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# Productive Efficiency of Soybean Production in the Mekong River Delta of Vietnam

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## 1. Introduction

Vietnam was an agricultural importing country during the 1970s. Since reforming its policies in 1986, through the removal of price controls on many goods, decollectivization of land, reduction or removal trade barriers and opening up to foreign direct investment, Vietnam has gradually become one of the biggest agricultural exporting countries in the world. Recently, it has been the world's leading exporter of cashews, coffee, rubber, and black pepper, and the second biggest rice exporter. Almost all Vietnamese export rice originates from the Mekong River Delta (MRD), an area of around 40,000 km<sup>2</sup>. More than 18 million tons of rice are produced in the MRD every year, and this comprises half of the total amount of rice produced in Vietnam. In addition, MRD farmers also grow vegetable crops like cassava and maize in paddy fields between two planting seasons of rice to gain extra income and improve soil fertility. Soybeans are one of the most popular vegetable crops in the MRD. This study used primary data on soybean farmers for analyzing productive efficiency in the MRD of Vietnam.

Although agriculture plays the most important role in the Vietnamese economy, its contribution to GDP is gradually decreasing every year. The slow rate of agriculture development results in low income, which seriously limits opportunities for savings and investment in rural households. Consequently, the rate of development of nonagricultural sectors is also declining, resulting in a lack of jobs and more serious poverty in rural areas. Some reports have found that low efficiency in agricultural production could damage the environment through deforestation or water pollution (Tewodros, 2001).

Most studies agree that economic development strategy for the agricultural sector should be based on the promotion of increasing yields or production amounts, especially for small-scale farmers. Some empirical evidence shows that small-scale farms not only provided jobs to reduce unemployment but also distributed income as well as commodity demand in other economic sectors (Bravo-Ureta & Evenson, 1994). For this reason, researchers and policymakers have paid much attention to the adaptation of new technologies to increase the productivity and income of households. However, in recent decades, the development of technologies in agricultural sectors is already high. This suggests that the increase in productivity originally from the more efficient use of available technologies is vindicated (Bravo-Ureta & Pinheiro, 1997).

The term "productive efficiency", as used in this study, refers to the amount of possible output gain without any additional inputs or new technologies. The measurement of

efficiency is to determine output gain because this improves the performance of agricultural production with available technologies. A policy mainly focusing on more efficiency in production is considered as using more efficient inputs, increasing outputs and then improving income. In the short-term, improvement in agricultural production with pre-existing technologies is better than the implementation of new technologies (Belbase & Grabowski, 1985; Shapiro, 1977).

The main objective of this study is to measure the possibilities of productivity gains from enhancing the efficiency of soybean farmers in the MRD of Vietnam. The analytical method of the study is to measure the productive efficiency of soybean farmers in the MRD by applying a stochastic frontier and to identify some determinants of productive efficiency. The first step is to estimate farm-level technical efficiency (TE), allocative efficiency (AE) and economic efficiency (EE). The second step of analysis is to calculate separated Tobit equations with the dependent variables TE, AE and EE and the independent variables of the important factors related to soybean production and social characteristics of the farmers. The study aims to provide policy makers and concerned people with more information on the present situation of agriculture and agricultural policies in Vietnam by not only estimating the efficiency score for soybean cultivation, but also determining some factors that have impact on this efficiency score.

## 2. Productive efficiency

Production efficiency is composed of two factors. The purely technical, or physical, component is defined as the producer's ability to avoid waste during production. In other words, producers use the given inputs to create an output as high as possible, or produce a given output by applying inputs as low as possible. Thus, the target of an estimate of technical efficiency is to find solutions to increase output or decrease input in the context of available technologies. The allocative, or price component is determined by the combination of inputs and outputs in the optimum level in terms of considering market prices (Lovell, 1993). Measuring technical efficiency means to use input and output quantity without introducing their prices. Technical efficiency can be further deconstructed into three components, which are scale efficiency (the potential productivity gain from achieving the optimal size of a firm), congestion (increase in some inputs could decrease output) and pure technical efficiency (Farrell, 1957).

Economic efficiency involves increasing output without using more than conventional inputs. The use of existing technologies is more cost-effective than applying new technologies if farmers currently cultivate their products with the existing technology inefficiently (Belbase & Grabowski, 1985; Shapiro, 1977). Economic efficiency can be classified into two categories: technical efficiency and allocative efficiency. Technical efficiency measures the ability of a farmer to achieve maximum output with given and obtainable technology, while allocative efficiency tries to capture a farmer's ability to apply the inputs in optimal proportions with respective prices (Farrell, 1957; Shapiro, 1977; Tim *et al.*, 2005).

