Efficiency Estimates for the Agricultural Production in Vietnam: A Comparison of Parametric and Non-parametric Approaches

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Abstract

This paper uses both parametric and non-parametric approaches to estimate technical, allocative, and economic efficiencies for the agriculture production in sixty provinces of Vietnam in the period 1990-2005. Under different technology specifications, both approaches show that the average technical, allocative, and economic efficiency estimates were not high, and there would be a large room for the studied provinces to improve their agricultural production efficiency. To examine consistency of the estimates from two approaches under different specifications of returns to scale, we use Spearman rank test, and the results indicate that parametric and non-parametric approaches provide different estimates.

Keywords: *data envelopment analysis (DEA), stochastic frontier production function (SFPF), Spearman rank*

JEL Classification: C14, N5

Introduction

Since the *Doi moi* (renovation) in the late 1980s to transform the country from a centrally–planned economy into a market economy, Vietnam has notched impressive achievements in both social and economic aspects. The economy recorded an average growth of 8 percent over the past decade. Although the agricultural sector has been reduced in terms of both share in gross domestic product (GDP) and number of labors over the past decade, it is still playing an important role in the country, as more than 70 percent of the Vietnamese population are living in rural areas, where agricultural production activities are predominant. In addition, the agricultural sector also recorded remarkable achievements in changing Vietnam from a country with a lot of people living in hunger to a country ranked as one of the biggest exporters of rice in the world since mid-1990s.

However, the agricultural sector in Vietnam is also facing a number of constraints and challenges. For instance, the structure of the agricultural sector has been changed

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very slowly, and agricultural production has been relied substantially on labor-intensive and low-technology production processes under relatively small production size (MOFA, 2007). Under such constraints and potential challenges from the accession to the World Trade Organization (WTO) in early 2007, various policy issues need to be considered for Vietnam as a whole, and the agricultural sector in particular, because competition will be fiercer in an equal playing field. Therefore, looking for appropriate development strategies for the agricultural production, including productivity growth and efficiency improvement, is a must. Comprehensive studies on efficiency estimates for the sector are thus required.

At the best of our knowledge, there have been no studies to estimate technical, allocative, and economic efficiencies for the agricultural production in Vietnam. Therefore, this paper will be the first attempt to do such an important analysis. We will use both parametric and non-parametric approaches to estimate these efficiency measures for agricultural production in sixty provinces of Vietnam in the period 1990-2005. We then provide a comparison of results obtained from these approaches in order to provide more concrete comments on the efficiency performance of the sector.

The remainder of the paper is organized as follows. Section 2 provides analytical framework for measuring efficiency, in which both parametric and non-parametric approaches are presented. Descriptions of data and variables are provided in Section 3. We will present empirical results and analysis in Section 4, and concluding remarks in Section 5.

Analytical Framework

This paper will use both parametric and non-parametric approaches to estimate efficiency of agricultural production in sixty provinces of Vietnam during 1990-2005. The former is based on stochastic frontier production function (SFPF) technique, while the latter is based on data envelopment analysis (DEA) technique.

Parametric Approach

Stochastic Frontier Production Function (SFPF)

The parametric approach in this paper is adopted from Kopp and Diewert (1982)'s cost decomposition procedure to estimate technical, allocative, and economic efficiency measures. In general, the technology of a decision-making unit (DMU) *i* (e.g., a firm, a sector, or a province) represented by a stochastic production frontier can be expressed as follows.

$$Y_i = f\left(X_i;\beta\right)+\varepsilon_i, \quad (i=1, 2, \ldots, N) \tag{1}$$

where Y_i denotes the outputs of the i^{th} DMU; $X_i = \left(x_{i1}, x_{i2}, ..., x_{iP}\right)$ is a vector of functions of actual input quantities used by the i^{th} DMU; β is a vector of parameters to be estimated; ε_i is the composite error term; and N is the number of DMUs.

In Aigner *et al*. (1977) and Meeusen and Van den Broeck (1977), ε_i is defined as follows.

$$e_i = v_i - u_i \ , \quad (i=1, 2, \ldots, N) \tag{2}$$

where v_is are assumed to be independently and identically distributed (i.i.d) random errors under distribution $N\left(0, \sigma_v^2\right)$, and they are independent of the u_is; and u_is are non-negative random errors, which are associated with technical inefficiency in production, and assumed to be i.i.d and truncated (at zero) under normal distribution with mean μ, and variance $\sigma_u^2 \left(\left|N\left(\mu, \sigma_u^2\right)\right|\right)$.

The maximum likelihood estimation for equation (1) provides estimators for β and variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$, as well as $\gamma = \sigma_u^2 / \sigma^2$.

Replacing equation (2) into equation (1), and then subtracting v_i from both sides of equation (1) to yield:

$$\tilde{Y}_i = Y_i - v_i = f\left(X_i; \beta\right) - u_i, \tag{3}$$

where $\tilde{Y}_i$ is the observed output of the i^{th} DMU, and it is adjusted for the stochastic noise captured by v_i.

