Parametric and Non-parametric Estimates of Technical Efficiency for Aquaculture-processing Firms in Vietnam

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Abstract

This paper focuses on technical efficiency measurement, mainly on pure technical efficiency, with an empirical study for the aquaculture-processing firms in Vietnam in 2002. Two widely used models, i.e., data envelopment analysis (as non-parametric estimation) and stochastic frontier production function (as parametric estimation with two-stage procedure), are employed for this purpose. Findings could imply some policies for this sector. It is found that that pure technical efficiency of Vietnam's aquaculture-processing firms averaged around 40 to 60 percent. Factorial effects were mainly from regional differences, external cost ratio, capital-labor ratio, wage, and firm size. Ownership seemed not to affect technical efficiency. Additionally, the northern firms were more efficient than the southern ones, and larger firms performed better than smaller ones.

Key words: aquaculture-processing firms, efficiency, data envelopment analysis (DEA), productivity, stochastic frontier production function (SFPF), Tobit regression, Vietnam.

JEL Classification: C14, Q22

1. Introduction

Efficiency has attracted many policy makers and empirical economists because of its important application in reality. Of course, it is impossible to measure "absolute" efficiency because there are no common production functions for the "absolute" maximum output for any specific firm while taking into account other firms. Farrell (1957) attempted to determine relative efficiency, estimating the level of efficiency of a specific firm by comparing it to the best-practice firms. He also classified efficiency into two types: allocative efficiency and technical efficiency.

Figure 1 represents these two types of efficiency. The technology is a neo-classical production function with a property of constant returns to scale[1]. In this Figure, IAI' is an iso-production curve with two inputs x1 and x2, and SS' is a budget constraint line with two fixed prices of the inputs. Microeconomic theory teaches that producers will behave optimally at point A, at which the substitution ratio is equal to the relative price between two inputs (Varian, 2002).

A firm at point B is able to use the minimum amount of inputs to produce a fixed amount of output in IAI'. Now, suppose that this firm has to use inputs at C in order to produce the same output in IAI'. Therefore, this firm has used more inputs than firms at B to produce the same output as B. Thus, OB/OC represents the technical efficiency of this firm. Additionally, firms at B could reduce their total cost from the through-B budget line to ASS'. Firms at A in comparison with firms at B have higher allocative efficiency, although firms at both points produce the same output. The allocative efficiency of firms at B is OD/OB. Overall efficiency is equal to the

[1] The assumption of constant returns to scale will be relaxed later.

product of technical and allocative efficiency. In this simple figure, the overall efficiency of firms at C is equal to OD/OC (= (OB/OC) x (OD/OB)). If the level of a firm's overall efficiency is equal to 1, this firm should optimize its current technology and minimize the total cost of inputs.

Figure 1: Technical Efficiency and Allocative Efficiency

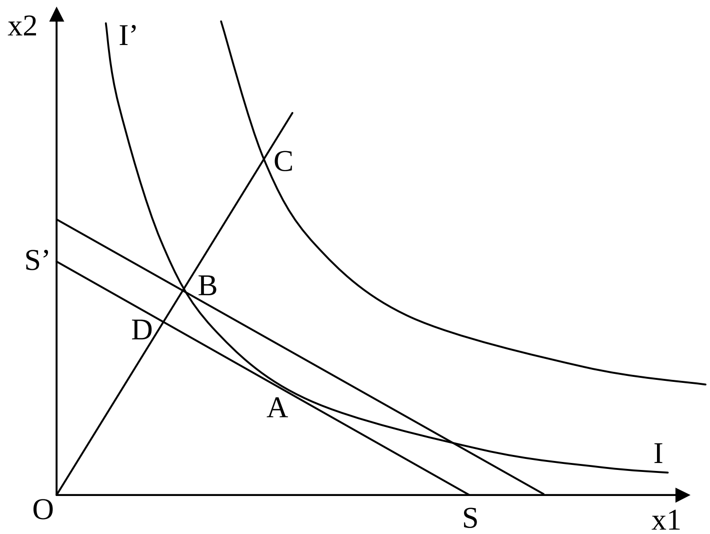
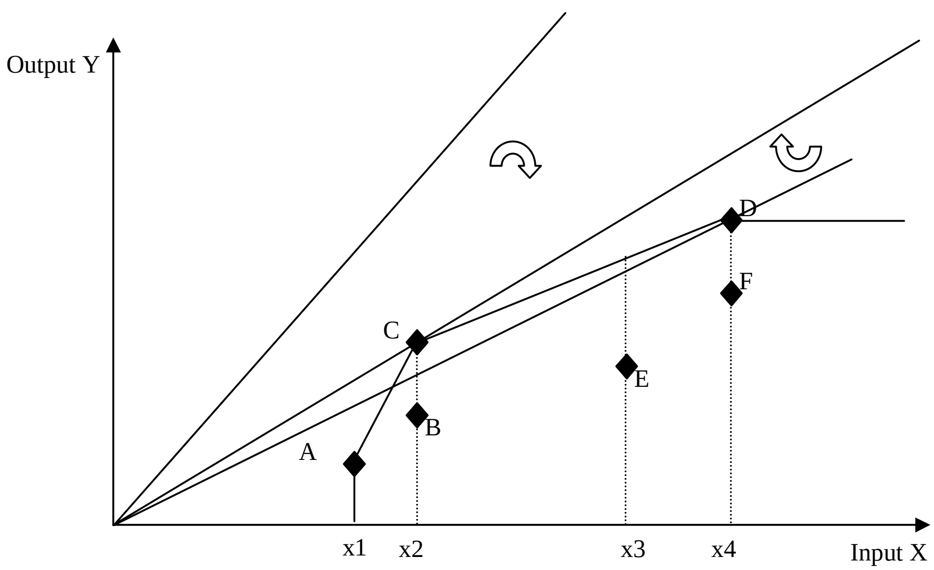


