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TECHNICAL EFFICIENCY OF SMALL AND MEDIUM MANUFACTURING FIRMS IN VIETNAM: PARAMETRIC AND NON-PARAMETRIC APPROACHES*

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There is evidence that small and medium firms usually do not have high productive efficiency. This phenomenon can be explained by several factors. In this paper, it is analyzed by using the panel data of 1,492 firms from the Economic Census for Enterprises conducted by the General Statistics Office of Vietnam (GSO) during the period 2000-2003 with a parametric approach (based on stochastic frontier production function—SFPF) and a non-parametric approach (based on data envelopment analysis—DEA). Under the specification of variable return to scale (VRS), the mean technical efficiency of these small and medium firms was about 50 percent under the SFPF approach, and about 40 percent under the DEA approach. We also explore possible factors determining the differences in technical efficiency levels of these firms, and find that there existed slightly heterogeneous efficiency level in these firms across sub-industries and regions in the study period.

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I. INTRODUCTION

Small and medium manufacturing firms (hereafter small firms) in Vietnam are of prime importance to the national economy. The past decade witnessed impressive improvements in the performance of the manufacturing sector. Recovering from great difficulties caused by the collapse of the former Soviet Union, the manufacturing industries have grown at the average growth rate of more than 10 percent per annum, and have made significant contributions to the Gross Domestic Product (GDP) growth. They have also entered the list of top exporting industries. Moreover, the manufacturing industries in Vietnam have been regarded as a spearhead sector in easing the unemployment burden, and making use of comparative advantages of labor-intensive production. Although business activities of the manufacturing firms have been considerably innovated over this period, the efficiency performance has still been low, particularly in terms of labor (Table 1). In general, the small firms face many problems, such as poor infrastructure, lack of information, and low skilled labor, which in turn may obstruct their production efficiency. Some interesting and key questions, including measurements and exploration of determinants of productive efficiency for these small firms, have been increasingly emerging. The answers for these questions will be important not only from economic efficiency standpoints, but also from income distribution perspectives because the small firms have accounted for a large part of employment in the economy.

As can be seen in Table 1, in the period 2000-2002, small firms made up more than 35 percent of total employment, but they accounted for only 9-17 percent of profit of the whole manufacturing industries. These figures might show their low productivity levels, which could result from various factors. Among them were low capability to take advantage of scale economies, difficulties in accessing to investment funds, and lack of

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resources, particularly qualified human capital. Therefore, their average level of technical efficiency, which is represented by the capability in either minimizing inputs with given outputs, or maximizing outputs with given inputs, remained poor.

[Table 1] Proportion of Small Firms in Manufacturing Industries

Of National Employees (%)	< 5	5-9	10-49	50-199	200-299	Total
Year 2000	0.79	2.13	7.37	16	7.7	34.02
Year 2001	0.79	2.46	8.57	16	7.4	35.22
Year 2002	0.74	2.72	9.41	15.9	7.1	35.86
Of National Profit (%)						
Year 2000	0.47	0.51	0.91	5.33	2.6	9.85
Year 2001	0.41	0.54	2.36	5.24	1.9	10.41
Year 2002	0.35	0.45	2.83	9.05	4.3	17

Note: Data obtained on 31st December of each year.

Source: GSO (2001, 2002, and 2003)

Although many papers suggest a number of explanations for this phenomenon for the small firms around the world, to our best knowledge, there have been no such studies in Vietnam so far. As a result, there have been also no satisfactory answers for such questions as which size is more efficient, and which factors play the key roles in determining efficiency. This paper, therefore, will estimate technical efficiency levels of small firms in Vietnam by sub-industries and regions to answer the above-mentioned questions.

The remainder of the paper is organized as follows. The following Section II is a discussion of methodology along with a review of some related studies. Section III describes data source by classifying small firms by size and business sector. In Section IV, we will show the estimated results for these firms according to firm size, sector, and region, and then identify the determinants of technical efficiency with both parametric and non-parametric approaches. To concretize the analysis, we will also compare the results obtained from these approaches. Some concluding remarks are presented in the last Section.

II. ANALYTICAL FRAMEWORK TO ESTIMATE TECHNICAL EFFICIENCY

1. Stochastic Frontier Production Function (SFPF) Approach

To estimate technical efficiency of the small firms, we need to refer to the maximum potential output obtained by a typical firm in question as a basis for comparisons. An estimated production function, however, just describes the average relationship between input(s) and output(s), and it does not reflect the maximum potential outputs with given amount of inputs. In most cases, the production frontier is used to get the maximum potential output with a certain level of inputs (so-called input-oriented estimation).

Farrell (1957) proposes a deterministic non-parametric frontier approach to estimate three kinds of production efficiency, i.e. technical efficiency, allocative efficiency, and price efficiency. With assumption of a Cobb-Douglas production function, Aigner and Chu (1968) employ the deterministic parameter frontier approach, by which they can estimate each factor's contribution. It is, however, more important to find an appropriate distribution for the disturbance terms in applying this approach.

