches use different techniques to envelop data more or less tightly in different ways. In so doing they make different accommodations for random noise and for flexibility in the structure of production technology. It is these two different accommodations that generate the strengths and weaknesses of the two approaches. The two approaches differ in many ways, but the essential differences, and the sources of the advantages of one approach to the other boil down to two characteristics.

– The econometric approach is stochastic, and so attempts to distinguish the effects of noise from the effects of inefficiency. The programming approach is nonstochastic, and lumps noise and inefficiency together and calls the combination inefficiency.

– The econometric approach is parametric, and confounds the effects of misspecification of functional form (of both technology and inefficiency) with inefficiency. The programming approach is nonparametric and less prone to this type of specification error.

In the paper, the discussion will focus on only on the econometric approach of measuring efficiency by using the stochastic production frontier. Further details on both approaches can be obtained from books edited by Fried, Lovell, and Schmidt (1993) and Coelli, Rao, and Battese (1998).

The stochastic production frontier

In order to estimate the technical, allocative and economic efficiency of soybean production, Cobb–Douglas production frontier function is estimated by using Maximum likelihood techniques to examine factors influencing the output of soybean production that affects income or profits from soybean production. From the production frontier, the corresponding dual cost frontier is determined. These two frontiers are the basis for deriving farm–level efficiency measures.

The stochastic production frontier can be written as

$$\ln(Y_i)=\beta_0+\sum_i \beta_i \ln X_{ij}+\varepsilon_i \qquad (4)$$

Where Y_i is output of the i farmers, X_{ij} is the j input used by farmer i. the essential idea behind the stochastic frontier model is that ε_i is a "composed" error term. The error term (ε_i) is now defined as

$\varepsilon_i=v_i-u_i$

i=1,...N, N=113

Where v_i is a two–sided ($-\infty<v<\infty$) normally distributed random error ($v \sim N[0, \sigma_v^2]$) that captures the stochastic effects outside the farmer's control (e.g., weather, natural disasters, and luck), measurement errors, and other statistical noise.

The term u_i is a one–sided ($u\geq0$) efficiency component that captures the technical inefficiency of the farmer. In other words, u_i measures the shortfall in output Y_i from its maximum value given by the stochastic frontier $\ln(Y_i)=\beta_0+\sum_i \beta_i \ln X_{ij}+\nu_i$. This one–sided term can follow such distributions as half–normal, exponential, and gamma (Aigner *et al.*, 1977; Greene, 1980; Meeusen and Van den Broeck, 1977). In this study, it is assumed that u_i follows a half–normal distribution ($u \sim N[0, \sigma_v^2]$) as it is typically done in the applied stochastic frontier literature. The two components v_i and u_i are also assumed to be independent each other.

The maximum likelihood estimation of equation (4) yields consistent estimators for β, λ and σ_v^2, where β is a vector of unknown parameters, $\lambda=\sigma_u/\sigma_v$, and $\sigma_u^2=\sigma_u^2+\sigma_v^2$. Jondrow *et al*. (1982) have shown that inferences about the technical inefficiency of individual farmers can be made by considering the conditional distribution of u given the fitted values of ε and the respective parameters. In other words, given the distribution assumed for v and u, and assuming that these two components are independent from each other, the conditional mean of u given ε is defined by

$$E(u_i|\varepsilon_i)=\sigma_*\left[\frac{f^*(\varepsilon_i\lambda/\sigma)}{1-F^*(\varepsilon_i\lambda/\sigma)}-\frac{\varepsilon_i\lambda}{\sigma}\right] \qquad (5)$$

Where $\sigma_*^2=\sigma_u^2\sigma_v^2/\sigma^2$, f^* is the standard normal density function, and F^* is the distribution function, both functions being evaluated at $\lambda\varepsilon/\sigma$.