Figure 2: Technical Efficiency



Technical efficiency consists of two types: pure technical efficiency and scale efficiency[2]. Figure 2 plots six points as six firms: A, B, C, D, E, and F. In this figure, the production frontier is the curve ACD. Points A, C, and D are on the frontier while points B, E, and F are under the frontier. Through-origin lines are for the property of constant returns to scale. Firms on the frontier have a level of pure technical efficiency of 100%. The through-origin line intersects the frontier at point C. Those firms that have their productions at point C are maximizing their technical efficiencies at the same time as maximizing their scale efficiencies: these firms reach

[2] Some authors classify technical efficiency into pure technical efficiency, scale efficiency, and congestion efficiency.

maximum pure technical efficiencies as well as ensure constant returns to scale. Points that lie on both the production frontier and the through-origin line, in general, guarantee maximum technical efficiencies.

One firm, however, may not reach both pure technical efficiency and scale efficiency. Figure 2 shows that points A and D do not lie on the though-origin line, but do lie on the production frontier. It can be understood that firms at points A and D do not achieve scale efficiency but do achieve maximum pure technical efficiency. Firms at points B and F reach maximum scale efficiency because they have the same input levels, x2 and x4, as firms C and D, so maximum pure technical efficiency is guaranteed.

Later studies based on Farrell's original ideas on technical efficiency are extended to focus mainly on the methods of estimation of production functions (or production technologies in other words) and found an appropriate production technology (Moorsteen, 1961; Afriat, 1972; Aigner *et al.*, 1977; Meeusen and Broek, 1977; Greene, 1980; and Kumbhakar, 1987). The production frontier has been used popularly until now. The difference between the actual production level of a firm and the frontier measures its technical inefficiency. The frontier can be fixed or stochastic and the estimation methodology can take a parametric or non-parametric approach.

A parametric approach can be used to estimate a production function when the specification of technology is given. The estimated production function is then used for all observations in order to estimate the inefficiency of a firm in comparison with the best-practice firms. Bauer (1990) argued that parametric estimations could maintain statistical tests on estimators. This approach has, however, a weak point: the technology, which is assumed to be known for all observations, is not always correctly specified. This matter possibly results in inconsistent estimators. A particular parametric method is stochastic parametric estimation, in which the residuals from this estimation consist of two components: inefficiency and random components.

Another approach is a non-parametric estimation, which is commonly known as the data envelopment analysis (DEA), and it was developed first by Farrell (1957) with a deterministic non-parametric frontier. Non-parametric estimation does not decompose the residuals as the stochastic parametric estimations. Llewelyn and Williams (1996) therefore argued that non-parametric estimations could estimate biased inefficiency of firms. The advantages of this approach are that specification of production technology and the statistical distribution of inefficiency residuals are not required (Seiford and Thrall, 1990). Additionally, DEA could be applied for firms of multiple outputs and inputs. DEA is able also to decompose technical efficiency into pure technical efficiency and scale efficiency. Recent studies focus on stochastic DEA and analyzing growth of productivity under the DEA approach (Sengupta, 1990, 1999, 2002).

This paper applies both approaches, using stochastic frontier production function (SFPF) as the parametric approach and data envelopment analysis (DEA) as the non-parametric approach, for the aquaculture-processing firms in Vietnam in 2002. Factorial effects to be concerned are regions (north[3] and south), ownership (private and non-private firms), wage, capital-labor ratio, and external expenditure ratio (which will be explained later). This paper consists of six sections. Model development is the content of Section 2. Section 3 will describe data and variables for two models. The estimated results and factorial effects on technical efficiency will be discussed in Section 4. Section 5 includes some concluding remarks as well as suggestions for further studies.

[3] The north contains all the firms located in the provinces from Thua Thien Hue to Lang Son.

2. Model Specifications

2.1. Data Envelopment Analysis (DEA)

DEA contains two stages of development. The first stage uses DEA as a non-parametric method of estimation in public sectors. The second stage employs DEA in private sectors, which have high competition (Sengupta, 2002). Lewelyn and Williams (1996) found that there were two approaches to DEA in production function analysis. The first one was based on such studies as Afriat (1972), Hanoch and Rothschild (1972), and Varian (1984), while the second one was from Farrell (1957) and then extended by Färe *et al.* (1985). The latter approach will be used in this paper.