In Fig. 1, it is assumed that a firm uses two inputs ( $X_1$  and  $X_2$ ) to produce a single output ( $Q$ ) under the assumption of constant returns to scale. The  $SS'$  curve represents the isoquant of fully efficient firms, and could be used to measure technical efficiency. If a given firm uses quantities of inputs at point  $A$  to produce a unit of output, the technical inefficiency of that firm could be represented as the distance  $AB$ . It is the amount by which the level of input

needed could be proportionally reduced without a decline in output. This is usually expressed in percentage terms by the ratio  $BA/OA$ , which represents the percentage by which all inputs need to be reduced to achieve technically efficient production. The technical efficiency (TE) of a firm ranges between 0 and 1, and is most commonly measured by the ratio

$$TE = OB/OA \quad (1)$$

If TE is equal to 1, the firm produces with full technical efficiency. For example, at point  $B$  firm could gain full technical efficiency because point  $B$  lies in the efficient isoquant curve.

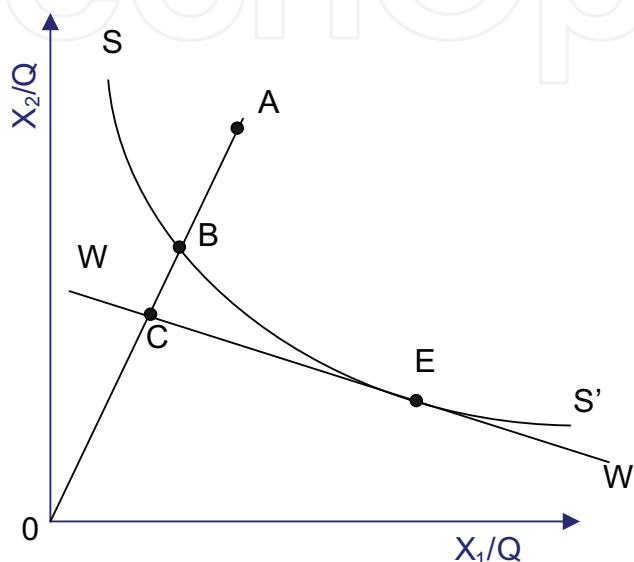


Fig. 1. Technical, allocative and economic efficiency

If the input price ratio, represented by the slope of the isocost line  $WW'$ , is also known, allocative efficiency (AE) at  $A$  can be calculated and identified by the ratio:

$$AE = OC/OB \quad (2)$$

A decrease in production costs with the distance from  $B$  to  $C$  would happen if production was performed at the allocatively and technically efficient point  $E$  instead of at the technically efficient, but allocatively inefficient point  $B$ .

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

$$EE = OC/OA \quad (3)$$

The distance from  $A$  to  $C$  also represents the cost reduction in production if a firm produces at point  $C$  with technical and allocative efficiency, instead of at point  $A$  with technical and allocative inefficiency. Economic efficiency is a combination of technical and allocative efficiency.

### 3. Techniques of efficiency measurement

There are two methods widely used in the literature to estimate technical efficiency of agricultural production. They are data envelopment analysis (DEA) and stochastic frontier analysis (Coelli, 2005).

DEA, which is a mathematical programming method, is useful for multiple-input and multiple-output production technologies. This method of analysis, initially studied by Charnes, Cooper and Rhodes (1978), uses linear programming methods to build a non-parametric piece-wise surface (or frontier) over the data and estimate each data point's efficiency relative to the frontier (Coelli, 2005). The DEA method assumes that the variables are reasonably separated into inputs and outputs. Each data point in DEA represents a decision making unit, or a producer in practice. The "decision" of a unit is to create outputs by using inputs as efficiently as possible (Zhiqiang *et al.*, 2004).

Stochastic frontier analysis uses econometrics based on the deterministic parameter frontier of Aigner and Chu (1968). The random noise around the estimated production frontier is recognized in the stochastic frontier analysis. For instance, using multiple inputs to predict one single output is based on the functional relationship  $y_i = f(x_i, \beta) + \varepsilon_i$ , where  $i$  indicates the number of the identified observations and  $\beta$  is the estimated parameters. The  $\varepsilon_i$  error term is formulated by a random error  $v_i$  and the technical inefficiency  $u_i$ . Stochastic frontier analysis will be decreased to the deterministic frontier analysis assuming  $v_i$  equals 0, and the central tendency analysis if  $u_i$  is equal to 0.

The different techniques are applied to generate the strengths and weaknesses of the two methods. The econometric approach is stochastic and parametric. It has the ability to separate the effects of noise from the effects of inefficiency and confound the effects of misspecification of functional form (of both technology and inefficiency) with inefficiency, but generates good results only for single output and multiple inputs. On the contrary, the mathematical programming approach is not stochastic and not parametric. It cannot separate the effects of noise and inefficiency during the calculation of technical efficiency, and less sensitive to the type of specification error (Tewodros, 2001), but could be useful to apply to farms with multiple-inputs and multiple-outputs production.

Since soybean production in the MRD is an example of single output and multiple-output production, this study focuses on the use of an econometric approach for measuring technical efficiency based on the production frontier model.