One of the major problems for the deterministic frontier approach is involved in the assumption that all firms have the same technology and production frontier. Hence, the discrepancies in production are basically derived from business mismanagement or inappropriate technology. Aigner *et al.* (1977) argue that there can be some non-technical random factors, which may strongly affect output level, such as central and local government policies. Therefore, there should be two components in the random terms, in which one is an uncontrollable symmetric random distribution (v), and the other is a technical inefficiency random term (u). In the stochastic frontier production function (SFPF) approach, Aigner *et al.* (1977) assume that u follows a truncated normal distribution, while v has a symmetric normal distribution. Afriat (1972) supposes that the error term has a two-parameter beta distribution, while Richmond (1974) applies a one-parameter gamma distribution to fit the model. In addition, there are also various assumptions of the random terms. For instance, Lee (1983) proposes methods to test appropriateness of random terms by using Lagrange multiplier techniques.

There are some empirical studies on technical efficiency of small firms. Alvarez and Crespi (2003) estimate technical efficiency for the small firms in Chile, and they find that small firms are less productive than large ones. They also find that efficiency will be positively associated with workers' experiences, modernization of physical capital, and innovation in products, while ownership and participation in some public programs do not affect efficiency of these firms. Batra and Hong Tan (2003) focus on the nexus between skills, technology and productivity in the manufacturing firms, and how this varies across different firm sizes to provide implications for the small medium enterprises (SMEs) policies in developing countries. Admassie (2002) explores technical efficiency level of the SMEs in Tanzania, and finds that the mean technical efficiency level for all firms is about 50 percent, meaning that by operating at the full technical efficiency levels, these firms could increase their productive level by about 50 percent. The study also indicates that technical inefficiencies of the Tanzanian SMEs are significantly related to firm age, firm size, and human capital development.

In this paper, we will consider two following models to estimate technical efficiency levels for small firms in Vietnam.

Model 1

To conduct the study on technical efficiency of small firms, and to compare production efficiency between industries and regions, we firstly use SFPF approach. Some uncontrollable factors influencing total output of small firms will also be considered.

Assuming the half-normal distribution of the error term, general production function for a small firm is defined as follows.

$$y_i = f(x_i, \beta_i)e^{\varepsilon_i}, \tag{1}$$

where $\varepsilon_i = v_i - u_i$ and it satisfies the following conditions: (i) $v_i \sim$ iid N(0, σ_v^2), and it is called the symmetric error component; (ii) $u_i \sim$ iid N$^+$(0,

σ_u^2), i.e. non-negative half-normal distribution, and it is called the one-sided error component; and (iii) u_i and v_i are distributed independently of each other and of the regressors.

The production variances of the firms are represented by $\sigma^2 = \sigma_u^2 + \sigma_v^2$. Moreover, the density function of $u \geq 0$ is described as follows.

$$f(u) = \frac{1}{\sigma_u \sqrt{2\pi}} \exp\left(-\frac{u^2}{2\sigma_u^2} \right). \tag{2}$$

And the density function of v is defined as follows.

$$f(v) = \frac{1}{\sigma_v \sqrt{2\pi}} \exp\left(-\frac{v^2}{2\sigma_v^2} \right). \tag{3}$$

Given the condition (iii), the joint density function of u and v is as follows.

$$f(u,v) = \frac{2}{2\pi\sigma_u\sigma_v} \exp\left\{ -\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2} \right\} . \tag{4}$$

Since $\varepsilon = v - u$, we can find the marginal density function of ε as follows.

$$f(\varepsilon) = \int_0^{\infty} f(u,\varepsilon)du = \frac{1}{\sigma\sqrt{2\pi}} \left[1 - \Phi\left(\frac{\varepsilon\gamma}{\sigma} \right) \right]$$
$$\exp\left(-\frac{\varepsilon^2}{2\sigma^2} \right) = \frac{2}{\sigma} \phi\left(\frac{\varepsilon}{\sigma} \right) \Phi\left(-\frac{\varepsilon\gamma}{\sigma} \right). \tag{5}$$

In the system of equations (2) to (5), $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $\Phi(.)$ is the cumulative standardized normal distribution, and $\phi(.)$ is the density function.

The marginal density function $f(\varepsilon)$ is asymmetrically distributed. Its respective mean and variance are as follows.

$$E(\varepsilon) = -E(u) = -\sigma_u \sqrt{2/\pi} \quad and \quad Var(\varepsilon) = \frac{\pi - 2}{\pi}\sigma_u^2 + \sigma_v^2 \tag{6}$$

It is suggested that [1-$E(u)$] is an estimator of the mean technical efficiency of all firms.

However, $$E\left[\exp(-u)\right] = 2\left[1 - \Phi\left(\sigma_u\right)\right]\exp\left(\frac{\sigma_u^2}{2}\right) \tag{7}$$

is preferred to [1-$E(u)$] as $E[\exp(-u)]$ is consistent with the definition of technical efficiency.

