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ABSTRACT

This study investigates the possibilities of productivity gains and the technical efficiency of maize farmers in the Mekong Delta (MD), Viet Nam. Using the stochastic production frontier measures such technical efficiency and productivity. The study using the survey data in the two provinces locating in the MD reveals that there was a wide range of variation in technical inefficiency. The latter mainly stems from experience and training participation of maize farmers. The study suggests that there is an opportunity to increase the technical efficiency level of the maize crop in the MD by enhancing the technical guidance of new technologies in maize production through launching several trainings to farmers.

Key words: maize, technical efficiency, productivity, stochastic production frontier.

1. Introduction

Vietnam has a population of 90 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 Delta (MD) is considered the biggest agricultural production area, especially rice production, for the whole country. With the population of 17 million people, the MD has been contributing to the country's food security policy with the diversification of agricultural production. Beside the rice production, farmers in the MD also produce other crops to feed themselves and supply to the market such as: cassava, maize, cashew, so on and especially among of these

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main crops, there is maize that is very popular with farmers in the MD. Although agriculture plays the most important role of economics, its contribution to gross domestic product (GDP) is annually declining (see Nguyen and Grote, 2004). 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). Consequently, several 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). 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 Rieger, 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 (Sharma and Leung, 1998).

To measure such technical efficiency and productivity, several studies (e.g., Ali and Flinn, 1989; Kumbhakar et al., 1991, Belete, et al., 1991; Battese and Coelli, 1992; Battese and Coelli, 1995; Seyoum et al., 1998; Coelli, et al., 2003; Masterson, 2007, Nyemeck et al., 2008) have employed stochastic production frontier models that are calibrated to farmer survey data. For instance, Coelli, et al. (2003) applies a stochastic production frontier model to measure total factor productivity growth, technical efficiency change and technological change in Bangladesh crop agriculture for the 31 observations from 1960/61 to 1991/92, using data for 16 regions. The results reveal that technical change followed a U-shaped pattern, rising from the early 1970s, when the green revolution varieties were adopted, giving an overall rate of technical progress at 0.27 per cent per year. However, technical efficiency declined throughout, at an estimated annual rate of 0.47 per cent. Then, the study of Nyemeck et al., (2008) uses survey data to examine the technical efficiency and productivity potential of cocoa farmers in West and Central Africa. Separate stochastic frontier models are estimated for farmers in Cameroon, Ghana, Nigeria, and Cote d'Ivoire, along with a stochastic meta-production frontier to obtain alternative estimates for the technical efficiencies of farmers in the different countries. The determinants of technical efficiency are assessed to identify the reasons for differences across countries from this paper.

In the shed light of these researches, the examination of technical efficiency of agricultural products has been recognized as an important task by policy makers. Furthermore, one of the important issues is examining what causes a farmer's productive efficiency. For those reasons, the objective of this paper is to measure the possibilities of productivity gains and the technical efficiency of maize farmers in the MD of Viet Nam by answering the research question: *How does the technical efficiency of maize farmers in the MD obtain*? To obtain the suggested aim, this study uses a stochastic production frontier which offers the result for measuring farm–level technical efficiency.

The remainder of this paper is constructed as following. Section 2 provides the technique and models to be used as well as describes the data used in this study. Empirical results are presented in Section 3. Finally, Section 4 is discussion, some concluding remarks, and further research.

2. Research methodology

2.1 Data collection and sample

The analyzed numbers mainly based on the primary data collected in a field survey by interviewing directly farmers in the MD. The survey was conducted at two provinces, namely An Giang and Soc Trang. In An Giang province, we collected the sample in two districts – Cho Moi and Tri Ton. At Soc Trang it is from Long Phu district. The reason that these areas were selected that in the MD, maize cultivation is mainly grown in An Giang and Soc Trang representing the upper and lower MD region, respectively. In addition, according to Department of Agriculture, these provinces have the highest rate of maize households in the MD. Figure 1 represents the map of the MD of Vietnam, in which the provinces were selected in the study. The process of data collection was conducted through the following steps:

- Step 1: Basing on the aim of the study, the questionnaire was designed. The pilot process was conducted in An Giang first to discern whether the current questionnaire is appropriate or not. The questionnaire was checked carefully and revised before the interviewing started. The final stage in this step, the interviewees, the researchers of Can Tho University, were trained to ensure that they precisely understand the purpose of the survey and the questionnaire.
- Step 2: a cluster sampling characterized by geographic location was used in the study. The reason to choose this sampling procedure is that the costs of survey, time to survey (limited by seasonal harvest), and the convenience in organizing the field trip to survey led the decision of this sampling method. Based on the map of crop production, the population was divided by area by area. Then, the areas with extensive crop production were selected in the sample frame. Finally, a random sampling procedure was applied for these areas to obtain the sample.