#### 4. The econometric approach to efficiency measurement

The calculation of technical efficiency using the production frontier model is only applied to single output production (Possibly also to multiple-output production if the multiple-outputs are aggregated into a single-output index). Depending on the structure of the data (cross-sectional or panel data), different estimates are applied. In this study, we assume that we have cross-sectional data on  $N$  farmers with the use of  $K$  inputs and generation of a single output. A production frontier model can be written as

$$y_i = f(x_i; \beta) \times TE_i, \quad (4)$$

where  $y_i$  represents the possible production level of the  $i^{\text{th}}$  producer ( $i = 1, \dots, N$ ),  $f(x_i; \beta)$  is the production frontier of the vector  $x_i$  of  $K$  inputs used by producer  $i$  and a vector  $\beta$  of unknown parameters, and  $TE_i$  is the output-oriented technical efficiency of producer  $i$ .

We could transform equation (4) into the following equation:

$$TE_i = \frac{y_i}{f(x_i; \beta)}, \quad (5)$$

Technical efficiency is defined as the ratio of observed output ( $y_i$ ) and maximum feasible output ( $f(x_i; \beta)$ ) with current available technologies. TE is equal to 1 if  $y_i$  is the same as the maximum output  $f(x_i; \beta)$ . Technical inefficiency exists if the observed value is below the estimated frontier or TE is less than 1.

According to the assumption of statistical noise and the definition of inefficiency, a production frontier model of cross-sectional data is estimated by the deterministic frontier and stochastic frontier models. Because  $y_i$  is bordered above by the deterministic quantity,  $f(x_i; \beta)$ , the model (5) is defined as a deterministic frontier production function. The technical efficiency of a given producer is estimated by the difference between the frontier output  $f(x_i; \beta)$  and the level of production for the producer  $y_i$  (Battese, 1992).

The measurement of technical inefficiency associated with the deterministic frontier model is larger and not reasonable because it includes out-of-control factors like disasters, diseases, and market uncertainties. Therefore, almost all current studies have applied the stochastic production frontier model, also including producer-specific random shock to estimate the technical efficiency of a given producer. The model is performed by the following equation:

$$y_i = f(x_i; \beta) \times \exp(v_i) \times TE_i \quad (6)$$

where  $v_i$  is a random zero-mean error in terms of specific random shocks (e.g., disasters, diseases, market uncertainties) that are out of the farm's control. Because the stochastic quantity,  $[f(x_i; \beta) \times \exp(v_i)]$ , lies above the possible output, the model (6) is identified as a stochastic frontier. Technical efficiency of an individual farmer is determined by the following equation:

$$TE_i = \frac{y_i}{f(x_i; \beta) \times \exp(v_i)} \quad (7)$$

The estimate of technical efficiency by the stochastic frontier model is also defined by the ratio of observed output to the corresponding frontier output ( $y_i$ ) over the maximum feasible output ( $f(x_i; \beta)$ ) and random out-of-control factors. Thus, TE is equal to 1 if  $y_i$  is the same as the maximum output of  $f(x_i; \beta) \times \exp(v_i)$ .

The stochastic production frontier model originally introduced by Aigner, Lovell, and Schmidt (1977), Battese and Corra (1977), and Meeusen and Van (1977) allows separating inefficient effects and random errors not under control of the farmer such as weather, luck, and market uncertainties, in the calculation of technical efficiency. Thus, the stochastic production frontier model is applied in this study in the hope of obtaining a more reasonable and correct technical efficiency estimate than the deterministic frontier model.

## 5. Analytical framework

In the calculation of the productive efficiency of soybean production, the Cobb-Douglas production frontier function is estimated by applying maximum likelihood techniques to analyze factors affecting output, then the income or profit of soybean farmers. The corresponding dual cost frontier is identified from the estimated production frontier. These two frontier functions form the basis for obtaining the measurement of productive efficiency. The stochastic production frontier can be written as:

$$\ln(y_i) = \beta_0 + \sum_j \beta_j \ln(x_{ij}) + \varepsilon_i \quad (8)$$

where  $y_i$  is the output of farmer  $i$ ,  $x_{ij}$  is the  $j$  input used by farmer  $i$ , and  $\varepsilon_i$  is a "composed" error term. The error term ( $\varepsilon_i$ ) is explained as  $\varepsilon_i = v_i - u_i$ ,  $i = 1, 2, \dots, N$ .

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

$u_i$  is a one-sided ( $u \geq 0$ ) efficiency component that represents the technical inefficiency of the farm (Thiam *et al.*, 2001). In other words,  $u_i$  estimates the shortfall in output  $y_i$  from its maximum value given by the stochastic frontier  $\ln(y_i) = \beta_0 + \sum_j \beta_j \ln(x_{ij}) + v_i$ . This one-

sided term of distribution can be half-normal, exponential, or gamma (Aigner *et al.*, 1977; Meeusen & Broeck, 1977). In this study, it is assumed that  $u_i$  is a half-normal distribution ( $u \sim N[0, \sigma_u^2]$ ) as it is typically used in the applied stochastic frontier literature. The two components  $v_i$  and  $u_i$  are also assumed to be independent of each other.