Equation (3) is the basis for deriving the technically efficient input vector and the dual cost frontier of the production function represented by equation (1). For a given level of output $\tilde{Y}_i$, the technically efficient input vector for the i^{th} DMU (X_i^t) is derived by simultaneously solving equation (3).

Assuming that the production function in equation (1) is self–dual (such as Cobb-Douglas form), the dual cost frontier can be derived algebraically. The cost function for the i^{th} DMU facing the fixed factor price $W_i > 0$ is defined as the minimum-value function of the cost minimization. Solving the problem, we can get:

$$C_i = h\left(W_i, \tilde{Y}_i, \psi\right), \tag{4}$$

where ψ is a vector of parameters, and Ws are input prices. The economically efficient input vector for the i^{th} DMU is derived by using Shephard's lemma, denoting X_i^e.

The observed technically efficient and economically efficient costs of production of the i^{th} DMU are equal to $\sum_{j=1}^{P} x_{ij}^t w_j$ and $\sum_{j=1}^{P} x_{ij}^e w_j$, respectively. These cost measures are used to compute technical efficiency (TE) and economic efficiency (EE) indices for the i^{th} DMU as follows.

$$TE_i = \frac{\sum_{j=1}^{P} w_{ij} x_{ij}^t}{\sum_{j=1}^{P} w_{ij} x_{ij}}. \tag{5}$$

$$EE_i = \frac{\sum_{j=1}^{P} w_{ij} x_{ij}^e}{\sum_{j=1}^{P} w_{ij} x_{ij}}. \tag{6}$$

Following Farrell (1957), the allocative efficiency (*AE*) index can be derived from equations (5) and (6) as follows.

$$AE_i = \frac{\sum_{j=1}^{P} w_j x_{ij}^e}{\sum_{j=1}^{P} w_j x_{ij}^t}. \tag{7}$$

Therefore, the total cost or economic inefficiency of the i^{th} DMU, i.e. $(W_i.X_i - W_i.X_i^e)$, can be decomposed into technical inefficiency, i.e. $\left(W_i.X_i - W_i.X_i^t\right)$, and allocative inefficiency, i.e. $\left(W_i.X_i^t - W_i.X_i^e\right)$.[1]

Empirical Models

Model 1: Production function and cost frontier

Under the parametric approach, we will use the Cobb-Douglas stochastic production frontier to estimate efficiency levels for the agricultural production activities in the sample provinces of Vietnam. The production function is generally specified as follows.

$$\ln Y_i = \beta_o + \beta_1 \ln x_{i1} + \beta_2 \ln x_{i2} + \beta_3 \ln x_{i3} + \varepsilon_i, \tag{8}$$

where Y_i is output and x_is are inputs for the agricultural production activities in the i^{th} province. Specifically, these variables are defined as follows.

- Y_i (Output) is the gross value-added (GVA) of the i^{th} province's agricultural production activities. It is calculated as the sum of the value-added of the main agricultural production activities in the i^{th} province, including farming, forestry, animal husbandry, fishing, and sideline activities. It is measured in billions of Vietnamese Dong (VND);
- x_{i1} (Labor) is the number of labors used in these agricultural production activities in the i^{th} province. It is measured in thousand persons.
- x_{i2} (Fertilizers): is total amount of fertilizers used in these agricultural production activities in the i^{th} province. It is measured in thousand tons;
- x_{i3} (Land): is the total area used for these agricultural production activities in the i^{th} province. It is measured in thousand hectares;
- βs are parameters to be estimated; and
- ε_i is the composite error term, which was defined previously.

Note that, the production frontier in equation (8) represents the variable returns to scale (VRS) technology.

In order to obtain the production frontier under the constant returns to scale (CRS) technology, we impose a restriction that the sum of the output elasticities of inputs equals to one, i.e., $\sum_{k=1}^{3} \beta_k = 1$. It means that, under CRS technology, we will estimate a production function as follows.

$$\ln(Y_i / x_{i3}) = \alpha_o + \alpha_1 \ln(x_{i1} / x_{i3}) + \alpha_2 \ln(x_{i2} / x_{i3}) + \varepsilon_i \,, \tag{9}$$

where

- (Y_i/x_{i3}) is per-hectare gross value-added of agriculture production activities in the i^{th} province during the study period;
- (x_{i1}/x_{i3}) is per-hectare number of labors. This variable implies the level of labor intensity in agriculture production activities in the i^{th} province during the study period; and
- (x_{i2}/x_{i3}) is per-hectare tons of fertilizers. This variable shows how much fertilizers were used in agriculture production activities in the i^{th} province during the study period.

The cost function can be obtained from production function in equation (8) by solving the cost-minimizing problem.