The survey was run from January to April, 2008. This means that the cross-sectional data analysis was applied for this study. Total samples are 111 farmers. In particularly, 55 farmers in An Giang and 56 farmers in Soc Trang were interviewed directly. Out of this sample, three of the 111 questionnaires did not fulfill the requirements of the questionnaire. Therefore, we left these observations out of the sample. Finally, the observation using in this study is 108.

Figure 1. Map of Vietnam’s Mekong Delta with selected provinces in the study

2.2 Measurement and specification models

Various approaches to efficiency analysis have been used by two parallel traditions, the econometrics methods and non–parametric Data Envelopment Analysis (DEA) methods. Given the available data, in this study, the discussion focuses on the econometric approach of measuring efficiency by using the stochastic production frontier to measure the technical efficiency and productivity of maize product. The basic stochastic frontier model was first proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), other various models have been suggested and applied in the analysis of cross-sectional and panel data on producers. Reviews of some of these models and their applications are given by Bauer (1990), Battese (1992), and Coelli (1995). Some models have been proposed in which the technical inefficiency effects in the stochastic frontier models are also modeled in terms of other observable explanatory variables. Kumbhakar et al. (1991), Huang and Liu (1994), Battese and Coelli (1995), and Coelli, et al. (2005) present different models for the technical inefficiency effects.

The stochastic production frontier

For this study, in order to estimate the technical efficiency of maize 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 maize production. We estimate separate stochastic frontier production functions, of the type proposed by Battese and Coelli (1995) and Coelli, et al. (2005), for maize producers in MRD. The stochastic frontier production model is defined as following:

$$LnY_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + V_i - U_i \quad (1)$$

where:

- Y_i: the subscript, i, indicates the *ith* farmer in the sample (i = 1, 2….108), the yield of maize production on an acre. This dependent variable was measured in maize kilogram/acre.
- X_{1i} (in man-day): the total labor per acre used including both hired labor and family labor. This variable is evaluated by number of labors used per acre.
- X_{2i} *(in kg):* Fertilizer quantities used on an acre. This variable is measured by the number of fertilizer kilograms used per acre.
- X_{3i} *(in ml):* Pesticide quantities used on an acre. This variable is measured by the number of pesticide ml used per acre.
- X_{4i} *(in day):* Machinery service hired on an acre. This variable is measured by the number of hired days used per acre.

β_S are unknown parameters unknown parameters to be estimated; the V_{iS} are assumed to be independent and identically distributed random errors having N(0, σ_v^2) – distribution U_{iS} are non-negative random variables, called technical inefficiency effects, which are assumed to be independently distributed such that U_i is defined by the truncation (at zero) of the normal distribution with mean, μ_i, and variance, σ^2, where μ_i is defined by

$$\mu_i = \delta_0 + \delta_1 Experience + \delta_2 Training \quad (2)$$

where experience is the number of the experience years of the farmers, training is dummy variable, which has value 1 if farmers have attended trainings or 0 if farmer had never attended any training

The maximum-likelihood estimates for all the parameters of the stochastic frontier and inefficiency model, defined by equation (1) and (2), are simultaneously obtained by using the program, FRONTIER Version 4.1 (see Coelli, 1994), which estimates the variance parameters in terms of the parameterization

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 ; (4) \qquad \gamma = \sigma_u^2 / \sigma^2 = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2} (3)$$

The technical efficiency of production of the *ith* farmer in the appropriate data set, given the levels of his inputs, is defined by

$$TE_i = Exp(-U_i) \quad (4)$$

3. Empirical results

3.1. Description and correlation

The frequency of dependent and independent variables are displayed in tables (A0-A5) in the appendix, whereas table 1 shows mean, standard deviation, minimum and maximum value and the statistical significant relationships between the dependent variable and independent variables. First, output is significantly associated with labour and pesticide at 5 percent of significant level and 1 percent for machinery service. Second, the relationship among explanatory variables is quite low; the highest value is 0.417 which is the correlation between machinery services and fertilizer; and that between ones and pesticide. This issue allows us to continue implementing the stochastic frontier production function with including these variables.