Farm specific technical efficiency will be obtained by using the relationship:

$$TE_i=\exp(-\hat{u}_i\Big/\sum_i \beta_i)=\exp(-E(u_i\,|\,\varepsilon_i)\Big/\sum_i \beta_i) \qquad (6)$$

We derive the estimates for v and u by replacing ε, σ_*, and λ in equations (4) and (5). Subtracting v from both sides of equation (3.1) yields the stochastic production frontier.

$$\ln(Y^*_i)=\beta_0+\sum_i \beta_i \ln X_{ij}-u_i=\ln(Y_i)-v_i \qquad (7)$$

Where $\ln(Y_i^*)$ is defined as the farm's observed output adjusted for the statistical noise contained in v_i.

The cost frontier dual to the production frontier:

$$\ln(C_i)=\alpha_0+\sum_i \alpha_i \ln P_{ij}+\gamma\ln(Y^*_i) \qquad (8)$$

Where C_i is the minimum cost to product output Y, P_{ij} is a vector of input price, and α is a vector of parameters. From this function, we also get allocative and economical efficiencies.

EMPIRICAL RESULTS

Technical, allocative and economic efficiencies of soybean production at farm level

For calculating the technical efficiency, Ordinary Least Square (OLS) estimation is made on the Cobb–Douglas production function. Based on the significance of the parameter estimates, information will be gained on which variables should be included in the stochastic frontier analysis. In the production function four inputs of production as labor, fertilizer, pesticides and machinery are included. The stochastic frontier model is given as:

$$\ln(Y_i)=\beta_0+\sum_i \beta_i \ln X_{ij}+\varepsilon_i \qquad (9)$$

Where Y_i: Soybean output in kg,
X_{1i}: Human labor used in days,
X_{2i}: Fertilizer quantities in kg,
X_{3i}: Pesticide quantities in ml,
X_{4i}: Machinery service hired in days,

Before the frontier function is defined, we should consider the summary statistics of the input variables gathered from 113 farmers that are presented in table1.

The table 1 shows that the soybean output is 1,789 kg per one soybean production season with standard deviation of 1,492 that indicates the large variability of output among the farmers. We also see in the table the number of days that farmers hire machinery service is about 73 days more than the days of hired labors and family labors, averagely 57 days per farm. This thing shows that soybean farmers begin using machine for their cultivation instead of by hand.

With the Stata software, the OLS and MLE of the production function were estimated. The estimated results are presented in table 2.

With the estimated determination coefficient (R^2) of

Table 1. Summary statistics for survey variables in technical efficiency model

	Unit	Mean	Standard Deviation	Minimum	Maximum
Output	Kg	1,788.76	1,492.57	172.90	8,008.00
Labor	Days	57.03	75.23	5.67	460.20
Fertilize	Kg	327.75	389.35	–	3,354.00
Pesticide	ml	81.26	114.31	4.96	699.97
Machinery	Days	73.49	153.32	–	1,341.45

Source: Own estimates; data appendix available from authors.

Table 2. OLS and Maximum likelihood estimates for technical efficiency

Variables	OLS		MLE	
	Coefficients	Standard Errors	Coefficients	Standard Errors
Labor	0.161***	0.053	0.163***	0.053
Fertilizer	0.359***	0.057	0.356***	0.056
Pesticide	0.174***	0.052	0.177***	0.052
Machinery	0.042*	0.024	0.041*	0.024
Constant	3.932***	0.239	4.158***	0.422
Function coefficient	0.736		0.737	
F–statistic model	54.01***			
F–statistic CRTS [a]	27.24***			
σ_ω			0.411	
σ_v			0.283	
σ^2			0.249	
$\lambda=\sigma_v/\sigma_\omega$			0.688	
Log Likelihood			–68.830	
R^2	0.67			

[a] CRTS=constant returns to size, ***= 1%, **=5%, *=10%
Source: Own estimates; data appendix available from authors.

the OLS estimation, the selected independent variables in the model explained 67 percent of the variation of the output. The models were statistically significant at 1% level. The impacts of dependent variables on the output of production were at various levels.