Using equation (5), the log likelihood function of a sample of I firms is as follows.

$$\ln L = const - I\ln\sigma + \sum_i \ln\Phi\left(-\frac{\varepsilon_i\gamma}{\sigma}\right) - \frac{I}{2\sigma^2}\sum_i \varepsilon_i^2 \tag{8}$$

The log likelihood function in equation (8) can be maximized with respect to the parameters to obtain maximum likelihood estimates of all the parameters. These estimates are consistent as i approaches to infinity.

We have estimates of ε_i, which contain information on u_i. The conditional distribution of u_i, given ε_i, is as follows.

$$f(u|\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sigma_*\sqrt{2\pi}}\exp\left[-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right] \Big/ \left[1 - \Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right], \tag{9}$$

where $\mu_* = -\varepsilon\sigma_u^2/\sigma^2$, and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$.

Since $f(u/\varepsilon) \sim N^*(\mu_*, \sigma^*)$, either the mean or mode of this distribution can serve as a point estimator of u, which is defined as follows.

$$E(u_i \mid \varepsilon_i) = \mu_{*i} + \sigma_*\left[\frac{\phi(-\mu_{*i}/\sigma_*)}{1-\Phi(-\mu_{*i}/\sigma_*)}\right] = \sigma_*\left[\frac{\phi(\varepsilon_i\gamma/\sigma)}{1-\Phi(\varepsilon_i\gamma/\sigma)} - \left(\frac{\varepsilon_i\gamma}{\sigma}\right)\right], \tag{10}$$

$$\text{and } M(u_i \mid \varepsilon_i) = \begin{cases} -\varepsilon_i \left(\dfrac{\sigma_u^2}{\sigma^2} \right) & with\ \varepsilon_i \le 0 \\ 0 & with\ \varepsilon_i > 0 \end{cases}. \tag{11}$$

Then the estimates of the technical efficiency (*TE*) of each firm can be obtained as:

$$TE_i = \exp(-\hat{u}_i), \tag{12}$$

where $\hat{u}_i$ is either $E(u_i|\varepsilon_i)$ or $M(u_i|\varepsilon_i)$.

Battese and Coelli (1988) proposed an alternative point estimator for TE_i as:

$$TE = E\{\exp[(-u_i)|\varepsilon_i]\} \left[\frac{1 - \Phi(\sigma_* - \mu_{*i}/\sigma_*)}{1 - \Phi(-\mu_{*i}/\sigma_*)} \right] \exp\left\{ -\mu_{*i} + \frac{1}{2}\sigma_*^2 \right\}, \tag{13}$$

and the joint density function for u and ε is $f(u,\varepsilon) = \dfrac{1}{\sigma_u \sigma_v \sqrt{2\pi}}$ $\exp\left\{ -\dfrac{u}{\sigma_u} - \dfrac{(u+\varepsilon)^2}{2\sigma_v^2} \right\}$.

To see how technical inefficiency influenced the production variances of the studied firms during the period, we introduce $\gamma = \sigma_u^2 / \sigma_v^2$.[1] On the

[1] As mentioned later, in this paper we will use the computer program FRONTIER version 4.1 by Coelli (1996a) to estimate efficiency levels for the studied firms. The program produces the parameter $\hat{\gamma}$, which is defined as $\hat{\gamma} = \dfrac{\sigma_u^2}{\sigma^2}$, where $\sigma^2 = \sigma_u^2 + \sigma_v^2$. However, to analyze inefficiency issue in this paper, we will use $\gamma = \dfrac{\sigma_u^2}{\sigma_v^2}$. The ratio between σ_u^2 and σ_v^2 can help us to show how production variance is attributed to the technical inefficiency as follows. Suppose that $\hat{\gamma}$ is the estimate we get from FRONTIER program, while γ is the parameter that we need to calculate for this paper. Since $\hat{\gamma} = \dfrac{\sigma_u^2}{\sigma^2}$, we have $\sigma_u^2 = \hat{\gamma}\sigma^2$. Furthermore, $\sigma^2 = \sigma_u^2 + \sigma_v^2$ so that $\sigma_v^2 = \sigma^2 - \sigma_u^2 = \sigma^2 - \hat{\gamma}\sigma^2 = (1-\hat{\gamma})\sigma^2$. Thus, $\gamma = \dfrac{\sigma_u^2}{\sigma_v^2} = \dfrac{\hat{\gamma}\sigma^2}{(1-\hat{\gamma})\sigma^2} = \dfrac{\hat{\gamma}}{(1-\hat{\gamma})}$. It can be seen that a large value of $\gamma = \dfrac{\sigma_u^2}{\sigma_v^2}$ indicates a large portion of the production variance is attributed to the technical

one hand, when γ approaches to 0 (because of either $\sigma_v^2 \to \infty$ or $\sigma_u^2 \to 0$), the symmetric error component dominates the one-sided error in the determination of ε. On the other hand, as γ approaches infinity (because of either $\sigma_u^2 \to \infty$ or $\sigma_v^2 \to 0$), the one-sided error component dominates the symmetric error component in determining ε. In other words, a large value of γ indicates a large portion of the production variance is attributed to the technical inefficiency error (σ_u^2), and vice versa. In the former case, an OLS production function model with no technical inefficiency component should be used, while a deterministic production frontier model with no noise should be used in the latter case.