Table 1. the matrix of correlation between variables and statistical description

Variables	Mean	S.D	Min.	Max.	1	2	3	4	5	6
1. Output (kg)	427.3	245.9	89.00	900.0	1					
2. Labor (days)	248.3	52.8	108.0	407.0	-0.198**	1				
3. Fertilizer (kg)	215.7	42.7	72.0	308.0	0.105	0.033	1			
4. Pesticide (ml)	101.1	47.7	0.00	233.0	-0.246**	0.336***	0.093	1		
5. Machinery services (days)	6.70	3.90	1.00	24.0	-0.310***	0.417***	0.023	0.417***	1	
6. Experience (years)	5.40	5.40	1.00	30.0	-0.148	-0.058	0.072	0.214**	0.011	1
7. Training (dummy)	0.14	0.34	0.00	1.0	-0.142	-0.177*	0.074	-0.005	0.058	0.185*

*, **, *** *Correlations are significant at the 0.1, 0.05, and 0.01 levels, respectively (2-tailed).*

3.2 The results of stochastic frontier analysis (SFA)

Estimated results from the SFA model are presented in the Table 2. First of all, we should examine the significance of this model to decide whether we can accept the null hypothesis or not; and whether the technical efficiency is affected by the random error (v_i) or technical inefficient factors (u_i).

We see that LR = 25.06, higher than the accepted value (α= 5%) of 6.25 presented in the distribution table χ^2(2α), which allows us to accept the null hypothesis and reject the alternative hypothesis. In other words, effect of technical inefficient factors has a significant level of 5 percent.

The table 2 show that $\gamma = \sigma_u^2 / \sigma^2 = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$= 0.898, and the coefficient $\sigma^2 = \sigma_v^2 + \sigma_u^2$=0.74, which allow us to calculate $\sigma_v^2 = 0.07$(close to zero); $\sigma_u^2 = 0.67$.

The estimated value of γ is 0.898, which means that 90 percent of the total variation in farm output is due to technical inefficiency. Therefore, we can conclude that the effect of technical inefficient factors comes mostly from the random error σ_u^2.

Labor

From the above table, we could see that the labor variable was not statistically significant at 1 percent in SFA model. This proved that using labor for cultivating maize did not affect its output. This conclusion is similar to the previous studies. They found that labor variable did not affect on the yield of maize very much (Ali and Flinn, 1989; Sharman et al., 1998). Indeed, since the agricultural area of the household was averagely 0.7 ha in the MD, this number of area could not create enough work for the household with 5 people. Thus, their attending to agricultural production in general and maize one in particular 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, etc.

Table 2. the estimated results of the SFA model

Variables	Parameters	Coefficient	Standard error	t- ratio
Constant	β_1	6.891***	1.972	3.494
Labour	β_2	-0.192	0.220	-0.873
Fertilizer	β_3	0.137***	0.012	11.42
Pesticide	β_4	0.019***	0.002	9.500
Machinery services	β_5	0.054***	0.008	6.750
<u>Technical inefficient effects</u>				
Experience year	δ_1	- 0.321***	0.061	-5.262
Training	δ_2	- 0.269***	0.019	-14.16
$\sigma^2 = \sigma_v^2 + \sigma_u^2$		0.746***	0.081	9.209
$\gamma = \sigma_u^2 / \sigma^2 = \dfrac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$		0.898***	0.004	224.5
Log maximum likelihood		-85.6		
LR test value		25.06		

**** indicates statistical significance at 1 percent*

Fertilizer

Among independent variables, fertilizer was one of the most important variables. It was sure that this variable was statistically significant at 1 percent level. Clearly, it could cause nearly 14 percent increase of maize production if farmer applied more fertilizer at the rate of 1 percent.

Pesticide

In fact, pesticides have relationship with the output of maize production. In the circle of life, maize regularly deals with some kind of pest incidences as 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, pesticides were statistically significant associated with the amount of maize production.