The function coefficient, which measures the proportional change in output when all inputs included in the model are changed in the same proportion, is given in table 2 for the two equations. The function coefficient for both the OLS and MLE estimates is approximately 0.74, which indicates that returns to size are decreasing. Restricted least squares regression was applied to formally test the null hypothesis of constant returns to size. The computed F statistic is 27.24 more than the critical F value of 4.13 at the 1 percent level of significance. Thus, the null hypothesis of constant returns to size was rejected.

The ratio of standard error of u (σ_u) to the standard error of v (σ_v), known as lambda (λ), is 0.688. Based on λ, we can derive gamma (γ) which measures the effect of technical inefficiency in the variation of observed output ($\gamma=\lambda^2/(1+\lambda^2)=\sigma_u^2/\sigma_\varepsilon^2$). The estimated value of γ is 0.32, which means that 32 percent of the total variation in farm output is due to technical inefficiency.

Labor

From the above table, we could see that the labor variable was statistically significant at α=1% in both MLE and OLS models. This proved that using labor for cultivating soybean affected its output. About 16 percent of soybean output could increase, if 1 percent of more labor was invested in soybean production. However, according to experts, labor variable did not affect on the yield of soybean very much. In fact, since the agricultural area of household was averagely 0.7 ha in the MRD, this number of area could not create enough work for the household with 5 people. Thus, their attending to agricultural production in general and soybean one in separation did not increase the yield of production. Farmers who have got unemployed labors usually earned their extra incomes by doing some non–agricultural work such as Motor taxi driver, constructive worker and so on.

Fertilizer

Among independent variables, fertilizer was one of the most important variables. It was sure that this variable was very significant at α=1%. Clearly, it could cause nearly 36 percent increase of soybean production if farmer applied more fertilizer at the rate of 1%.

Pesticide

In fact, pesticides have relationship with the output of soybean production. In the circle of life, soybean regularly deals with some kind of pest incidences as diaphama indicas, stem borers, fruit borers and so forth. These pest incidences may have negative impacts on both the quality and the yield of the products. Thus in these two models, pesticides were also related with the amount of soybean produced because pesticide variable was statistically significant at α=1%.

Machinery

Machinery was used in the preparation of land, the period of irrigation and the harvest time. This machinery also affected the amount of soybean harvested at the end of crop at α=10%. But the amount of soybean increase was rather small and not worth considering.

Deriving from the MLE estimate, the technical efficiency level of farmers may be computed using the formula of $TE_i=\exp(-\hat{u}_i\big/\sum_i\beta_i)$ to eliminate the impact of random errors.

For the estimation of allocative efficiency, we use the cost frontier dual to the production frontier presented in (9) function. In this function, independent variables are the price of inputs for soybean production and the total soybean output that is adjusted for any statistically noise calculated by function (9). The model is given as:

$$\ln C=\ln(0.012)+0.221\ \ln P_1+0.483\ \ln P_2+0.240\ \ln P_3 +0.056\ \ln P_4+1.357\ \ln Y^*, \quad (10)$$

Where:

C_i: The cost of Soybean production per farm measured in VND,

Table 3. Frequency distribution of technical, allocative and economic efficiency

Efficiency level (%)	Technical Efficiency		Allocative Efficiency		Economic Efficiency	
	Number	%	Number	%	Number	%
>85	3	3	1	1	0	0
>75≤85	52	46	4	4	0	0
>65≤75	47	42	22	19	1	1
>55≤65	10	9	24	21	7	6
>45≤55	1	1	25	22	23	20
>35≤45	0	0	18	16	35	31
>25≤35	0	0	14	12	31	27
>15≤25	0	0	4	4	14	12
>5≤15	0	0	0	0	1	1
≤5	0	0	1	1	1	1
Mean (%)	73.9		51.5		38.0	
Minimum (%)	52.4		4.4		3.8	
Maximum (%)	86.5		86.4		67.5	

Source: Own estimates; data appendix available from authors.