Suppose that there are *n* inputs *X*, *m* outputs *Y*, and *k* firms with $X = (x_1, x_2, ..., x_n) \in R_+^n$ and $Y = (y_1, y_2, ..., y_m) \in R_+^n$. The set described below is the set of all inputs and outputs that should be feasible for firms:

$$T = \{(x, y) : y \le Yz, Xz \le x, z \in R^{n+}\}, \tag{1}$$

where *z* stands for intensiveness of firm *i* given (x_i, y_i). *T* in (1) can represent the maximum output that a firm can have. For firm *i*, pure technical efficiency can be solutions to:

$$\theta^*(x_i, y_i) = \max\left\{\theta : (x_i, \theta_i y_i) \in T\right\}, \tag{2}$$

where $\theta_i y_i$ is the maximum output that firm *i* can reach. If θ is equal to 1, the firm has technical efficiency at 100 percent. If θ is greater than 1, firm *i* is inefficient. The solutions to the following linear equation system are used to calculate levels of technical efficiency of the firms in the sample:

$$\begin{aligned} Max(\theta) \text{ subject to: } & \theta_i y_{j,i} \le y_{j1}z_1 + y_{j2}z_2 + ... + y_{jk}z_k \text{, where } j = 1, 2, \ldots, m \\ & x_{11}z_1 + x_{12}z_2 + ... + x_{1k}z_k \le x_{1i} \\ & x_{21}z_1 + x_{22}z_2 + ... + x_{2k}z_k \le x_{2i} \\ & \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ & x_{31}z_1 + x_{32}z_2 + ... + x_{nk}z_k \le x_{ni}, i = 1, 2, ..., n. \end{aligned} \tag{3}$$

However, technical efficiency consists of pure technical efficiency and allocative efficiency. To extract pure technical efficiency, we add an additional condition that the sum of all the insensitiveness levels is equal to one. The set *T* in (1) becomes:

$$T' = \{(x, y) : y \le Yz, Xz \le x, z \in R^{n+}, \sum_{i=1}^{n} z_i = 1\}. \tag{4}$$

As a result, pure technical efficiency will be found by solving:

$$\lambda^*(x_i, y_i) = \max\{\lambda : (x_i, \lambda_i y_i) \in T'\}. \tag{5}$$

Rewrite (5), $\lambda^*(x_i, y_i)$ will be the solutions to the following linear equation system:

$$\begin{aligned} Max(\lambda_i) \text{ subject to } & \lambda_i y_{j,i} \le y_{j1}z_1 + y_{j2}z_2 + ... + y_{jk}z_k \text{, where } j = 1, 2, \ldots, m \\ & x_{11}z_1 + x_{12}z_2 + ... + x_{1k}z_k \le x_{1i} \\ & x_{21}z_1 + x_{22}z_2 + ... + x_{2k}z_k \le x_{2i} \end{aligned} \tag{6}$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$x_{31}z_1 + x_{32}z_2 + ... + x_{nk}z_k \le x_{ni}, i = 1, 2, ..., n$$

$$z_1 + z_2 + ... + z_k = 1.$$

Using $\theta^*(x_i, y_i), \lambda^*(x_i, y_i)$ as the solutions to (3) and (6), scale efficiency can be calculated as:

$$\phi^*(x_i, y_i) = \lambda^*(x_i, y_i) / \theta^*(x_i, y_i). \tag{7}$$

A firm may be at constant returns to scale, increasing returns to scale, decreasing returns to scale. To find the scale property of firms, the set *T* in (4) should be transformed as:

$$T^* = \{(x, y) : y \le Yz, Xz \le x, z \in R^{n+}, \sum_{i=1}^{n} z_i \le 1\}. \tag{8}$$

The set *T** in (8) can be used for firms that are at decreasing returns to scale. Similar procedures to (5) and (6) are then applied to find pure technical efficiency and scale efficiency.

2.2. Stochastic Frontier Production Function (SFPF)

Another method of estimation of the production function is parametric estimation given a specification of production technology[4]. This type of estimation was discussed fully in Nguyen and Dau (2005). Therefore, we hereby only sketch out some important ideas within this method, which will be applied in this paper. One note is that Nguyen and Dau (2005) applied one-stage estimation to get technical efficiency with variable returns to scale (or pure technical efficiency in DEA terms). Because two-stage estimation is used in DEA, this paper will use two-stage estimation to determine the production frontier, and then decomposition of factorial effects will be estimated.

Suppose $X_i(x_{i1}, x_{i2}, ..., x_{in})$ is the input vector of firm *i*, and Y_i is the single output of firm *i*. The production function $f(.)$ is neo-classical, and $f(.)$ satisfies

$$f(.) > 0; \frac{\partial f(.)}{\partial x} > 0; \frac{\partial^2 f(.)}{\partial x^2} < 0. \tag{9}$$

The real output is then represented through an estimated production function, an inefficiency residual, and a stochastic residual. The following estimation form is widely used:

$$Y_i = f(X_i)\exp(-V_i + U_i). \tag{10}$$

In equation (10), V_i and U_i are estimated and assumed to follow some particular probability distributions. U_i is stochastically and assumed normally distributed. V_i is firm-level inefficiency, and it is always non-negative. V_i is supposed to follow such special distributions as half-normal distribution and positively truncated normal distribution at zero. Technical efficiency of firms is then calculated by:

$$\frac{Y_i}{f(X_i)} = \frac{f(X_i)E[\exp(-V_i + U_i)]}{f(X_i)} = \exp(-V_i) = \frac{1}{\exp(\mathrm{V_i})}. \tag{11}$$