The dual cost frontier of the production function in equation (8) is then expressed as follows.

$$\ln(C_i / W_{i3}) = \alpha_0 + \alpha_1 \ln(W_{i1} / W_{i3}) + \alpha_2 \ln(W_{i2} / W_{i3}) + \alpha_3 \ln Y_i \,, \tag{10}$$

where C_i is the minimum cost for agricultural production activities in the i^{th} province; and Y_i is the output of the province *i*.

Model 2: Inefficiency effects model

With regard to the technical inefficiency effect model, the component of technical inefficiency effects in the frontier production function is defined to rely on province-specific factors, including capital-labor ratio (which is approximated by the ratio of number of tractors and number of labors) and geographic location (or economic regions). The following is the specification for the model 2:

$$u_{it} = \delta_0 + \delta_{kl} Ln(tractor / labor) + \delta_1 x_1 + \delta_2 x_2 + \delta_4 x_4 + \delta_5 x_5 + \delta_6 x_6 + \delta_7 x_7 + \delta_8 x_8 + \delta_9 t + w_t \,, \tag{11}$$

where:

- *Ln(tractor/labor)* is the natural logarithm of number of tractors per labor.
- x_1 is dummy variable =1 if province is in the region 1,[2] and = 0 otherwise.
- x_2 is dummy variable =1 if province is in the region 2, and = 0 otherwise.
- x_4 is dummy variable =1 if province is in the region 4, and = 0 otherwise.
- x_5 is dummy variable =1 if province is in the region 5, and = 0 otherwise.
- x_6 is dummy variable =1 if province is in the region 6, and = 0 otherwise.
- x_7 is dummy variable =1 if province is in the region 7, and = 0 otherwise.
- x_8 is dummy variable =1 if province is in the region 8, and = 0 otherwise.
- t is time; and
- w_t is errors terms which are assumed to be independently and identically distributed followed by the truncation of the normal distribution with zero mean and unknown variance σ_w^2.

Non-parametric Approach

The non-parametric approach in this paper is based on the data envelopment analysis (DEA) technique (Charnes *et al*., 1978; and Färe *et al*., 1985, 1994) in order to estimate technical, scale, allocative, and economic efficiency measures for agricultural production activities in the sampled provinces.

Suppose that we have N provinces (N=60), each producing one output by using k=1, 2, …, P inputs. Let Y_i be the output the i^{th} province (i=1,2,…, N), and x_{ik} be the k^{th} input of the i^{th} province (i=1,2,…, N; k=1,2,…, P). Also, let λ_j (j=1, 2,…, N) be a weight.

The CRS input-oriented measure of technical efficiency (TE) for the i^{th} province is calculated as the solution to the following programming problem.

$$\theta = \min_{\theta_i^{CRS},\lambda} \theta_i^{CRS} \tag{12}$$

subject to:

$$Y_i \le \sum_{j=1}^{N} \lambda_j Y_j, \quad \text{where } i=1, 2, \ldots, N \tag{13}$$

$$\sum_{j=1}^{N} \lambda_j x_{jk} \le \theta_i^{CRS} x_{ik}, \quad \text{where } i=1, 2, \ldots, N;\ k=1, 2, \ldots, P \tag{14}$$

$$\lambda \ge 0, \tag{15}$$

where θ_i^{CRS} is the technical efficiency (TE) measure of the i^{th} province under CRS technology.

If $\theta_i^{CRS} = 1$, the i^{th} province's agriculture production is on the frontier and is technically efficient under CRS. If $\theta_i^{CRS} < 1$, the i^{th} province's agriculture production is below the frontier and is technically inefficient under CRS. Under CRS DEA, the technically efficient cost of production of the i^{th} province is given by $W_i\ .\left(\theta_i^{CRS} X_i\right)$.

In order to derive a measure of the total or overall economic efficiency (CE) index, we solve the cost–minimizing DEA model (Färe *et al*., 1985, 1994) as follows.

$$\min_{x_j^*\lambda} \sum_{k=1}^{P} w_{ik} x_{ik}^*, \tag{16}$$

subject to:

$$Y_i \le \sum_{j=1}^{N} \lambda_j Y_j, \quad \text{where } i=1, 2, \ldots, N \tag{17}$$

$$\sum_{j=1}^{N} \lambda_j x_{jk} \le x_{ik}^*, \quad \text{where } i=1, 2, \ldots, N;\ k=1, 2, \ldots, P \tag{18}$$

$$\lambda \ge 0, \tag{19}$$

where x_i^* is the cost–minimizing or economically efficient input vector for the i^{th} province, given its input price vector and output level. The CE index for the i^{th} province is then computed as follows.

$$CE_i = \frac{\sum_{k=1}^{P} x_{ik}^* w_{ik}}{\sum_{k=1}^{P} x_{ik} w_{ik}}, \tag{20}$$

which is the ratio of the minimum cost to the observed cost.

The allocative efficiency (*AE*) index, derived from equations (12) and (20), is expressed as follows.

$$AE_i = \frac{CE_i}{\theta_i^{CRS}}. \tag{21}$$

It should be noted that equation (17) also accounts for the input slacks, which are not captured by equation (15). Following Ferrier and Lovell (1990), this procedure attributes any input slacks to allocative inefficiency on the ground that slack reflects an inappropriate input mix.