P_{1i}: The hired price per one man day in VND/man day,

P_{2i}: The price of fertilizer in VND/kg,

P_{3i}: The price of pesticide in VND/ml,

P_{4i}: The price of machinery in VND/day,

$\ln(Y_i^*)$: The soybean output adjusted for any statistical noise (calculated by function 9)

The result of efficiency level calculated is presented in table 3.

Technical efficiency (TE) indices range from 52.4 percent to 86.5 percent for the farmers in the sample, with an average of 73.9 percent. This means that if the average farmer in the sample was to achieve the TE level of its most efficient counterpart, then the average farmer could realize a 14.6 percent cost savings (i.e., 1–[73.9/86.5]). A similar calculation for the most technically inefficiency farmer reveals cost saving of 39.4 percent (i.e., 1–[52.4/86.5]). Moreover, farmers who got the highest score of technical efficiency from 75 percent to 90 percent were 55 households which counted for above 49 percent. On the contrary, the group of the lowest score of technical efficiency under 65 percent was only 11 farmers dominated about 10 percent compared to the whole surveyed farmers. The average allocative efficiency of sample is 51.5 percent with a low of 4.4 percent and a high of 86.4 percent.

The economic efficiency is estimated by multiplying TE score with AE score and then we could determinate that the mean economic efficiency of sample is 38 percent, with a high of 67.5 percent and a low of 3.8 percent. These indicate that if the average farmer in the sample were to reach the EE level of its most efficient counterpart, then the average farmer could experience a cost savings of 43.7 percent (i.e., 1–[38/67.5]). The same computation for the most economically inefficient farmer suggests a gain economic efficiency of 94.4 percent (i.e., 1–[3.8/67.5]).

To compare the efficiency measures in this study with ones in other studies, table 4 show average efficiency indices from other researches that was estimated by using stochastic production frontiers. We calculated the average technical efficiency of 74 percent in this study which is close to 70 and 71 percent figures calculated by Bravo–Ureta and Pinheiro (1997); Boris E. Bravo–Ureta and Rieger (1991); and Tewodros Aragie Kebede (2001) in their estimation of Dominican Republic, Pakistan crops and Nepal rice farmers. The 51 percent average AE found in this paper is not almost similar, more around 7 percent than AE in the paper written by Bravo–Ureta and Pinheiro (1997). By contrast, Bravo–Ureta and Evenson (1994) for a sample of cotton and cassava farmers in Paraguay reported higher estimates of AE (70 and 88 percent). Moreover, the mean EE level of 38 percent in this study is very close to the 40 percent reported by Boris E. Bravo–Ureta and Evenson (1994). Furthermore, we also saw in the table 4 that the highest EE of 85 percent is in the paper of Boris E. Bravo–Ureta and Rieger (1991).

In the above parts, we could estimate the technical, allocative and economic efficiencies of soybean production of farmers in the MRD. For understanding clearly in detail, in the second step we must find and analyze the factors that influence the efficiency of farm. In other words, finding the source of efficiency is necessary for calculation of efficiency of soybean production.

Source of efficiency

In this part, we would use six variables in the model. They are Training, Credit, Government, Experience, Area, and Local. The purpose is to consider how these variables have an impact on the TE, AE and EE of soybean production, the function is given as:

$$\begin{aligned} EFFICIENCY = {} & b_1 TRAINING + b_2 CREDIT \\ & + b_3 GOVERNMENT \\ & + b_4 \ln(EXPERIENCE) \\ & + b_5 \ln(AREA) + b_6 LOCAL \end{aligned} \tag{11}$$

Where:

EFFICIENCY is Technical Efficiency/Allocative Efficiency/Economic Efficiency of farmers calculated in the previous frontier functions,

TRAINING is equal to 1 if farmer has attended trainings or 0 if farmer had never attended any training,

CREDIT is equal to 1 if farmer borrowed money from banks or 0 otherwise,

GOVERNMENT is equal to 1 if farmer received support from government or 0 otherwise,

EXPERIENCE is the number of years that farmer has grown soybean,

AREA is the area of soybean that farmer is growing,

LOCAL=0 equal to An Giang, 1 equal to Can Tho.