Equation (11) can be rewritten as follows:

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[4] Actually, there is no specific technology for all industries. It is difficult to find the correct technology for any sector. All studies commonly apply some basic technologies, such as Cobb-Douglas, constant elasticity of substitution (CES), and translog.

$$\ln(Y_i) - \ln(f(X_i)) = -V_i . \quad (12)$$

The remaining problem is how to set up a suitable specification of production function. In this paper, we use a specification of translog form. Equation (12) can be rewritten as follows:

$$\ln Y_i = \sum \alpha_j \ln x_j + \sum \beta_j (\ln x_j)^2 + \sum \gamma_{jh} (\ln x_j) \ln(x_h) - V_i + U_i . \quad (13)^5$$

In this equation, we also assume that U_i is normally distributed with mean zero, and V_i is truncated non-negatively normally distributed at zero.

2.3. Decomposition of the Factorial Effects

The estimated technical efficiencies derived from DEA and SFPF are then analysed on socio-economic factors.

$$TE = \mathrm{R}(\varphi_0 + \sum \varphi_l s_l) , \quad (14)$$

where *TE* is estimated technical efficiency, s_l represents the socio-economic factors that affect efficiency, φ_0 and φ_1 are coefficients to be estimated, and R is a particular type of estimation.

Note that TE in equation (14) is equal to $1/\theta^*$ from equations (2) and (3) for the DEA model, and is equal to $1/\exp(\mathrm{V})$ in equation (11) for the SFPF model. Regression in the later equation (16) is possibly ordinary least square (OLS). However, *TE* is in the range $[0;1]$, which violates one of the assumptions of OLS, and thus Tobit regression is often used as in equation (16) (Green, 2003).

Socio-economic factors include geographical and industrial features (Aigner and Chu, 1968; Timmer, 1971; and Aly *et al*., 1990), firm size (Wu, Devadoss, and Lu, 2003; Salinas-Jimenez, 2003)[6], ownership (Nguyen Thang, 2000), managerial structure of firms, such as age of workers, education, management policy, capital structure, and capital-labor ratio, and transitions in economic policies of a nation and a region (Pustay, 1978).

The procedure to decompose factorial effects on technical efficiency described above is called a two-stage procedure. Kumbhakar *et al.* (1991) criticized this procedure due to the possibility of biased estimators in the decomposition stage because the second stage contained some variables also contained in the first stage[7]. Kalirajan (1991), however, reasonably stated that this procedure was acceptable because economic variables always interacted with each other in every period of production and affected technical efficiency directly or indirectly.

3. Descriptions of Data and Variables

The sample in this paper contains 135 aquaculture-processing firms in Vietnam in 2002. The output, *VA*, is the total value-added of a firm (in VND million). Two inputs are net capital (*K*), which is measured in VND million, and total number of workers (*L*).

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[5] This specification is the second order Taylor expansion of the production function around X=(0). The translog production function covers Cobb-Doulas production function form and approximates to CES production function form.

[6] These studies use different units as measurement of firm size. These units may be in number of workers, cultivated areas, total revenue, and total capital.

[7] Concerning one-stage procedure in estimating technical efficiency and factorial effects in SFPF, Nguyen and Dau (2005) applied the model set up by Battese and Coelli (1995). They also carried out some statistical tests for a one-stage procedure.

Table 1: Summary of Inputs and Output

Variable	*Number of Observations*	*Mean*	*Standard Deviation*	*Min*	*Max*
VA	135	16,945.73	29,965.24	49	163,901
K	135	41,862.97	76,515.35	250	620,680
L	135	466.7778	636.7215	5	3,589

Source: Authors' estimates

Table 1 shows that there was a big gap in firms' inputs and output. Some firms were relatively small, while others were big. Using variables in Table 1, equation (13) becomes:

$$\ln VA_i = A + \alpha_K \ln K_i + \alpha_l \ln L_i + \alpha_{Kl} \ln K_i \ln L_i + \alpha_{K2} (\ln K_i)^2 + \alpha_{l2} (\ln L_i)^2 - V_i + U_i . \qquad (15)$$

Variables in factorial effect decomposition are summarized in Table 2. We also see that there was a big gap within each variable. It is possible that these variables could explain well the difference in firms' technical efficiency.

Table 2: Summary of Factorial Effect Variables

Variable	*Number of Observations*	*Mean*	*Standard Deviation*	*Min*	*Max*
l	135	466.7778	636.7215	5	3,589
l2	135	620,292.7	1,596,141	25	1.29E+07
k2l	135	102.8663	102.2255	3.252854	590.1
k2l2	135	20,954.11	51,765.21	10.58106	348,218
tytrong	135	0.048035	0.0723308	0	0.6592191
ktk	135	0.5684079	0.322498	0.0394632	1.228128
ktk2	135	0.4263222	0.3961522	0.0015573	1.508297
wl	135	9.837134	5.340089	1.207921	38.385
Dopwl	135	4.346501	6.480672	0	38.385
Dop	135	0.4444444	0.4987547	0	1
D4	135	0.4074074	0.4931818	0	1