The overall technical efficiency under CRS (TE_{CRS}) can be decomposed into two components, i.e., "purely" technical efficiency and scale efficiency, by solving a VRS DEA model, which is in turn obtained by imposing the additional constraint $\sum_{j=1}^{N} \lambda_j = 1$ on equation (15) (Banker *et al*., 1984). Let θ_i^{VRS} denote the *TE* index of the i^{th} province under VRS (TE_{VRS}), then the technically efficient costs of production of the i^{th} province under VRS is equal to $\sum_{k=1}^{P} w_{ik} x_{ik}^* \theta_i^{VRS}$.

Because the VRS analysis is more flexible and envelops the data in a tighter way than the CRS analysis, we usually have VRS TE measure (θ^{VRS}) to be equal or greater than the CRS TE measure (θ^{CRS}). This relationship is used to obtain a measure of scale efficiency (*SE*) of the i^{th} province as follows.

$$SE_i = \frac{\theta_i^{CRS}}{\theta_i^{VRS}}, \tag{22}$$

where $SE = 1$ indicates scale efficiency, and $SE < 1$ indicates scale inefficiency.

Scale inefficiency is due to the presence of either increasing or decreasing returns to scale, which can be determined through a non-increasing returns to scale (NIRS) DEA model by substituting the VRS constraint $\sum_{j=1}^{N} \lambda_j = 1$ with $\sum_{j=1}^{N} \lambda_j \leq 1$. Let θ^{NIRS} represent the technical efficiency measure under NIRS specification. If $\theta^{NIRS} = \theta^{CRS}$, there are increasing returns to scale, and if $\theta^{CRS} < \theta^{NIRS}$ there are decreasing returns to scale (Färe *et al*., 1994).

Descriptions of Data and Variables

In this paper, we will use panel data of inputs and output for agricultural production activities in sixty provinces of Vietnam in the period 1990-2005. The data were collected by the General Statistics Office of Vietnam (GSO) through the years.

Table 1 provides statistical summary for output (gross value-added or GVA) and inputs (labor, machinery, fertilizers, and land).

Table 1. Summary of Inputs and Output

Year	*Obs.*	*GVA (VND Million)*	*Labor (1,000 persons)*	*Tractor (unit)*	*Fertilizers (1,000 tons)*	*Land (1,000 hectares)*
1990	60	35,650	17,674	25,155	748	6,989
1991	60	36,248	18,270	35,412	1,452	6,921
1992	60	39,003	21,854	37,278	1,426	7,214
1993	60	40,499	22,647	45,026	1,449	7,257
1994	60	41,479	23,276	87,188	2,253	7,276
1995	60	43,541	23,901	95,527	2,398	7,276
1996	60	45,774	23,978	108,397	3,038	7,589
1997	60	48,272	24,601	113,117	3,180	7,743
1998	60	50,767	24,869	120,605	3,297	7,973
1999	60	53,518	25,082	143,360	3,462	8,601
2000	60	55,395	25,221	162,246	3,553	9,230
2001	60	56,147	25,426	161,492	3,513	9,391
2002	60	57,891	25,876	167,322	3,437	9,250
2003	60	62,384	26,620	179,670	3,719	9,554
2004	60	63,960	26,550	193,504	3,776	9,648
2005	60	65,928	26,714	201,490	3,791	9,715

Source: Authors' estimates.

As mentioned earlier, the output is the sum of the value-added of production from farming, forestry, animal husbandry, fishing, and sideline activities. All the values of GVA reported in Table 1 are adjusted by the Vietnam's GDP deflator, in which the year 1994 is the base year. As can be seen, the GVA of the agricultural production has increased significantly over the past decade.

The number of labors used in the empirical models excludes labor force working for the rural industries, construction, transportation, commerce, and other miscellaneous occupations. Only labors working for farming, forestry, animal husbandry, fishery, and sideline production activities are included.

Machinery is considered as capital input for the agricultural production activities in this paper, and it is measure by the number of tractors used for farming, forestry, animal husbandry, fishery, and sideline production activities, such as plowing, irrigating, draining, harvesting, farm product processing, transportation, plant protection, and stock breeding.

Fertilizers refer to the sum of pure weight of nitrogen, phosphate, potash, and complex fertilizers, while land refers to total cultivated areas at the end of each year.

Empirical Results and Analysis

Estimated Results from Parametric Approach

We first conduct some hypotheses tests with the maximum–likelihood estimates of parameters in the Cobb-Douglas stochastic frontier production function, defined in equations (8) and (9), which are obtained for the total sample.