The effect of truncation occurs when sample data are drawn from a subset of a larger population of inter-

Table 4. Comparison of efficiency indexes from various using production frontiers

Author(s)	Country	Product	TE	AE	EE
Boris E. Bravo–Ureta and Evenson (1994)	Paraguay	Cotton	58	70	40
Boris E. Bravo–Ureta and Evenson (1994)	Paraguay	Cassava	59	88	52
Bravo–Ureta and Pinheiro (1997)	Dominican Republic	Crops	70	44	31
Boris E. Bravo–Ureta and Rieger (1991)	United States	Dairy	70	83	85
Ali and Chaudry	Pakistan	Crops	84	61	51
Taylor et al.	Brazil	Multiproduct	17	74	13
Kalirajan and Flinn (1983)	Philippines	Rice	80		
Tewodros Aragie Kebede (2001)	Nepal	Rice	71		
This study	**Viet Nam**	**Soybean**	**74**	**51**	**38**

Table 5. The truncated estimates for the sources of efficiency

Variables	TE		AE		EE	
	Coefficients	Z	Coefficients	Z	Coefficients	Z
TRAINING	0.021	0.92	0.040	0.72	0.038	0.86
CREDIT	–0.008	–0.62	0.029	0.98	0.020	0.86
GOVERNMENT	0.033*	1.44	0.053	0.93	0.058*	1.30
EXPERIENCE	0.007	1.05	0.024*	1.46	0.021*	1.55
AREA	0.028***	3.84	–0.079***	–4.36	–0.042***	–2.89
LOCAL	–0.022**	–1.73	–0.010	–0.30	–0.017	–0.69
Constant	0.688***	37.52	0.581***	12.92	0.399***	11.17
Log likelihood	160.142		60.536		85.693	

***=1%, **=10%, *=20%
Source: Own estimates; data appendix available from authors.

est. Truncation is essentially a characteristic of the distribution from which the sample data are drawn (Greene 2000). In the model specification of equation (11), the dependent variable, level of efficiency attains values between 0 and 1. Hence, the dependent variable can be considered as truncated between 0 and 1. Applying OLS on equation (11) yields biased results usually towards zero. Thus, maximum likelihood estimation will be used to estimate the equation taking the truncation of the dependent variable into consideration. The following table 5 shows the result of truncated estimates for the sources of efficiency.

TRAINING is a variable that is included to estimate the impact of training courses given by extensive service systems. We expect that farmer get higher efficiency if they have took part in training courses. The expected sign of this variable is positive. In the study, this variable is not statistically significant in all TE, AE and EE models. This indicates that trainings given by government do not change the efficiency of soybean cultivation. This thing appropriates the fact very much. Almost all farmers said that technical instruction given by extension service were not useful for improving the yield of their products when they were interviewed about the effect of short training courses.

CREDIT is a variable that was used to capture the effect of credit on the efficiency of farmers. The availability of credit will lose the constraints of production facilitating to get the inputs on a timely basic and hence is supposed to increase the efficiency of farmers. But credit variable in this study is not statistically significant in all TE, AE and EE functions. This suggests that the availability of credit is not important factor for attaining higher levels of technical, allocative and economic efficiencies. The credit policies simply help farmers borrow more capital from a bank for soybean production, but do not promote them to apply new technologies and get more efficiency.

GOVERNMENT is a dummy variable trying to capture the effect of governmental policies (e.g., fertilizer, pesticides, and seed policies) on the efficiency of farmers. We expect that if farmer has received any support activities from government, they would get the higher efficiency. The expected sign of the estimated coefficient is positive. In accordance with this expectation, the variable is positive. Yet it is only statistically significant at 20% level in TE and EE functions. Because the error is rather large, the result is only useful for reference. Like *CREDIT* and *TRAINING*, the supports of Government are also useless to raise the economic efficiency of soybean production of farms.