The maximum likelihood analysis of equation (8) produces consistent estimators for  $\beta$ ,  $\lambda$  and  $\sigma_v^2$ , where  $\beta$  is a vector of unknown parameters,  $\lambda = \sigma_u / \sigma_v$ , and  $\sigma^2 = \sigma_u^2 + \sigma_v^2$ . In Jondrow *et al.* (1982), inferences about the technical inefficiency of individual farmers are estimated by using the conditional distribution of  $u$  given the fitted values of  $\varepsilon$  and the respective parameters. In other words, with the assumption that  $v$  and  $u$  are independent from each other, the conditional mean of  $u$  given  $\varepsilon$  is identified by:

$$E(u_i | \varepsilon_i) = \sigma^* \left[ \frac{f^*(\varepsilon_i \lambda / \sigma)}{1 - F^*(\varepsilon_i \lambda / \sigma)} - \frac{\varepsilon_i \lambda}{\sigma} \right] \quad (9)$$

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 estimated at  $\varepsilon \lambda / \sigma$ .

With the assumption of a half-normal model, a simple z-test will be used for examining the existence of technical inefficiency, the null and alternative hypotheses are  $H_0: \lambda = 0$  and  $H_1: \lambda > 0$  (Coelli, 2005). The test statistic is

$$z = \frac{\tilde{\lambda}}{se(\tilde{\lambda})} \sim N(0,1) \quad (10)$$

where  $\tilde{\lambda}$  is the ML estimator of  $\lambda$  and  $se(\tilde{\lambda})$  is the estimator for its standard error.

The technical efficiency of a farm will be determined by using the relationship:

$$TE_i = \exp(-\hat{u}_i) = \exp(-E(u_i | \varepsilon_i)) \quad (11)$$

For obtaining the estimation of  $v$  and  $u$ , we replace  $\varepsilon$ ,  $\sigma^*$ , and  $\lambda$  in equations (8) and (9), then subtract  $v$  from both sides of equation (1) and finally yield the stochastic production frontier.

$$\ln(y^*_i) = \beta_0 + \sum_j \beta_j \ln(x_{ij}) - u_i = \ln(y_i) - v_i \quad (12)$$

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 can be expressed as:

$$\ln(C_i) = \alpha_0 + \sum_k \alpha_k \ln(P_{ik}) + \gamma \ln(y^*_i) \quad (13)$$

where  $C_i$  is the minimum cost to produce output  $y_i$ ,  $P_{ik}$  is a vector of  $k^{\text{th}}$  input price, and  $\alpha$ ,  $\gamma$  is a vector of parameters.

## 6. Data and the empirical model

### 6.1 Data

Rice is a main crop in the MRD. Farmers often apply mixed farming systems such as one-rice and one-fish crop, or two-rice and one-vegetable crop to improve income and soil conditions. Consequently, farmers grow soybean once a year. The soybean crop is usually cultivated in January and February after the Winter-Spring rice crop and harvested in March and April. In this study, farmers who grow two-rice and one-soybean crop were selected for interview.

Primary data for this study were collected in a field survey in two agro-ecological areas of the MRD in 2004. Samples were collected from Can Tho Province, representing the lower reaches of the MRD and An Giang Province, representing the upper one. A total of 113 farmers, of whom 58 were in Can Tho and 55 were in An Giang, were interviewed following a stratified random sampling procedure.

### 6.2 Empirical model

First, the calculation of technical efficiency involves measuring the capacity of a farmer to achieve the maximum output with given and obtainable technology (Farrell, 1957; Tim *et al.*, 2005). There are several functional forms for estimating the physical relationship between inputs and output. One of the most popular functions is the Cobb-Douglas production function. In this study, the Cobb-Douglas production function is estimated with four important inputs of soybean production, namely labor, fertilizer, pesticides and machinery. The stochastic frontier model is specified as:

$$\ln(y_i) = \beta_0 + \beta_1 \ln(LAB) + \beta_2 \ln(FER) + \beta_3 \ln(PES) + \beta_4 \ln(MACH) + \varepsilon_i \quad (14)$$

where  $y_i$  is soybean output in kg,  $LAB$  is human labor used in days,  $FER$  is fertilizer quantities in kg,  $PES$  is pesticide quantities in ml, and  $MACH$  is machinery service hired in days.

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

Second, the cost frontier is based on the duality of the production frontier and estimated for calculating allocative efficiency to capture a farmer's ability to apply the inputs in optimal proportions with respective prices (Farrell, 1957; Tim *et al.*, 2005). The function includes independent variables that are the price of inputs for soybean production ( $P_{ik}$ ) and the total soybean output  $\ln(y^*_i)$  that is adjusted for any statistical noise. The model is given as:



$$\ln(C_i) = \alpha_0 + \sum_{k=1}^4 \alpha_k \ln(P_{ik}) + \gamma \ln(y^*_i) \quad (15)$$

Last, economic efficiency, the combination of technical efficiency and allocative efficiency, is calculated by multiplying the TE score with the AE score.