Table 2a presents the test results of various null hypotheses on the sample. The null hypotheses are tested by using likelihood ratio test. The likelihood–ratio test statistic is $\lambda = -2\left[L(H_0) - L(H_1)\right]$, where $L(H_0)$ and $L(H_1)$ are the values of the log-likelihood function under the specifications of the null and alternative hypotheses, H_0 and H_1, respectively. If the null hypothesis is true, then λ has approximately a Chi-square (or mixed Chi-square) distribution with degrees of freedom equal to the number of restrictions.

Table 2a. Statistics for Tests of Hypotheses

Null Hypothesis	Log-likelihood Function	Test Statistics (λ)	Critical Value		Decision
			1%	0.5%	
Under the assumptions of CRS					
$H_0: \mu = 0$, η=0 $H_1: \mu \neq 0$, η=0	300.502 331.251	61.489	6.63		Reject
$H_0: \mu = 0$, η=0 $H_1: \mu = 0$, $\eta \neq 0$	300.502 322.45	61.489	6.63		Reject
$H_0: \mu = 0$, η=0 $H_1: \mu \neq 0$, $\eta = 0$	300.502 322.45	62.676	8.273	9.634	Reject
$H_0: \mu = \gamma = \eta = 0$	-296.68	1257.04			Reject
Under the assumptions of VRS					
$H_0: \mu = 0$, η=0 $H_1: \mu \neq 0$, η=0	353.55 362.352	17.604			Reject
$H_0: \mu = 0$, η=0 $H_1: \mu = 0$, $\eta \neq 0$	353.55 365.482	23.864			Reject
$H_0: \mu = 0$, η=0 $H_1: \mu \neq 0$, $\eta \neq 0$	353.55 378.161	49.22			Reject
$H_0: \mu = \gamma = \eta = 0$	-276.863	1310.048			Reject

Note: The critical value for this test involving γ=0 is obtained from Kodde and Palm (1986). Every null hypothesis is rejected at the 1 percent significance level.

Source: Authors' estimates

The first null hypothesis test, i.e. u_i is nonnegative half normal distribution with μ=0. The results suggest that the technical efficiency component is following the truncated normal distribution.

The second null hypothesis, i.e. there are no technical inefficiency effects or $\left(H_0 : \gamma = \mu = \eta = 0\right)$, is rejected at 1% significance level for both cases. If the null hypothesis is true, there are no frontier parameters in the regression equation, and the estimation becomes an ordinary least square estimation. The results suggest that the average production function is an inadequate representation of the Vietnamese agricultural sector, and it will underestimate the actual frontier due to technical inefficiency effects.

To estimate production frontier for the agricultural production in the sampled provinces, both cases of Cobb-Douglass production function under the CRS and VRS are employed in this paper.

We use the computer program FRONTIER Version 4.1 (Coelli, 1996a) for our estimation. The maximum-likelihood (ML) estimates of the parameters for the stochastic production frontier obtained from the program are presented in Table 2b.

Table 2b. Maximum Likelihood Estimates for Parameters Models under the Assumption of Constant Returns to Scale (CRS)

	Parameter	**Model 1**			**Model 2**		
		coefficient	***Standard-error***	***t-ratio***	***coefficient***	***standard-error***	***t-ratio***
Constant	α_0	9.3890	0.0749	125.2765	8.9459	0.0271	330.1344
Ln(labor/land)	α_1	0.2737	0.0251	10.8914	0.7315	0.0252	29.0078
Ln(fertilizer/land)	α_2	0.1782	0.0157	11.3187	0.1526	0.0195	7.8303
Constant	δ_0				1.1704	0.0421	27.7921
Ln(tractor/labor)	δ_{kl}				-0.0867	0.0089	-9.7453
x_1	δ_1				-0.3208	0.0425	-7.5422
x_2	δ_2				-0.1643	0.0349	-4.7145
x_4	δ_4				0.0370	0.0346	1.0704
x_5	δ_5				-0.0777	0.0471	-1.6503
x_6	δ_6				-0.4448	0.0526	-8.4517
x_7	δ_7				-0.3398	0.0494	-6.8804
x_8	δ_8				-0.3879	0.0421	-9.2212
t	δ_9				0.0071	0.0019	3.7263
Sigma-squared	σ^2	0.1755	0.0332	5.2819	0.0653	0.0028	23.6183
Gama	γ	0.8752	0.0207	42.2103	1.0000	0.0000	190801
	μ	0.7839	0.0824	9.5163			
	η	0.0017	0.0018	0.9711			
Log Likelihood		331.8482	0.0000	0.0000	-50.2924	0.0000	0.0000

Note: $\sigma^2 = \sigma_u^2 + \sigma_v^2$; and $\gamma = \sigma_u^2 / \sigma^2$.

Source: Authors' estimates.

As expected, the signs of the slope coefficients of the stochastic production frontier are positive and highly significant. The estimate of the variance parameter, γ, is also positive and significantly different from zero, implying that the inefficiency effects are significant in determining the level and the variability of output of the agricultural production activities in the sampled provinces.

The estimation of Cobb-Douglass production function under the VRS assumption in Table 2b also shows that the output elasticity of labor (0.2737) is higher than the output elasticities fertilizers (0.1782). Thus, it is obvious that the agricultural production activities in the sampled provinces of Vietnam during the study period were heavily relied on labor.