Model 2

Given the estimated efficiency level for each firm, we proceed further by identifying the determinants of the firm's efficiency level. In general, there are some factors which can affect firm's production, including capital–labor ratio, firm size, firm age, ownership, and geographic location.

Intuitively, a firm with higher capital intensity has higher production efficiency because it has to yield higher efficiency to cover the larger expenditure on capital, or because a higher capital intensive production may simply mean a better technology. Lee and Tyler (1978) and Albach (1980) respectively find in Brazil and Germany that firms with higher capital–labor ratio can have a higher production frontier than that of firms with a low capital–labor ratio.

The second factor affecting firm's production efficiency is firm size. Various studies confirmed that an industry with a large size could take advantage of organizational structure and acquirements of new technology, and thus would have a higher production skill. However, some economists have argued that the production scale could cause a less flexible production performance. Sharma *et al.* (1999) study technical, allocative, and economic efficiencies in the swine production in Hawaii, and find that farm size has a negative and significant impact on inefficiency levels. They suggest that, on average, large farms operate at higher efficiency levels than the small ones. Bagi (1982), Bravo-Ureta

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inefficiency error σ_u^2.

(1986), and Byrnes *et al.* (1987) also find that technical efficiency will be independent of the farm size. Nguyen (2005), exploring technical inefficiency in the manufacturing industries in Hanoi and Ho Chi Minh City (HCMC) in Vietnam, finds that industry size (represented by revenue) does have a negative and statistically insignificant coefficient for Hanoi, but a positive and statistically insignificant coefficient for HCMC.

The third factor used in the literature to explain variation in efficiency level is firm age. Firm age is a factor that affects firm's production efficiency for several reasons, e.g. an efficient production process can be learned by a firm with experience, or it is hard to believe that a private firm without an efficient production can last long.

Another factor is regional difference. The industrial map of Vietnam is usually divided into 8 regions.[2] Region 1 (including the capital Hanoi) and Region 7 (including HCMC) are much more industrially developed than the other regions. Our data in this paper cover all provinces in Vietnam. We will also conduct tests to see whether the regional factor had impacts on the technical efficiency of the studied firms during the period.

In addition, the dummy variables indicating to the ownership structure, and types of industry will also be used for the inefficiency model.

In this paper, we follow the methodology of Battese and Coelli (1995), which advance a model for technical inefficiency effects in a SFPF with panel data. The non-negative technical inefficiency effects are defined as a function of firm-specific variables, including the time trend. Following truncation normal distribution with a constant variance as usual, the inefficiency effects have means that are linearly related to the observable variables. The model allows simultaneous estimations of both technical change in the stochastic frontier and time-variant technical inefficiencies. Their model assumes that:

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[2] Each region includes some cities and provinces as follows. *Region 1* includes Hanoi, Hai Phong, Vinh Phuc, Ha Tay, Bac Ninh, Hai Duong, Hung Yen, Ha Nam, Nam Dinh, Thai Binh, and Ninh Binh. *Region 2* includes Ha Giang, Cao Bang, Lao Cai, Bac Can, Lang Son,Tuyen Quang, Yen Bai, Thai Nguyen, Phu Tho, Bac Giang, and Quang Ninh. *Regions 3* includes Lai Chau, Son La, and Hoa Binh. *Region 4* includes Thanh Hoa, Nghe An, Ha Tinh, Quang Binh, Quang Tri, and Thua Thien Hue. *Regions 5* includes Da Nang, Quang Nam, Quang Ngai, Binh Dinh, Phu Yen, and Khanh Hoa. *Region 6* includes Kon Tum, Gia Lai, Dak Lak, and Lam Dong. *Region 7* includes Ho Chi Minh city, Ninh Thuan, Binh Phuoc, Tay Ninh, Binh Duong, Dong Nai, Binh Thuan, and Ba Ria-Vung Tau. *Region 8* includes Long An, Dong Thap, An Giang, Tien Giang, Vinh Long, Ben Tre, Kien Giang, Can Tho, Tra Vinh, Soc Trang, Bac Lieu, and Ca Mau.

$$y_{it} = f(x_{it}, \beta).e^{v_{it} - u_{it}} \quad \text{with} \quad u = Z.\delta + w, \tag{14}$$

where Z is a vector of firm characteristics associated with the technical inefficiency effects; δ is a vector of unknown parameters to be estimated; $Z.\ \delta$ is the dot product of vector Z and vector δ ; and u is non-negative random variable, and it is assumed to be independently distributed.

The technical inefficiency (uit) follows $N(\mu, \sigma_u^2)$, and it is the product of an exponential function of time as $u_{it} = \eta_t u_i = u_i \exp[-\eta(t-T)]$, $t \in \tau(i)$, in which the unknown parameter η represents the rate of change in technical inefficiency over time. The parameter η shows inefficiencies are time-varying or time-invariant, e.g. the value of η, which is significantly different from zero, indicates time-varying inefficiencies. Parameter μ determines the distribution of the inefficiency effects to be either a half-normal distribution or a truncated normal distribution, e.g. if $\mu = 0$ then the inefficiency effects follow half-normal distribution.