Table 1 presents the descriptive statistics of some important variables applied in the stochastic frontier production function. Labor is defined as the number of working days including hired and family laborers used for land preparation, seeding, weeding, fertilizing, pesticide spraying, watering and harvest. Machinery in soybean cultivation is the number of machine service days that farmers hire from private services for preparing land, harvesting and sometimes irrigating. There are around two-thirds of farmers using machinery for harvest, one-third for land preparation and few for irrigation in the sample. In Table 1, farmers use machinery for 73 days, which is more than the hired labor and family day total of 57 days. This result reveals that machinery service utility is gradually gaining in popularity among soybean farmers. In other words, farmers are beginning to use machinery for their cultivation instead of doing it by hand. The soybean output of 1,789 kg with standard deviation of 1,492 kg indicates large variability of output among the farmers.

	Unit	Mean	Standard Deviation	Minimum	Maximum
<i>y</i>	kg	1,788.76	1,492.57	172.90	8,008.00
<i>LAB</i>	days	57.03	75.23	5.67	460.20
<i>FER</i>	kg	327.75	389.35	-	3,354.00
<i>PES</i>	ml	81.26	114.31	4.96	699.97
<i>MACH</i>	days	73.49	153.32	-	1,341.45

Source: Own estimates; data appendix available from authors.

Table 1. Descriptive statistics of variables in the production function

## 7. Results and discussion

Table 2 provides the results of the OLS estimate for choosing the relevant variables and stochastic frontier production function. The coefficient  $R^2$  of the OLS estimation is 67 %, which shows that around 67 % of dependent variables are explained by the selected independent variables. Both models are statistically significant at the 1 % level.

The important test to check the absence of technical inefficiency effects must be done in most efficiency studies. The key parameter of log-likelihood in the half-normal model is  $\lambda = \sigma_u / \sigma_v$ . If  $\lambda = 0$  there are no technical inefficiency effects and all deviations from frontier are due to noise (Aigner, Lovell, & Schmidt, 1977). The estimated value of  $\tilde{\lambda} = 0.688$  is significantly different from 0 and the null hypothesis that the absent inefficiency effects are rejected at the 5 % level in terms of the Z-statistic (the test statistic is  $Z = \tilde{\lambda} / se(\tilde{\lambda}) = 0.688 / 0.335 = 2.05$ , exceeding the critical value  $Z_{0.95} = 1.96$ ), revealing that inefficiency effects exist among soybean farmers.

For testing the proportional output change in the same proportion when inputs in the model are varied, restricted least squares regression is used with the null hypothesis of constant

returns to size. In Table 2, the function of both the OLS and stochastic frontier models is around 0.74, meaning that returns to size are decreasing. The computed F statistic is 27.24, higher than the critical value of  $F(1,108) = 6.88$  at the 1 % level of significance <sup>1)</sup>. The result shows that the null hypothesis of constant returns to size is rejected. This reveals that farmers need more marginal cost for additional products, maybe due to the limitation of their knowledge about management, technologies or market information.

Variables	OLS		Stochastic Frontier	
	Coefficients	Standard Errors	Coefficients	Standard Errors
<i>LAB</i>	0.161***	0.053	0.163***	0.053
<i>FER</i>	0.359***	0.057	0.356***	0.056
<i>PES</i>	0.174***	0.052	0.177***	0.052
<i>MACH</i>	0.042*	0.024	0.041*	0.024
<i>Constant</i>	3.932***	0.239	4.158***	0.422
Function coefficient	0.736		0.737	
F-statistic model	54.01***			
F-statistic CRTS	27.24***			
$\sigma_v$			0.411	
$\sigma_u$			0.283	
$\sigma^2$			0.249	
$\lambda = \sigma_u / \sigma_v$			0.688	0.335
Log Likelihood			-68.83	
R <sup>2</sup>	0.67			

Notes: 1) \*\*\*, \*\*, \* indicate statistical significance at the 0.01, 0.05 and 0.1 level respectively.

2) CRTS is constant returns to size.

Source: Own estimates; data appendix available from authors.

Table 2. OLS and Stochastic Frontier production function estimates

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

This result shows that the estimated coefficient of *LAB* is statistically significant at the 1 % level for both the OLS and stochastic frontier estimates. The soybean output increases by 0.16 % for each extra percentage of labor. However, in fact the yield does not always have a positive relationship with agricultural labor in developing countries. In this study, a household with 5 members only cultivates 0.7 ha of soybeans on average. This could not create enough jobs for the members of the household; thus numbers of agricultural laborers on farms are normally higher than needed. Consequently, almost all farmers, besides attending to agricultural labor, also do some non-agricultural jobs, such as motor taxi driving or construction work, for extra income.