As mentioned, the variance σ^2 helps to know whether the sampled provinces had higher production efficiency during the study period, as it represents the total variance of output. This variance contains a random error term (σ_v^2) and a technical inefficiency term (σ_u^2). Table 2c indicates that σ^2 is small (only 0.2286), meaning that there were insignificant changes in the agricultural outputs of the sampled provinces over the past decade.

Table 2c. Maximum Likelihood Estimates for Parameters of Inefficiency Model under the Assumption of Variable Returns to Scale (VRS)

Variables	***Parameter***	**Model 1**			**Model 2**		
		coefficient	***Standard-error***	***t-ratio***	***coefficient***	***standard-error***	***t-ratio***
Constant	β_0	11.4232	0.2350	48.6146	8.7966	0.1148	76.6476
Ln(labor)	β_1	0.0850	0.0335	2.5352	0.7451	0.0390	19.0901
Ln(fertilizer)	β_2	0.1772	0.0165	10.7407	0.1523	0.0327	4.6583
Ln(land)	β_3	0.4044	0.0264	15.3105	0.1425	0.0279	5.1145
Constant	δ_0				1.2204	0.1529	7.9802
Ln(tractor/labor)	δ_{kl}				-0.0878	0.0101	-8.6637
x_1	δ_1				-0.3365	0.0534	-6.3016
x_2	δ_2				-0.1823	0.0434	-4.1995
x_4	δ_4				0.0310	0.0521	0.5943
x_5	δ_5				-0.0988	0.0509	-1.9398
x_6	δ_6				-0.4420	0.0672	-6.5750
x_7	δ_7				-0.3390	0.0596	-5.6901
x_8	δ_8				-0.3668	0.0506	-7.2486
t	δ_9				0.0083	0.0032	2.5759
Sigma-squared	σ^2	0.2286	0.0154	14.8205	0.0658	0.0040	16.5584
Gama	γ	0.9127	0.0070	130.2018	1.0000	0.0855	11.6983
	μ	0.9137	0.0578	15.8193			
	η	0.0079	0.0014	5.5913			
Log Likelihood		378.1612	0.0000	0.0000	-48.5002	0.0000	0.0000

Note: $\sigma^2 = \sigma_u^2 + \sigma_v^2$; and $\gamma = \sigma_u^2 / \sigma^2$.

Source: Authors' estimates.

In both Table 2b and 2c, the estimates for variables representing regions show a positive and statistically significant coefficient for the Region 4, while negative and statistically significant coefficients for other seven regions. In other words, location had significant impacts on the efficiency of the studied agricultural production activities. Also, in both Tables 2b and 2c, the coefficients for the variable representing capital-labor ratio, i.e. *Ln(tractor/labor)*, are both negative and statistically significant, meaning that technical inefficiency would have been reduced if agricultural labors had been more technically equipped.

Table 2d. Maximum Likelihood Estimates for Parameters for Cost Frontier under the Assumptions of Constant Returns to Scale (CRS)

Variables / Parameters	*Coefficient*	*Standard-error*	*t-ratio*
LnA	-1.4352	0.4400	-3.2614
$Ln(W_1/W_3)$	0.4297	0.0258	16.6502
$Ln(W_2/W_3)$	0.0762	0.0192	3.9787
LnY	0.4953	0.0369	13.4086
σ^2	0.1733	0.0142	12.2297
γ	0.9219	0.0074	124.2878
μ	0.7995	0.1447	5.5241
η	-0.0103	0.0017	-5.9350
Log likelihood	499.8574	0.0000	0.0000
A	0.3187		

Source: Authors' estimates.

The dual cost frontier model, derived from the stochastic production function, is presented in Table 2d. In the form of Cobb-Douglas cost function, we have:

$$C(W,Y) = 0.3187 W_1^{0.43} W_2^{0.0076} W_3^{0.494} Y^{0.495}$$

Again, significant differences between the coefficients for labor (0.43), land (0.494), and fertilizers (0.0076) show that the costs of the agricultural production activities in the sampled provinces were heavily depended on the costs of labor and land.

Table 3 shows the frequency distribution of the estimated technical efficiency measures for the agricultural production of the sampled provinces under CRS and VRS assumptions and cost efficiency estimated from cost function under the assumption of CRS. The estimated mean technical efficiency was 46.88 percent under the CRS assumption, and 37.32 percent under VRS assumption. These estimates imply that there were considerable inefficiencies in the agricultural production activities of the sampled provinces. In other words, there would be a substantial room for these provinces to improve their agricultural production efficiency.

More than 90 percent of the sampled provinces had technical efficiency at less than 60 percent, while only about 5 percent of these province had technical efficiency of more than 80 percent. The estimated results also show that there was a wide range of technical efficiency of agricultural production between the sampled provinces, as the highest efficiency was about 82.68, while the lowest efficiency was only 13.38 percent.