In the parametric approach, it is necessary to assume a specific production function to characterize firm's production behavior. In this paper, we will consider two forms of production functions, i.e. the log-linear Cobb-Douglas production function, and the translog production function. To choose the most appropriate production function with the available data between these functions, we will use the maximum likelihood test.

In the case of the log-linear Cobb-Douglas production function, we have:

$$LnVA_i = LnA + \beta_1 LnL_i + \beta_2 LnK_i + v_i - u_i, \tag{15}$$

and for the case of the translog production function, we will employ:

$$\begin{aligned} LnVA_i = \alpha_0 + \alpha_L LnL_i + \alpha_K LnK_i + 0.5\beta_{LL}(LnL)_i^2 + 0.5\beta_{KK}(LnK)_i^2 \\ + \beta_{LK}(LnL)_i(LnK)_i + v_i - u_i, \end{aligned} \tag{16}$$

where:

- VA_i is value-added of the i^{th} firm per annum, and it is measured in millions of Vietnamese Dong (VND).

- L_i is labor, which is measured in person, representing the total employment in the i^{th} firm per annum.
- K_i is net capital of the i^{th} firm per annum. It is measured in VND million, and estimated by subtracting depreciation from total capital of the firm in a year.
- v_i and u_i are disturbance terms, which were defined earlier.

In our empirical study, the technical inefficiency effect model is specified with some determinants as follows.

$$\begin{aligned} u_{it} = {} & \delta_0 + \delta_1 Z_{1t} + \delta_2 Z_{2t} + \delta_3 Z_{3t} + \delta_4 Z_{4t} + \delta_5 Z_{5t} + \delta_6 Z_{6t} + \delta_7 Z_{7t} \\ & + \delta_8 Z_{8t} + \delta_9 Z_{9t} + \delta_{10} Z_{10t} + \delta_{11} Z_{11t} + \delta_{12} Z_{12t} + \delta_{13} Z_{13t} \\ & + \delta_{14} Z_{14t} + \delta_{15} Z_{15t} + \delta_{16} Z_{16t} + w_{it}, \end{aligned} \tag{17}$$

where:

- Z_1 is the natural logarithm of firm age.
- Z_2 is the natural logarithm of revenue.
- Z_3 is the natural logarithm of firm's capital-labor ratio.
- $Z_{4\text{-}9}$ are dummy variables. They are equal to 1 if firm is located in region 1, 2, 4, 5, 7, and 8, respectively, and = 0 otherwise.
- Z_{10} is dummy variable = 1 if firm is in the sub-industry of food products and beverages, and = 0 otherwise.
- Z_{11} is dummy variable =1 if firm is in the sub-industry of textiles, wearing apparel, dressing and footwear, and = 0 otherwise.
- Z_{12} is dummy variable = 1 if firm is in the sub-industry of wood and wood-made products, and = 0 otherwise.
- Z_{13} is dummy variable = 1 if firm is in the sub-industry of other non-metallic mineral products, and = 0 otherwise.
- Z_{14} is dummy variable = 1 if firm is in the sub-industry of fabricated metal products, and = 0 otherwise.
- Z_{15} is dummy variable = 1 if state firm, and = 0 otherwise.
- Z_{16} is dummy variable = 1 if foreign invested firm, and = 0 otherwise.
- w_{it} are error 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.

2. Data Envelopment Analysis (DEA) Approach

In this paper, we also use non-parametric deterministic frontier methodology to estimate technical efficiency for each firm. Since we have data of these small firms, we can estimate the frontier for them. This frontier represents the maximum output level that a firm can reach, given a certain level of input. For this purpose, we use the methodology of linear programming developed by Farrell (1957).

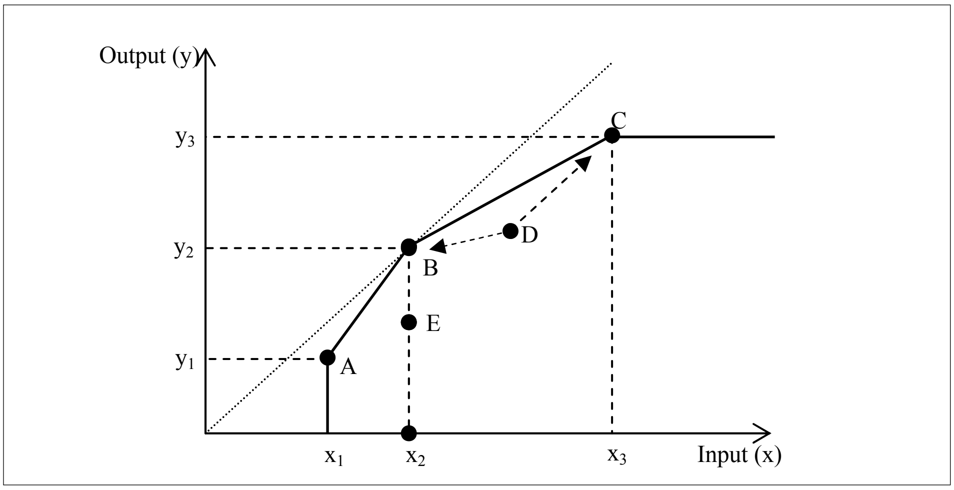
The methodology in this paper, known as Data Envelopment Analysis (DEA), has some advantages over the SFPF approach. First, it is not necessary to assume a specific functional form for the production function. Second, it makes no *priori* distinction between the relative importance of outputs and inputs considered as relevant in firm decision-marking process. Third, DEA is relatively insensitive to model specification because the efficiency measurement is similar, regardless of input-oriented or output-oriented measurements.