- *D_{4i}, a regional dummy variable, is equal 1 if firm i is located in the south (including all the provinces from Thua Thien Hue to the south), and D_{4i} is equal to 0 otherwise. In the sample, there are 55 firms of the south, accounting for 40.7% of the sample.*
- *$D_{op,i}$, an ownership dummy variable, is equal to 1 if firms are private[8] and zero otherwise. There are 60 private firms, accounting for 44.4% of the sample.*
- *Firm size (l_i) is the average number of workers of firm i.*
- *Firm i's capital structure (ktk_i) is equal to the ratio of total equity to total capital[9].*
- *Capital-labor ratio ($k2l_i$) is equal to total capital divided by total workers.*
- *External cost ratio (tytrong) is equal to costs that are not involved in production process divided by total cost.*
- *Per capital income (wl) is the average wage that a worker is paid annually.*
- *$D_{opwl,i}$ is a variable of cross-section effect between $D_{op,i}$ and wl.*

Three variables l2, k2l2, and ktk2 are l, k2l, and ktk squared respectively (Kim [2003] and Gumbau-Albert [2000] argued that capital-labor ratio, capital structure, and firm size might affect technical efficiency quadratically).

Source: Authors' estimates

[8] Firms are private if their private share in terms of equity is more than 50 percent.
[9] *ktk* should not be less than zero, but this variable may be greater than one if firms lend capital to others.

4. Estimated Results and Analysis[10]

4.1. Estimates from DEA and SFPF

It should be a common understanding that technical efficiency in SFPF is not involved in firms' returns to scale. It is reasonable to argue that technical efficiency in SFPF is equivalent to pure technical efficiency in DEA. Therefore, we can only compare pure technical efficiency of the two models. Table 3 contains the first general results of the models. Pure technical efficiency in terms of regions and ownership types are represented in Table 4. The detailed results for each firm's technical efficiency are in the Appendix.

Table 3: General Results of Technical Efficiency

Type of Efficiency	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
DEA model					
vrste	**135**	**0.412**	**0.277**	**0.015**	**1.000**
scale	135	0.499	0.229	0.050	1.000
crste	135	0.186	0.157	0.007	1.000
SFPF model					
tesfpf	**135**	**0.676**	**0.127**	**0.133**	**0.893**
vrste	*Pure technical efficiency in DEA model*				
scale	*Scale efficiency in DEA model*				
crste	*Overall technical efficiency in DEA model*				
tesfpf	*Pure technical efficiency in SFPF model*				

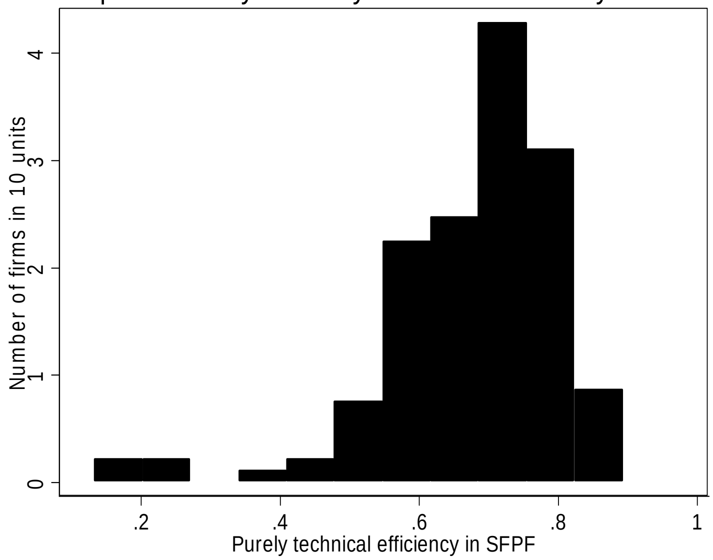
Source: Authors' estimates

Pure technical efficiency scores derived from the two models are rather different. SFPF estimates an average pure technical efficiency of 67.6 percent, which is 26.4 percent greater than the results from DEA (at 41.2 percent). The range of pure technical efficiency in DEA is much larger than that in SFPF ([0.015; 1.000] vs. [0.133; 0.893]). This means that SFPF seems to be better than DEA at correcting stochastic variations among firms. Intuitively, Graph 1 and Graph 2 in Figure 3 show that the frequency distribution of pure technical efficiency resulting from SFPF is more central than that from DEA.

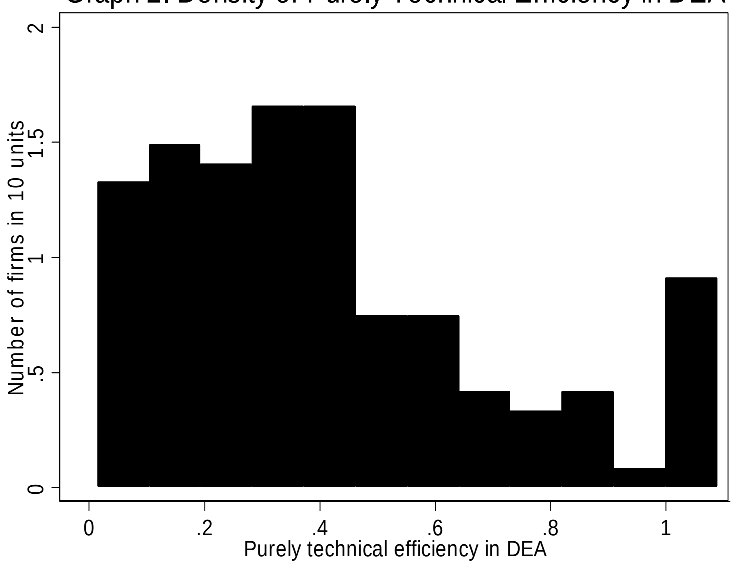
Figure 3: Technical Efficiency Distribution

[10] SFPF will be estimated by Stata Version 8.2, or Frontier Version 4.1. DEA will be estimated by DEAP-XP.