Table 3. Frequency Distribution of Production Efficiency under CRS, VRS, and Cost Efficiency (CE)

Efficiency Range	**Variable Returns to Scale (TEVRS)**			**Constant Returns to Scale (TECRS)**			**Cost Efficiency (CE)**		
	Mean	***Std. Dev.***	***Obs.***	***Mean***	***Std. Dev.***	***Obs.***	***Mean***	***Std. Dev.***	***Obs.***
[0, 0.2)	0.1761	0.0206	9	0.1866	n.a	1			
[0.2, 0.4)	0.2722	0.0598	22	0.2972	0.0573	19	0.3282	0.0463	31
[0.4, 0.6)	0.4812	0.0578	25	0.4910	0.0536	26	0.4852	0.0567	25
[0.6, 0.8)	0.6542	0.0148	3	0.6422	0.0303	12	0.6708	0.07034	3
[0.8, 1)	0.8268	n.a	1	0.9101	0.0409	2	0.9951	n.a	1
All	0.3732	0.1577	60	0.4688	0.1618	60	0.4219	0.1326	60
Mean	0.3732			0.4688			0.4219		
Median	0.3808			0.4770			0.3942		
Maximum	0.8268			0.9390			0.9951		
Minimum	0.1338			0.1866			0.2246		
Std. Dev.	0.1577			0.1618			0.1326		
Obs.	60			60			60		

Source: Authors' estimates.

Estimated Results from Non-parametric Approach

The DEA models are estimated by using the computer program DEAP Version 2.0 (Coelli, 1996b).

Table 4 presents the technical, allocative, and economic efficiency measures estimated from the DEA, as well as their frequency distributions. The estimated mean technical efficiency was 66.3 percent for the CRS DEA model (*crste*), and 72.6 percent for the VRS DEA model (*vrste*). Only 21.7 percent of the sampled provinces (or 13 out of 60) were in interval of [80 %, 100%) efficient under the CRS DEA model, while 35.6 percent of the sample (or 22 out of 60) were interval of [80 %, 100%) efficient under VRS DEA model. The scale efficiency varied from 60 percent to 100 percent, with a mean of 90.9 percent.

The estimated allocative efficiency indices under CRS assumptions are presented in Table 5. The mean allocative efficiency (*AE*) and cost efficiency (*CE*) indices under the CRS assumptions estimated from the cost-minimizing DEA model were 80.52 percent and 50.92 percent, respectively. Therefore, under DEA models, especially with CRS assumption, it is shown that there were substantial inefficiencies in the agricultural production activities in the sampled provinces during the past decade.

The distribution of the estimated economic efficiency indices in Table 5 shows that there was a wide range of economic efficiency differences. The minimum economic efficiency level was only 24 percent, while the maximum level was as high as 98.69 percent. About 61.7 percent of the sampled provinces (or 37 out of 60) had economic efficiency level between 20 percent and 60 percent, meaning that there was a large room for these economically inefficient provinces to improve their economic efficiency of the agricultural production activities. The number of provinces with economic efficiency ranged from 80 percent to 100 percent was extremely low, only about 5 percent (3 out of 60) under CRS DEA model.

Table 4. Frequency Distribution of Production Efficiency

Range	*crste (DEA model)*			Range	*vrste (DEA model)*			Range	*Scale*		
	Mean	*Std. Dev.*	*Obs.*		*Mean*	*Std. Dev.*	*Obs*		*Mean*	*Std. Dev.*	*Obs.*
[0.2, 0.4)	0.376	0.007	3	[0.4, 0.6)	0.502	0.037	11	[0.6, 0.7)	0.670	0.032	2
[0.4, 0.6)	0.521	0.064	21	[0.6, 0.8)	0.691	0.060	27	[0.7, 0.8)	0.780	0.018	4
[0.6, 0.8)	0.702	0.056	23	[0.8, 1)	0.870	0.056	20	[0.8, 0.9)	0.855	0.027	16
[0.8, 1)	0.887	0.064	13	[1, 1.2)	1.000	0.000	2	[0.9, 1)	0.957	0.028	38
All	0.663	0.162	60	All	0.726	0.150	60	All	0.909	0.078	60
Mean	0.663				0.726				0.909		
Median	0.652				0.731				0.927		
Maximum	0.989				1.000				0.995		
Minimum	0.370				0.446				0.647		
Std. Dev.	0.162				0.149				0.078		
Obs.	60				60				60		

Source: Authors' estimates.