EXPERIENCE, the number of years of soybean cultivation achieved by household head, is used as a proxy for managerial input. Increased farming experience may lead to better assessment of importance and complexities of good farming decision, including efficient use of inputs. The expected sign for experience variable is positive. In accordance with this expectation, the variable is positive. But it is only statistically significant at 20% level in the AE and EE functions, and not significant in the TE model. These mean the more experience farmers have, the higher AE and EE scores they get. This rule is not correct in the TE model.

AREA, the number of soybean area the farmer cultivates. This variable is aimed at capturing the effect of the scale production on efficiency of the farm. The more soybean area the farm has, the more productive is the farm operation. Hence, the expected sign for this variable is positive. For TE model, *AREA* variable is positive like our expectation and statistically significant at 1% level. It indicates the more areas farmers have, the higher technical efficiency they get. However, this result is not correct for AE and EE since the variable is negative in the AE and EE models.

LOCAL is other farm characteristic that is used to account for any site–specific factors (e.g., soil fertility, differences in weather) not included in the production function but that may affect the level of farmers' efficiency. TE model shows that there is the difference of TE among farms in Can Tho and An Giang at 10% level. Farmers in An Giang that grow soybean with higher TE than those in Can Tho are about 2.2 percent. However, farmers in both provinces have the same AE and EE because *LOCAL* variable is not statistically significant in the AE and EE functions.

CONCLUSION

Agricultural productivity varies due to differences in production technology, differences in the setting in which production occurs and differences in the efficiency of the production process. Efficiency measurement has been the concern of researchers with an aim to investigate the efficiency levels of farmers engaged in agricultural activities. Identifying determinants of efficiency levels is major task in efficiency analysis. Empirical studies suggest that farmers in developing countries fail to exploit fully the potential of a technology making inefficient decisions. Policy makers have started to recognize that one important source of growth for the agricultural sector is efficiency gain through greater technical and economic efficiency. This paper attempted to measure technical and economic efficiency of soybean farmers in the MRD and identified its determinants. As part of the methodology used in this paper, Maximum likelihood techniques were used to estimate a Cobb–Douglas production frontier, which was then used to derive its corresponding dual cost frontier. These two frontiers were the basis for deriving farm–level efficiency measures.

The analysis shows that, for our sample of MRD soybean farms, average technical efficiency is 74 percent, average allocative efficiency is 51 percent, and average economic efficiency is 38 percent. These results suggest increases in output and decreases in cost can be achieved by given existing technology and it is very necessary to estimate not only TE, but also AE and EE when we want to calculate productive efficiency. We also found that there was a wide range of variation in technical inefficiency that mainly came from the difference in farming practices of farmers. Thus, there may be a big opportunity to increase the technical efficiency level of the crop in the Mekong Delta by enhancing the technical guidance of new technologies in soybean production. In addition, big variation in economic inefficiency was mainly due to the inadequate responses to market price changes. Therefore, there were opportunities to increase the profits by the improvement of market information systems in the rural areas.

In a second step analysis, relationships between TE, AE and EE and various attributes of the farm and farmer were examined. The second step analysis relied on the truncated regression techniques to estimate three separate equations, where TE, AE and EE were expressed as functions of six farm characteristics: training, credit, government, experience, area, and local. The results show that the larger–scale farmers have, the higher technical efficiency they get. The supports from Government also have a few effects on the technical efficiency of soybean farmers. The AE and EE models show that farmers who have more experiences on cultivating soybean have higher allocative and economic efficiencies. Due to the favorable natural conditions, farms in An Giang obtain the TE score higher than those in Can Tho. Moreover, in this study almost all activities given by the Government such as opening short trainings for introducing farmers to apply and improve the new technologies, credit with low interest, and so on have no impacts on increasing the efficiency of soybean farmers.

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