Graph 1. Density of Purely Technical Efficiency in SFPF



Graph 2. Density of Purely Technical Efficiency in DEA



Note: rs: returns to scale; irs: increasing returns to scale; drs: decreasing returns to scale; and crs: constant returns to scale.

Source: Authors' estimates

Table 4: Pure Technical Efficiency in Terms of Regions and Ownership

Group	***Model***	***Obs.***	***Mean***	***Min***	***Max***
A: Southern and private	DEA	28	0.438	0.072	1.000
	SFPF	28	0.665	0.385	0.846
B: Non-southern and private	DEA	32	0.317	0.015	1.000
	SFPF	32	0.669	0.186	0.844
C: Southern and non-private	DEA	27	0.547	0.132	1.000
	SFPF	27	0.727	0.492	0.893
D: Non-southern and non-private	DEA	48	0.386	0.024	1.000
	SFPF	48	0.658	0.133	0.838

Source: Authors' estimates

In terms of regions and ownership type, both DEA and SFPF confirmed that pure technical efficiency for the southern and non-private firms were highest. Table 4 also gives us a precise result of technical efficiency ranking as follows:

DEA: $B < D < A < C$

SFPF: $D \cong A \cong B < C$ (Groups D, A, and B are close, around 1% different)

It is obvious that, except regarding the firms in Group C, the two models give different estimated results.

Note that, in addition to estimating technical efficiency with variable returns to scale, DEA also can estimate overall technical efficiency and scale efficiency[11]. SFPF, however, can estimate only pure technical efficiency (or technical efficiency with variable returns to scale). In order to compare the results from two models, overall technical efficiency and scale efficiency are not analyzed in these empirical results.

4.2. Factorial Effects on Pure Technical Efficiency

Using Tobit regression for equation (14) and factorial effects in Table 2, Tobit regression will be:

$$\begin{aligned} TE_i = R(&\varphi^* + \varphi_0 l_i + \varphi_1 l2_i + \varphi_3 k2l_i + \varphi_4 k2l2_i + \varphi_5 tytrong_i + \\ &+\varphi_6 ktk_i + \varphi_7 ktk2_i + \varphi_8 \text{wl} + \varphi_9 D_{op,i} + \varphi_{10} D_{opwl,i} + \varphi_{11} D_{4,i} + \varepsilon_i). \end{aligned} \tag{16}$$

Tables 5 and 6 contain the results of Tobit regression in equation (16) for DEA and SFPF, respectively.

Table 5: Factorial Effects on Pure Technical Efficiency, DEA Model

Log likelihood = -26.580641			Number of Obs. = 135		
Pseudo R2 = 0.3832			LR chi2(11) = 33.03		
vrste	Coef.	Std. Err.	P>t	[90% Conf. Interval]	
l	0.0001	0.0001	0.5660	-0.0001	0.0003
l2	0.0000	0.0000	0.8860	0.0000	0.0000
k2l	-0.0021	0.0007	0.0030	-0.0032	-0.0009
k2l2	0.0000	0.0000	0.0010	0.0000	0.0000
tytrong	-0.7189	0.3621	0.0490	-1.3191	-0.1188
ktk	-0.6403	0.3393	0.0620	-1.2027	-0.0779
ktk2	0.5422	0.2718	0.0480	0.0918	0.9926
wl	0.0146	0.0080	0.0690	0.0014	0.0278
Dop	-0.0650	0.1112	0.5600	-0.2493	0.1193
Dopwl	0.0010	0.0095	0.9190	-0.0148	0.0168
D4	0.1292	0.0534	0.0170	0.0406	0.2177
_cons	0.5054	0.1253	0.0000	0.2977	0.7130
_se	0.2641	0.0173	(Ancillary parameter)		

Source: Authors' estimates

Table 6. Factorial Effects on Pure Technical Efficiency, SFPF Model

Log likelihood = 96.419693			Number of Obs. = 135		
Pseudo R2 = -0.1832			LR chi2(11) = 29.85		
tesfpf	Coef.	Std. Err.	P>t	[90% Conf. Interval]	
l	-0.0001	0.0000	0.0330	-0.0002	0.0000

[11] An empirical analysis of these two types of technical efficiency can be found in Nguyen and Vu (2004).