Table 5. Frequency Distributions of Production Efficiency under CRS and VRS, estimated from the cost-minimizing DEA model

AE				CE			
Range	*Mean*	*Std. Dev.*	*Obs.*	*Range*	*Mean*	*Std. Dev.*	*Obs.*
[0.6, 0.7)	0.6615	0.0202	5	[0.2, 0.4)	0.3275	0.0540	13
[0.7, 0.8)	0.7591	0.0279	24	[0.4, 0.6)	0.4968	0.0567	24
[0.8, 0.9)	0.8457	0.0313	25	[0.6, 0.8)	0.6703	0.0446	20
[0.9, 1)	0.9411	0.0310	6	[0.8, 1)	0.9215	0.0648	3
All	0.8052	0.0775	60	All	0.5392	0.1627	60
Mean	0.8052				0.5392		
Median	0.8038				0.5427		
Maximum	0.9978				0.9869		
Minimum	0.6344				0.2400		
Std. Dev.	0.0775				0.1627		
Obs.	60				60		

Source: Authors' estimates.

A Comparison of Parametric and Non-parametric Estimates

In this paper we applied two approaches to estimate technical, allocative, and economic efficiency measures for the agricultural production activities, in which the parametric approach is based on SFPF technique, while the non-parametric is based on DEA technique. It might not be expected that efficiency estimates obtained from one technique would be more (or less) than those obtained from the other technique. However, in this paper, we can see that the estimated average efficiency levels based on SFPF model under CRS and VRS (37.32 percent and 46.88 percent, respectively) are much lower than those obtained from DEA model (66.3 percent and 72.6 percent, respectively).

The question is why these approaches provided different estimated results under the same assumptions on returns to scale, and the same set of data? To examine this question, we compute the Spearman rank correlations between efficiency rankings of the sampled provinces. The results are presented in Table 6.

Table 6. Spearman Rank Correlations

Efficiency	*SFPF*	*DEA*	*Spearman rank correlation (p)*	*Probability*
TE_{CRS}	46.88	66.3	0.8724	0.000
TE_{VRS}	37.32	72.6	0.6472	0.000
CE_{CRS}	42.18	53.92	0.3025	0.0178

Source: Authors' estimates.

The results show that, on average, the estimated technical efficiency levels under CRS and VRS assumptions from SFPF model are significantly smaller than those from DEA model. Therefore, under the same set of data, the assumption on returns to scale is found to be critical in explaining the differences in efficiency measures obtained from these approaches.

However, it is not really surprised to have such different estimates from two approaches, as these estimates are consistent with the expectation that efficiency scores obtained from the non-parametric approach would be higher than those from the parametric approach. This comment has been indicated in a number of existing studies. For instance, Drake and Weyman-Jones (1996), exploring the UK building firms, produced insignificant rank correlation coefficients between the estimated efficiency levels from both approaches. Ferrier and Lovell (1990) found higher technical efficiency, but lower economic efficiency for the parametric method in comparison with the non-parametric method, and insignificant rank correlations between the estimated efficiencies from two approaches. Using the data for the Guatemalan farmers, Kalaitzandonakes and Dunn (1995) reported a significantly higher level of mean technical efficiency under CRS DEA than under the stochastic frontier.

The differences in the estimated results from two approaches could be mainly attributed to the different characteristics of the data, the choice of input and output variables, measurement and specification errors, as well as estimation procedures.

Concluding Remarks

This paper uses and compares both parametric and non-parametric approaches in estimating technical, allocative, and economic efficiency measures for the agricultural production activities in sixty provinces of Vietnam during 1990-2005. The parametric approach is based on Kopp and Diewert (1982)'s cost decomposition to estimate efficiency measures for a Cobb-Douglas stochastic production function and dual cost frontier, while the non-parametric approach is based on various input-oriented DEA models.

Under the CRS specification, the average technical, allocative, and economic efficiency estimates were 66.3 percent, 80.52 percent, and 53.92 percent, respectively, in parametric approach, and 46.88 percent, 90.35 percent, and 42.18 percent, respectively, in non-parametric approach. Under the VRS specification, technical efficiency estimated from parametric approach was 37.32 percent, in non-parametric approach, while it was 72.6 percent. On average, the estimated technical and economic efficiencies were significantly higher in the non-parametric approach than in parametric approach. However, the efficiency rankings of the sampled provinces based on these two approaches are positively and significantly correlated.

By operating at full economic efficiency levels, the sampled provinces would be able to reduce their costs of agricultural production activities about 46 to 76 percent, depending upon the estimation approach and the assumption on returns to scale. In other words, there would be a large room for the studied provinces to improve their agricultural production efficiency.

The comparison of the estimated results from two approaches shows that they were different, in which DEA provided higher estimates than those from SFPF. The differences could be attributed to various reasons, such as the choice of input and output variables, and measurements and specification errors.

Notes

1 $X.Y$ denoting dot product (or scalar product) for two vectors $X = (x_1, x_2, ..., x_n)$ and $Y = (y_1, y_2, ..., y_n)$. Thus, $X.Y = \sum_{i=1}^{n} x_i y_i$.

2 In Vietnam, there are eight economic regions: Northeast (Region 1), Northwest (Region 2), Red River Delta (Region 3), North Central Coast (Region 4), South Central Coast (Region 5), Central Highlands (Region 6), Southeast (Region 7), and Mekong River Delta (Region 8).

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