*FER* and *PES*, the most important independent variables, are statistically significant at the 1 % level for both estimated coefficients. The soybean output increases nearly 0.36 or 0.17 %, respectively, for the each additional percentage of fertilizer or pesticide applied.

The estimated coefficient of *MACH* also has significantly positive impact on the increase of output at the 10 % level. However, the soybean output does not increase so much with additional investment in machinery.

The calculation of the cost frontier dual to the production frontier is given as 2):

$$\ln(C_i) = \ln(0.012) + 0.221\ln(P_{i1}) + 0.483\ln(P_{i2}) + 0.240\ln(P_{i3}) + 0.056\ln(P_{i4}) + 1.357\ln(y_i^*) \quad (16)$$

where  $C_i$  is the minimum cost of soybean production per farm measured in VND;  $P_{i1}$  is the hired price of labor in VND/man day;  $P_{i2}$  is the price of fertilizer in VND/kg;  $P_{i3}$  is the price of pesticide in VND/ml;  $P_{i4}$  is the price of machinery in VND/day and  $\ln(y_i^*)$  is the soybean output adjusted for any statistical noise.

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.

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

Table 3 shows the results of the frequency distribution of technical, allocative and economic efficiency of soybean farmers. The study reveals technical efficiency (TE) of farmers in the sample ranging from 52.4 % to 86.5 %, with an average of 73.9 %. It indicates that the average farmer in the sample could save 14.6 % (i.e.,  $1 - [73.9/86.5]$ ) of costs and the most technically inefficient could realize a 39.4 % cost saving (i.e.,  $1 - [52.4/86.5]$ ) compared with the TE level of his most efficient counterpart. In addition, the highest TE level ranging from 75 % to 90 % comprises 55 farms, which is 49 % of the total. The lowest TE score of fewer than 65 % comprises 11 farms, or 10 %, indicating that almost all farms in the sample achieve rather high technically efficient production.

The mean of allocative efficiency is only 51.5 %, with the lowest 4.4 % and the highest 86.4 %. The reason for too low an allocative efficiency score could be explained by farmers in the sample deciding the amount of inputs for cultivation only based on their experiences, not using inputs flexibly according to markets.

The economic efficiency ratio is calculated by multiplying the TE score by the AE score. Because the soybean farmers use inputs with low allocative efficiency, they also score poorly for economic efficiency with an average EE score of 38 %, the highest being 67.5 % and the lowest 3.8 %.

To analyze which factors could have an impact on the soybean productive efficiency, the Tobit model is applied with *EFFICIENCY* as a dependent variable and four independent variables, *POLICY*, *LOCAL*, *EXPERIENCE*, *AREA*, used instead of the OLS estimate that might produce biased results, often toward zero (Boris E. Bravo-Ureta and Antonio E. Pinheiro, 1997). The model can be written as:

$$EFFICIENCY = \delta_0 + \delta_1 POLICY + \delta_2 LOCAL + \delta_3 EXPERIENCE + \delta_4 \ln(AREA) + \delta_5 \ln(AREA^2) \quad (17)$$

where *EFFICIENCY* is technical efficiency, allocative efficiency or economic efficiency of farmers calculated in the previous frontier functions; *POLICY* is a dummy variable of agricultural policies; *LOCAL* is a dummy variable of a specified area, equal to 1 if Can Tho or 0 if An Giang; *EXPERIENCE* is the number of years that the farmer has grown soybeans; and *AREA* is the soybean area cultivated in 1,000m<sup>2</sup>.

Variables	TE		AE		EE	
	Coefficients	t	Coefficients	t	Coefficients	t
<i>POLICY</i>	-0.0049	-0.45	0.0397 <sup>†</sup>	1.46	0.0293 <sup>†</sup>	1.34
<i>LOCAL</i>	-0.0154	-1.45	0.0102	0.38	-0.0001	-0.01
<i>EXPERIENCE</i>	0.0020***	4.02	0.0002	0.13	0.0011	1.13
<i>AREA</i>	0.0254***	3.62	-0.0801***	-4.54	-0.0444***	-3.12
<i>AREA</i> <sup>2</sup>	-0.0034	-0.98	0.0182**	2.07	0.0112	1.58
Constant	0.6934***	39.82	0.5628***	12.86	0.3896***	11.07
Sigma	0.0558		0.1404		0.1129	

Notes: 1) \*\*\*, \*\*, \* indicate statistical significance at the 0.01, 0.05 and 0.1 level respectively.

2) <sup>†</sup> indicates one-tailed test.

Source: Own estimates; data appendix available from authors.