However, DEA is not costless. One problem is that it infers the best practice production function from the reported input–output combinations of some small number of the most efficient firms. For this reason, the result may be highly sensitive to measurement errors in inputs and outputs. Another problem may arise when a large number of inputs are employed because, given enough inputs, all or most of the firms may be rated as efficient. This problem will be minimized in this paper since we will only use two inputs, i.e. labor and capital. Thus, we minimize potential measurement errors in inputs, and also reduce probability of rating most of the firms as efficient.

Despite the prevalence of the stochastic frontier production function techniques, non-parametric methodologies, i.e. the DEA, is the appropriate choice in the case of unknown production technology.

Technical efficiency can be defined as the ability of a firm to produce as much output as possible, given a certain level of inputs and certain technology. Figure 1 illustrates this terminology. In the Figure, five points A, B, C, D, E associated with different levels of input and output are shown. Line ABC describes the frontier for this production process. Observations A, B, and C are on the frontier, while observations D and E lie below the frontier. There exists a 45-degree ray from the origin that is tangent to the frontier at point B, and this ray shows the constant return to scale (CRS) technology that is represented by the data of those observations. Also in this Figure, observation B depicts the relative technical efficiency, meaning that this firm is both purely technically efficient and scale efficient because it lies on the frontier, and has the property of CRS.

[Figure 1] Illustration of Technical Efficiency



Although a firm may be technically inefficient in general, it is also possible to be purely technically efficient while experiencing scale inefficiency. This is also shown in Figure 1. Observations A and C are purely technically efficient since they belong to the frontier, but they incur scale inefficiencies. Observation D is both scale and technically inefficient because it lies below the frontier. Theoretically, the same level of input could be used to achieve a higher level of output, which would allow the firm at point D to move upward to the frontier between points B and C. Observation E is purely technically inefficient since it lies below the frontier, but is scale efficient, because it produces at input level of x_2—the scale-efficient level of input.

In order to obtain separate estimates of technical efficiency and scale efficiency, we apply the input-oriented technical efficiency measurements to the data of the small manufacturing firms. This measurement must satisfy three different types of scale behavior, i.e. constant returns to scale

(CRS), non-increasing returns to scale (NRS), and variable returns to scale (VRS).

In our empirical work, we compute technical efficiency by using input-oriented DEA approach. Assuming that there are $r = 1,2,\ldots,R$ regions (8 regions), K industries, and I firms, and these firms use $n = 1,2,\ldots,N$ inputs. These inputs are then used to produce $m = 1,2,\ldots,M$ outputs in each firm in each industry. In our data set, each observation of inputs and outputs is strictly positive.

Let $y^{k}_{m,i,r}$ be the m^{th} output of the i^{th} firm of k^{th} industry in r^{th} region. Let $x^{k}_{n,i,r}$ be the n^{th} input of the i^{th} firm of k^{th} industry in r^{th} region, and z be a matrix of weights, whose elements denote $z^{k}_{i,r}$ with $i = 1,2,\ldots,I$; $k = 1,2,\ldots,K$ and $r = 1,2,\ldots,R$.

The CRS input-oriented measure of technical efficiency for the i'^{th} firm in r'^{th} region and k'^{th} industry is calculated as the solution to the following mathematical programming problem:

$$\min \ \theta \tag{18}$$

Subject to:

$$\begin{aligned}
& y^{k'}_{m,i',r'} \le \sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{k=1}^{K} z^{k}_{i,r} y^{k}_{m,i,r} \\
& \qquad\qquad m = 1,2,\ldots,M; r' = 1,2,3,4,5,6,7,8; i' = 1,2,\ldots,I \\
& \sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{k=1}^{K} z^{k}_{i,r} x^{k}_{n,i,r} \le \theta x^{k'}_{n,i',r'} \\
& \qquad\qquad n = 1,2,\ldots,N; k' = 1,2,\ldots,K \\
& z^{k}_{i,r} \ge 0
\end{aligned} \tag{19}$$

The scalar value θ represents a proportional reduction in all inputs such that $0 \le \theta \le 1$.