l2	0.0000	0.0000	0.0710	0.0000	0.0000
k2l	-0.0008	0.0003	0.0040	-0.0013	-0.0004
k2l2	0.0000	0.0000	0.0080	0.0000	0.0000
tytrong	-0.3693	0.1548	0.0190	-0.6258	-0.1128
ktk	-0.1066	0.1460	0.4670	-0.3485	0.1353
ktk2	0.0373	0.1168	0.7500	-0.1562	0.2309
wl	0.0129	0.0034	0.0000	0.0073	0.0186
Dop	0.0316	0.0474	0.5070	-0.0470	0.1102
Dopwl	-0.0054	0.0040	0.1810	-0.0121	0.0013
D4	0.0313	0.0230	0.1750	-0.0068	0.0694
_cons	0.6926	0.0540	0.0000	0.6032	0.7820
_se	0.1143	0.0070	(Ancillary parameter)		

Source: Authors' estimates

At significance level of 10%, socio-economic variables, which could affect technical efficiency, are capital-labor ratio, wage, external cost ratio, capital structure, and region. Table 5 provides some implications. Firstly, pure technical efficiency was not affected by ownership types. Secondly, regions strongly affected technical efficiency. These results could be explained by availability of inputs due to region. Thirdly, firm size was not related to pure technical efficiency. This means that firms' number of workers did not make pure technical efficiency divergent. Fourthly, capital-labor ratio was quadratically related to efficiency. The signs prove such relation to be convex, which differs from recent empirical studies that held this relation should be concave (making an optimal level of capital-labor ratio)[12]. Lastly, higher average wages (which imply higher quality of labor) were correlated with higher pure technical efficiency scores. Productivity, quality of labor, and pure technical efficiency were found to be positively related.

Tobit regression for SFPF gives almost the same results in terms of effect directions (the signs of coefficients). However, there are some differences between Tables 5 and 6. The first different point is that capital-labor ratio is not significant in the SFPF model, while it is significant in the DEA model. The second different point is that firm size in the SFPF model was related to technical efficiency in the study period, but it did not affect pure technical efficiency in the DEA model.

5. Concluding Remarks and Suggestions for Further Studies

Our parametric and non-parametric analysis of the aquaculture-processing firms in Vietnam in 2002 led to several findings. Pure technical efficiency was found to be low; it was just around 41.2 percent in the data envelopment analysis (DEA) model, and 67.6 percent in the stochastic frontier production function (SFPF) model. Ownership did not seem to have a significant impact on technical efficiency. However, it should be noted that the southern non-private firms were the most efficient. This implies a possibility that recent privatization and equitization policies have not increased technical efficiency in Vietnam (although more data should be provided to support this conclusion). Human resource development policies and increasing labor quality were very important factors in improving efficiency. Capital-labor ratio was positively related to technical efficiency. Increasing the capital-labor ratio should be considered intensively to increase productivity and competitiveness for these firms.

Although our study could provide the above implications, we acknowledge that the DEA and SFPF models and Tobit regression in Equation (16) could not take all socio-economic

[12] A convex relation implies that there is the worst level of capital-labor ratio, at which firms should not be, since this level would minimize pure technical efficiency, holding other things equal.

factors into account. Some missing variables should be corrected in later studies to achieve better results. Additionally, the demand side should also be considered. Regional differences would have been more precise if prices differences among regions had been adjusted. Finally, this paper did not provide a complete comparison in all indices of technical efficiency; it focused only on pure technical efficiency.