Table 4. Agricultural policy impacts on soybean productive efficiency

Table 4 presents the results of agricultural policies and some key factors having an impact on the productive efficiency of farmers. *POLICY* is a dummy variable trying to recognize the effect of government agricultural policies (e.g., credit, short education, input and output policies) on the efficiency of farmers. In the study, households were asked about their perceptions of some important government policies, for example credit, vocational training, and practical support by outreach services. The variable is equal to 1 if farmers have perceived benefits from one of these policies, and 0 if they do not receive any advantages from government support programs. The expectation for this coefficient is positive because efficient policies might make farmers obtain higher efficiency in their cultivation either

directly or indirectly. The *POLICY* variable is expected to be positive and so is checked by the one-tailed test. The estimated coefficient is statistically significant at the 10 % level in the AE and EE models, but insignificant in TE, indicating that policies have a partial positive effect on AE and EE in soybean cultivation.

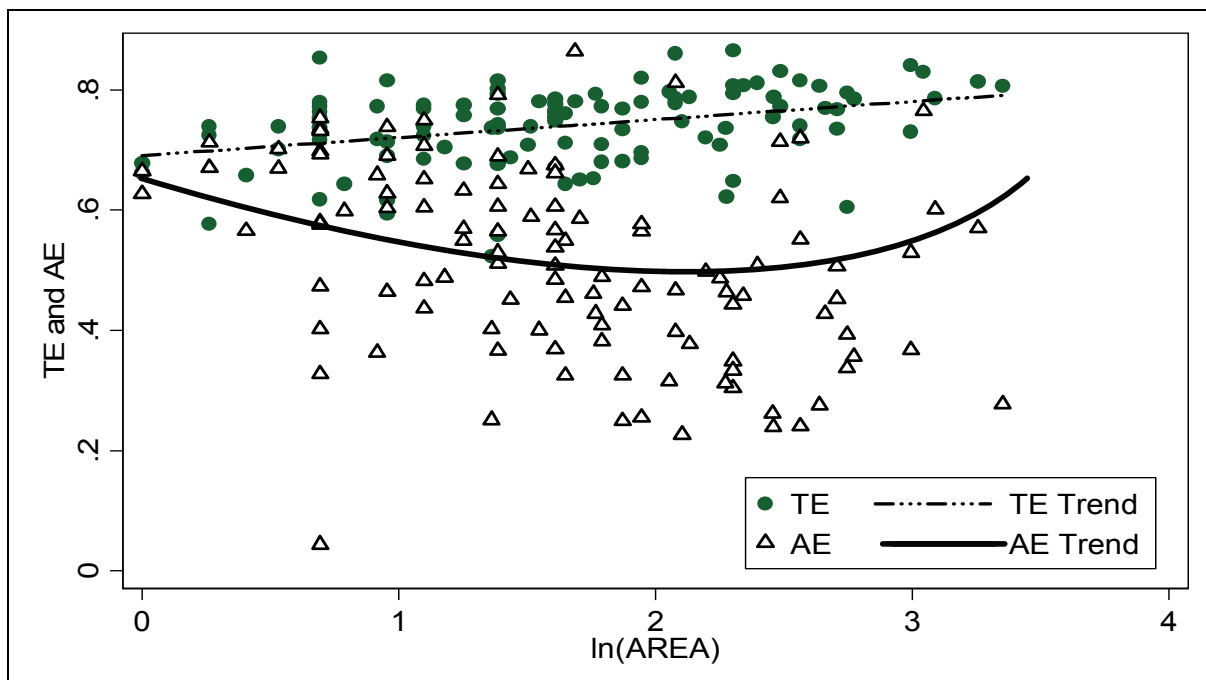


Fig. 2. The relationship between TE, AE and soybean area

*LOCAL* is applied for the measurement of any site-specific factors (e.g., soil fertility, differences in weather) not included in the production function that could have an impact on farms' efficiency level. The estimated result shows there is no difference in productive efficiency between the two provinces because the estimated coefficient of *LOCAL* is not significant in any of the three models.

*EXPERIENCE*, the number of years that farmers have been involved in soybean farming, is applied as a proxy for managerial inputs. Farmers with more years of experience may make better farming decisions and use inputs more efficiently. This coefficient is expected to be positive. In accordance with this expectation, the variable is positive. However, it is statistically significant at the 1 % level in the TE model only, and not significant in the AE or EE models. The effect of additional years of experience on technical efficiency is positive, but not for allocative or economic efficiency of farmers in the sample.

*AREA*, the size of soybean area cultivated, is used to capture the effect of economics of scale on the farms. The larger the soybean area that farmers cultivate, the higher the efficiency that they obtain. This coefficient is expected to be positive. It is statistically significant at 1 % in the three models. Its positive coefficient in the TE function shows that the larger the size of the farm, the more technical efficiency that farmers obtain. Moreover, the study shows that the estimated coefficient of *AREA* is negative, but  $AREA^2$  is significantly positive at the 5 % level in the AE model, meaning the allocative efficiency of farmers was decreasing for cultivating additional soybean area until 0.9 ha<sup>3</sup>) and increasing after that (see Fig. 2). A possible explanation for the negative coefficient of *AREA* in the EE model is that it could partly be due to decreasing returns to size in soybean cultivation.