Machinery

Machinery was used in the preparation of land, the period of irrigation and the harvest time. This machinery also affected the amount of maize harvested at the end of crop, and has statistical significance at 1 percent. However, the amount of maize increase was rather small and not worth considering.

As for the technical inefficiency model, the negative sign of parameters has a significant positive impact on the technical inefficiency. First, the higher farmers' experience is less inefficient than the less ones. This means that the longer the maize cultivation, the greater productivity they obtain. Second, the negative estimate for training implies that farmers with greater training tend to be less inefficient because the application of new technology and production knowledge is considered as important factors to decide in business and household income (Minot, 2003). These findings are appropriate to the previous researches (Battese and Coelli, 1995; Coelli, et al., 2003).

Table 3 shows the frequent distribution of technical efficiency. Technical efficiency indices range from 11.1 percent to 95.6 percent for the farmers in the sample, with an average of 50.1 percent. This means that if the average farmer in the sample was to achieve the technical efficiency level of its most efficient counterpart, then the average farmer could realize a 47.6 percent cost savings (i.e., 1–[50.1/95.6]). A similar calculation for the most technically inefficiency farmer reveals cost saving of 88.5 percent (i.e., 1–[11.1/95.6]). Moreover, farmers obtaining the highest score of technical efficiency from 65 percent to 90 percent were 56 households which counted for above 51.9 percent. On the contrary, the group of the lowest score of technical efficiency below 65 percent was 52 farmers dominated about 48 percent compared to the whole surveyed farmers.

Table 3. Frequent distribution of technical efficiency

Technical level (%)	**Technical efficiency**	
	Frequency	*Percent*
>85	15	13.9
$>65\leq 85$	24	22.2
$>45\leq 65$	17	15.7
$>25\leq 45$	14	13.0
$>10\leq 25$	38	35.2
≤ 10	0	0
Mean (%)	0.501	
Minimum (%)	0.111	
Maximum (%)	0.956	

4. Discussion, concluding remark and further research

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 maize farmers in the MD 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. The more detail is discussed on the determinants of technical efficiency of maize farmers in MD as following:

Labor Seyoun et al. (1998) argued that the more labor has been employed in producing maize, the higher farmers' productivity they have obtained. However, they failed to find evidence to support this claim because of the insignificant coefficient for the relationship between output and labor. Otherwise, others found that there was positively significant relationship between labor and the outcome of farmers (see Ali and Flinn, 1989; Sharman et al., 1998; Battese and Coelli, 1992). Our paper also finds positively relationship between labor and the outcome of maize farmers, but statistically insignificant.

Fertilizer This study finds that farmers applied more fertilizer in their maize production leading significant increase in their product. This issue confirmed the finding of Ali and Flinn (1989) indicating the fertilizer has been used more, the farmers' productivity will be enhanced. Thus, fertilizer is one of the most important factors in deciding whether farmer's production is efficient or not.

Pesticide The finding of the present study is associated with the previous findings is that farmers' productivity is higher when they used more pesticide in production (Ali and Flinn 1989; Seyoun et al., 1998). Therefore, this recommends that pesticide should be considered to examine the technical efficiency of farmers.

Machinery services This study also finds evidence to support the argument that machinery services have directly positive relationship with the efficiency in producing maize in the MD. This issue emphasizes that machinery services play quite important role to enhance the farmers' productivity.

The analysis shows that, for our sample of the maize farmers in the MD, the average technical efficiency is 50.1 percent. In addition, this paper also found that there was a wide range of variation in technical inefficiency that mainly originates from experience of maize farmers and training. Thus, there may be a big opportunity to increase the technical efficiency level of the maize crop in the MD by enhancing the technical guidance of new technologies in maize production with launching several trainings to farmers.

To sum up, this study shows that fertilizer, pesticide and machinery services are the important factors affecting the efficiency of maize producers in the MD. And, their average efficiency obtains at medium level (50.1 percent). Thus, in order to enhance more productivity, they need to obtain more experience and attend more training course.

This paper applied the stochastic frontier method to measure the technical efficiency of maize farmers in MD. This would be the opportunity that the future research can employ other research methods which will create different results, for instance DEA. Hence, the further research should compare the results in different methods to both practical and theoretical implications developed.

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