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APPENDIX

Estimated Efficiency Scores from DEA and SFPF

	SFPF	**DEA**					**SFPF**	**DEA**					**SFPF**	**DEA**			
Obs.	**tesfpf**	**vrste**	**scale**	**crste**	**rs**	Obs.	**tesfpf**	**vrste**	**scale**	**crste**	**rs**	Obs.	**tesfpf**	**vrste**	**scale**	**crste**	**rs**
1	0.488	0.605	0.057	0.034	irs	46	0.771	0.268	0.608	0.163	drs	91	0.744	1	0.619	0.619	drs
2	0.259	0.015	0.934	0.014	drs	47	0.729	0.276	0.672	0.186	drs	92	0.27	0.061	0.557	0.034	drs
3	0.472	0.438	0.112	0.049	irs	48	0.723	0.217	0.477	0.103	drs	93	0.74	0.522	0.314	0.164	drs
4	0.602	1	0.05	0.05	irs	49	0.747	0.442	0.983	0.434	irs	94	0.716	0.334	0.436	0.146	drs
5	0.588	0.897	0.058	0.052	irs	50	0.836	0.404	0.945	0.381	drs	95	0.716	0.453	0.306	0.138	drs
6	0.55	1	0.121	0.121	irs	51	0.734	0.299	0.501	0.15	drs	96	0.708	0.362	0.323	0.117	drs
7	0.186	0.016	0.673	0.011	drs	52	0.813	1	0.895	0.895	irs	97	0.731	0.85	0.485	0.412	drs
8	0.713	1	0.159	0.159	irs	53	0.777	0.453	0.746	0.338	drs	98	0.733	0.681	0.348	0.237	drs
9	0.559	0.072	0.855	0.062	irs	54	0.777	0.404	0.583	0.236	drs	99	0.689	0.378	0.281	0.106	drs
10	0.555	0.048	0.906	0.043	drs	55	0.618	0.293	0.506	0.148	drs	100	0.695	0.372	0.277	0.103	drs
11	0.748	0.564	0.325	0.183	irs	56	0.627	0.153	0.577	0.088	drs	101	0.741	0.503	0.296	0.149	drs
12	0.589	0.095	0.922	0.088	irs	57	0.522	0.143	0.33	0.047	drs	102	0.749	1	0.586	0.586	drs
13	0.665	0.082	0.971	0.08	irs	58	0.682	0.309	0.417	0.129	drs	103	0.71	0.375	0.339	0.127	drs
14	0.712	1	0.227	0.227	irs	59	0.644	0.306	0.632	0.193	drs	104	0.632	0.315	0.263	0.083	drs
15	0.544	0.182	0.862	0.157	irs	60	0.624	0.233	0.593	0.138	drs	105	0.712	0.496	0.282	0.14	drs
16	0.704	0.215	0.698	0.15	irs	61	0.844	0.555	0.757	0.42	drs	106	0.492	0.132	0.362	0.048	drs
17	0.712	0.127	0.945	0.12	irs	62	0.712	0.318	0.38	0.121	drs	107	0.583	0.231	0.595	0.138	drs
18	0.563	0.085	0.65	0.055	drs	63	0.796	0.443	0.437	0.193	drs	108	0.789	0.866	0.295	0.256	drs
19	0.624	0.085	0.69	0.059	drs	64	0.589	0.238	0.362	0.086	drs	109	0.712	0.457	0.353	0.161	drs
20	0.643	0.105	0.909	0.095	drs	65	0.672	0.37	0.453	0.168	drs	110	0.775	0.62	0.375	0.232	drs
21	0.577	0.097	0.783	0.076	drs	66	0.893	1	1	1	crs	111	0.789	0.928	0.506	0.469	drs
22	0.563	0.08	0.565	0.045	drs	67	0.483	0.131	0.292	0.038	drs	112	0.841	1	0.537	0.537	drs
23	0.78	0.437	0.541	0.236	irs	68	0.547	0.168	0.304	0.051	drs	113	0.712	0.479	0.26	0.125	drs
24	0.592	0.099	0.593	0.058	drs	69	0.435	0.127	0.288	0.036	drs	114	0.724	0.55	0.266	0.147	drs
25	0.568	0.137	0.927	0.127	drs	70	0.838	0.634	0.662	0.42	drs	115	0.671	0.425	0.256	0.109	drs
26	0.591	0.124	0.835	0.103	drs	71	0.814	0.717	0.463	0.332	drs	116	0.593	0.223	0.335	0.075	drs
27	0.635	0.123	0.556	0.068	drs	72	0.67	0.336	0.347	0.117	drs	117	0.776	0.748	0.272	0.203	drs
28	0.133	0.024	0.3	0.007	drs	73	0.693	0.304	0.566	0.172	drs	118	0.797	0.761	0.344	0.262	drs
29	0.756	0.167	0.758	0.126	drs	74	0.658	0.241	0.335	0.081	drs	119	0.784	0.722	0.377	0.273	drs
30	0.558	0.093	0.662	0.062	drs	75	0.757	0.525	0.384	0.202	drs	120	0.659	0.262	0.401	0.105	drs
31	0.795	0.314	0.897	0.282	irs	76	0.765	0.632	0.424	0.268	drs	121	0.718	0.451	0.609	0.275	drs
32	0.525	0.083	0.587	0.049	drs	77	0.663	0.366	0.351	0.128	drs	122	0.684	0.338	0.321	0.108	drs
33	0.656	0.146	0.735	0.107	drs	78	0.599	0.269	0.327	0.088	drs	123	0.787	0.847	0.316	0.267	drs
34	0.811	0.313	0.943	0.295	irs	79	0.756	0.493	0.359	0.177	drs	124	0.811	1	0.37	0.37	drs
35	0.671	0.188	0.638	0.12	drs	80	0.702	0.448	0.361	0.161	drs	125	0.766	0.448	0.528	0.237	drs
36	0.701	0.288	0.983	0.283	irs	81	0.584	0.19	0.313	0.059	drs	126	0.717	0.442	0.334	0.147	drs
37	0.65	0.156	0.466	0.073	drs	82	0.722	0.628	0.447	0.281	drs	127	0.727	0.38	0.452	0.172	drs
38	0.705	0.211	0.635	0.134	drs	83	0.824	0.697	0.609	0.424	drs	128	0.593	0.461	0.566	0.261	drs
39	0.73	0.214	0.603	0.129	drs	84	0.579	0.213	0.283	0.06	drs	129	0.806	1	0.282	0.282	drs
40	0.385	0.075	0.335	0.025	drs	85	0.724	0.437	0.325	0.142	drs	130	0.803	0.698	0.394	0.275	drs
41	0.64	0.134	0.598	0.08	drs	86	0.67	0.351	0.317	0.111	drs	131	0.83	0.888	0.599	0.532	drs
42	0.777	0.272	0.716	0.195	drs	87	0.67	0.391	0.326	0.128	drs	132	0.757	0.565	0.316	0.179	drs
43	0.846	0.501	0.84	0.421	irs	88	0.741	0.359	0.454	0.163	drs	133	0.779	0.74	0.329	0.243	drs
44	0.823	0.522	0.855	0.446	irs	89	0.562	0.217	0.269	0.059	drs	134	0.806	0.788	0.433	0.342	drs
45	0.71	0.218	0.5	0.109	drs	90	0.703	0.329	0.363	0.12	drs	135	0.742	0.555	0.299	0.166	drs