The NRS technical efficiency for the i'^{th} firm in r'^{th} region and k'^{th} industry is calculated as the solution to the following mathematical programming problem:

$$\min \ \theta \tag{20}$$

Subject to:

$$y^{k'}_{m,i',r'} \leq \sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{k=1}^{K} z^{k}_{i,r} y^{k}_{m,i,r}$$
$$m = 1,2,\ldots,M; r' = 1,2,3,4,5,6,7,8; i' = 1,2,\ldots,I$$
$$\sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{k=1}^{K} z^{k}_{i,r} x^{k}_{n,i,r} \leq \theta x^{k'}_{n,i',r'}$$
$$n = 1,2,\ldots,N; k' = 1,2,\ldots,K \tag{21}$$

$$\sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{k=1}^{K} z^{k}_{i,r} \leq 1 \quad and \quad z^{k}_{i,r} \geq 0 \tag{22}$$

Likewise, the VRS technical efficiency for the i'^{th} firm in r'^{th} region and k'^{th} industry is calculated as the solution to the following mathematical programming problem:

$$\min \ \theta \tag{23}$$

Subject to:

$$y^{k'}_{m,i',r'} \leq \sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{k=1}^{K} z^{k}_{i,r} y^{k}_{m,i,r}$$
$$m = 1,2,\ldots,M; r' = 1,2,3,4,5,6,7,8; i' = 1,2,\ldots,I$$
$$\sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{k=1}^{K} z^{k}_{i,r} x^{k}_{n,i,r} \leq \theta x^{k'}_{n,i',r'}$$
$$n = 1,2,\ldots,N; k' = 1,2,\ldots,K \tag{24}$$

$$\sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{k=1}^{K} z^{k}_{i,r} = 1 \quad and \quad z^{k}_{i,r} \geq 0 \tag{25}$$

The results obtained from DEA include all the above-mentioned measures of each firm's efficiency.

III. DATA DESCRIPTIONS

The paper uses the data obtained from the Economic Census for Enterprises conducted by General Statistics Office of Vietnam (GSO) in the period 2000-2003, in which the core information collected from enterprises includes the types of enterprise, business and production activities, number of employees, income, assets and liabilities, turnover, financial obligations to the state, means and equipments used for business and production purposes, and investment costs. This Census covered more than 72,000 enterprises, in which more than 10,000 were asked for detailed information on business and production costs in terms of inputs, e.g. information on the raw materials, fuels, instruments and spare parts, and labor costs. In this paper, we will use the panel data of 1,492 small firms over the four-year period (2000-2003), or we have 5,968 observations in total to be analyzed.

[Table 2] Firm Size by Average Number of Labors

Year	2000			2001			2002			2003		
	L0	KL0	RL0	L1	KL1	RL1	L2	KL2	RL2	L3	KL3	RL3
Mean	37	22	100	38	57	103	39	67	103	40	80	103
Median	18	10	41	20	36	44	19	42	48	20	47	55
Maximum	287	576	6,195	296	900	7,391	292	900	5,028	294	9,201	7,365
Minimum	1	0.2	1.6	2	1.2	0.7	2	1	1.9	1	0.8	1.9
Std. Dev.	48.7	37.8	323	48.4	67.7	331.2	49.2	82.4	269.1	49	257.6	259.5
Observations	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492

Note: Number 0, 1, 2, and 3 attached to variables to indicate the year 2000, 2001, 2002, and 2003, respectively. L is the number of labors, KL is capital-labor ratio, and RL is revenue-labor ratio. All numbers are rounded.

Source: Authors compiled from the dataset

There are several ways of classifying firms by size, in which employment and total assets are the most common indicators in Vietnam. For the purpose of this paper, we use both indices. According to the GSO, a small and medium firm is defined as a firm that has less than 299 workers per year. In this paper, we classify the studied firms by five types as follows.

- Type one is a firm having less than 5 workers per year.

- Type two is a firm having 5 to 9 workers per year.
- Type three is a firm having 10 to 49 workers per year.
- Type four is a firm having 50 to 199 workers per year.
- Type five is a firm having 200 to 299 workers per year.

Some characteristics by firm size are shown in Table 2. We find that there is consistency between classifications by employment levels with respect to capital stocks, i.e. the sample of small firms had less than 10 billion in total assets.

As shown in Table 3, on average, firms in type one had 3 workers, firms in type two had 7 workers, firms in type three had 23 workers, firms in type four had 93 workers, and firms in type five had 235 workers in 2000.

In terms of capital-labor ratio, we find a trend that the mean of capital-labor ratio increased during the study period. In fact, the revenue-labor ratio also increased over time, but the rate was smaller than that of the capital-labor ratio. Using the classification of firm size above, we also find that the capital-labor ratio decreased when number of workers increased. For instance, in the year 2000, the mean capital-labor ratio of the firms that had less than 5 workers, from 5 to 9 workers, from 10 to 49 workers, from 50 to 199 workers, and from 200 to 299 workers were 34, 30, 22, 16, and 9, respectively.

For the purpose of efficiency analysis, as mentioned, added value is output, while labor and net capital are inputs of the model.