## 8. Conclusions

Agricultural yield depends mostly on differences in technology, cultivation performance and efficient production. The priority when measuring efficiency is to investigate the productive efficiency of farmers and to identify factors affecting efficiency. Since literature studies revealed that farmers in developing countries mostly do not use all potential technological resources, they often make inefficient decisions in their agricultural production. Therefore, policymakers should recognize and master important factors positively affecting the level of productive efficiency, then find suitable methods to recommend farmers grow their crops more efficiently through higher technical and economic efficiency. This study attempted to estimate soybean productive efficiency in the MRD of Vietnam and identify its determinants. The analysis estimated the TE level to be 74 %, AE to be 51 %, and EE to be 38 %. These results suggest that increase in output and decrease in cost could be obtained using available technology. The study also suggested that it is very important and useful to calculate not only TE, but also AE and EE when estimating productive efficiency.

The low AE and EE in soybean production can be attributed to the inflexible responses of farmers to changes in market prices or to their applying inputs mainly based on experience. The underlying cause is that Vietnamese farmers lack market information, which they receive mainly from their neighbors, relatives, collectors or fertilizer and pesticide shops. They often suffer from accepting a low price for their products, but paying a high price for inputs. To solve these problems and increase the AE and EE of farmers, creating better rural market information systems is recommended. There is a need for the government to supply farmers with enough market information by organizing and improving the system of market information in rural communities. This could be done by broadcasting the agricultural product information and market prices every morning, which has already been applied successfully in some communities in the Mekong River Delta.

The study also examined the relationship of the various attributes with the productive efficiency of farmers. The Tobit model was applied to analyze three separate equations, where TE, AE and EE were demonstrated as functions of four main factors: policy, locality, area and experience. The results revealed that the farmers cultivating soybeans on a large-scale achieved higher TE, but less EE due to decreasing returns to scale in soybean production. Though the average AE is low, households could receive more AE for extra soybean area cultivated above 0.9 ha. Improving farmer's cultivation experience might also help in obtaining higher TE. The government policies had a partial positive impact on increasing the AE and EE score of the farmers in the sample.

The decreasing return to size of soybean production meant that the larger the scale of the farm, the bigger the economic inefficiency. This is possibly due to limited knowledge about expenditure management, technology or market information. Thus, the government should not recommend growing soybean on a large scale unconditionally, but encourage the rotation between soybean and other vegetables such as cassava and maize in the vegetable crop period. Besides guiding farmers on how to apply new technologies, the current outreach services should include training farmers on how to manage their agricultural inputs and expenditure to adjust their resources relatively at competitive prices, which could help farmers solve decreasing returns to scale in soybean cultivation.

## 9. Notes

1) Calculated by the formula  $F = \frac{(SSE_R - SSE_U) / J}{SSE_U / (I - K)}$ , where  $SSE_R$  and  $SSE_U$  are the restricted

and unrestricted sums of squared residuals and  $J$  is the number of restrictions (Coelli, 2005).

2) For the analytical derivation of a Cobb-Douglas cost function from its dual production (Varian 1992, ch. 4)

In the study, applying the formula as:

$$\ln(C_i) = \ln\left(\sum_{j=1}^4 \beta_j\right) - \frac{1}{\sum_{j=1}^4 \beta_j} \left\{ \ln \beta_0 + \ln(\beta_1^{\beta_1} \beta_2^{\beta_2} \beta_3^{\beta_3} \beta_4^{\beta_4}) \right\} +$$

$$+ \frac{\beta_1}{\sum_{j=1}^4 \beta_j} \ln(P_{i1}) + \frac{\beta_2}{\sum_{j=1}^4 \beta_j} \ln(P_{i2}) + \frac{\beta_3}{\sum_{j=1}^4 \beta_j} \ln(P_{i3}) + \frac{\beta_4}{\sum_{j=1}^4 \beta_j} \ln(P_{i4}) + \frac{1}{\sum_{j=1}^4 \beta_j} \ln(y_i^*)$$

3) At the minimum of AE curve is  $\ln(\text{AREA}) = 2.2005$ , equal to 0.9 ha.

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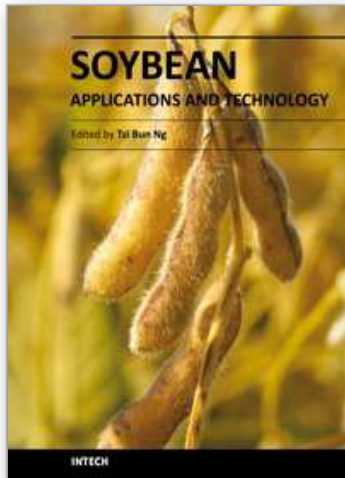


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Soybean is an agricultural crop of tremendous economic importance. Soybean and food items derived from it form dietary components of numerous people, especially those living in the Orient. The health benefits of soybean have attracted the attention of nutritionists as well as common people.

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