DEA approach can produce very different estimates because there are some outliers in the dataset. Most outliers are commonly due to insufficient information of the number of workers, net capital, and costs of intermediate raw materials. One thing that we can do before our estimation is to convert all nominal variables into real ones. Ideally, each input and output variable should be deflated with its own deflator. However, we could not do it in such way due to the lack of relevant data for those types of deflators. Alternatively, we will employ the annual consumer price index (CPI) as a discount factor for all observations in three later years, i.e. 2001, 2002, and 2003.

[Table 3] Firm Size in terms of Labor, Capital, and Revenue

Firm size	2000			2001			2002			2003		
<5	L0	KL0	RL0	L1	KL1	RL1	L2	KL2	RL2	L3	KL3	RL3
Mean	3	34	47	4	93	130	3	114	72	3	216	74
Median	4	17	39	4	50	40	4	61	39	4	60	36
Maximum	4	561	175	4	900	3,926	4	863	863	4	9,201	578
Minimum	1	2	4	2	12	8	2	9	4	1	7	6
Observations	88	88	88	77	77	77	84	84	84	80	80	80
5-9												
Mean	7	30	195	7	75	187	7	88	168	7	106	148
Median	7	10	46	7	52	50	7	48	48	7	56	57
Maximum	9	577	6,195	9	473	7,392	9	900	5,028	9	1,320	7,365
Minimum	5	0.2	4	5	3	4	5	4	2	5	3	2
Observations	321	321	321	310	310	310	311	311	311	306	306	306
10-49												
Mean	23	22	86	23	57	86	23	67	98	23	73	104
Median	20	10	44	20	37	47	20	45	55	20	49	57
Maximum	49	265	1,390	49	771	1,793	49	616	2,058	49	743	1,899
Minimum	10	0.3	3	10	1.2	2.4	10	1	2.6	10	0.8	1.9
Observations	750	750	750	759	759	759	734	734	734	734	734	734
50-199												
Mean	93	16	57	91	36	61	95	41	67	95	46	76
Median	79	10	39	77	29	42	84	34	47	85	39	56
Observations	297	297	297	307	307	307	332	332	332	338	338	338
200-299												
Mean	235	9	35	233	18	32	241	20	38	235	21	36
Median	228	5	24	220	15	24	243	21	34	231	23	27
Maximum	287	27	203	296	38	143	292	43	129	294	45	157
Minimum	200	0.5	4.9	200	1.7	5.8	200	2	6	200	2.3	4.5
Observations	36	36	36	39	39	39	31	31	31	34	34	34

Note: L is the average number of labors, KL is capital-labor ratio, and RL is revenue-labor ratio. All numbers are rounded.

Source: Authors compiled from the dataset

For the model that identifies the factors affecting efficiency levels of these firms, some other variables could also be used. Firms' reevaluation, denoted for values adjusted with annual CPI, stands for the effects of firm size on technical inefficiency. Table 4 presents the distribution of firm size by sub-industry in 2003.

[Table 4] Distribution of Firms by Sub-industry and Size, 2003

Productive Sector	< 5	5-9	10-49	50-199	200-299	*Total*	Percent (rounded)
Food products and beverages (15)	70	179	145	27	1	422	22
Textiles (17)	1	0	15	10	3	29	1.5
Wearing apparel (18)	0	3	12	30	11	56	2.9
Footwear (19)	0	0	14	7	2	23	1.2
Wood and wood-made products (20)	6	54	100	51	6	217	11.2
Paper and paper products (21)	0	2	37	22	0	61	3.1
Publishing, and printing (22)	0	9	39	23	1	72	3.7
Chemicals, and chemical products (24)	1	6	23	10	0	40	2.1
Rubber and plastics products (25)	1	6	27	21	1	56	2.9
Other non-metallic mineral products (26)	0	19	142	59	3	223	11.5
Basic metals (27)	0	3	13	4	0	20	1.0
Fabricated metal products, except machinery and equipments (28)	0	10	58	19	3	90	4.6
Machinery and equipments (29)	0	5	18	10	0	33	1.7
Electrical machinery (31)	0	1	6	1	0	8	0.4
Radio, communication equipments, and apparatus (32)	0	6	1	0	0	7	0.4
Medical, precision, and optical (33)	0	0	4	0	0	4	0.2
Motor vehicles, trailers, and semi-trailers (34)	0	2	18	9	0	29	1.5
Other transport equipments (35)	0	3	18	9	0	30	1.5
Furniture (36)	1	4	39	26	2	72	3.7

Note: The number in parenthesis indicates code of the industry in the dataset.

Source: Authors compiled from the dataset

IV. ESTIMATED RESULTS AND ANALYSIS

1. Hypothesis Tests

To estimate technical efficiency for the small manufacturing firms in the sample, we first need to choose the production function form as presented in the equations (15) and (16), and then conduct tests for the technical inefficiency model as specified in the equation (17).

To choose production frontier for these firms, we will select the most appropriate function for our available data between the Cobb-Douglas production function and the translog production function. In addition, because we assume that there exist some uncontrollable stochastic shocks that could influence production efficiency of these firms, a stochastic production frontier approach will also be used. The maximum-likelihood estimates of the parameters for the production function can be obtained by using the computer program FRONTIER Version 4.1 by Coelli (1996a). The estimated results from Model 1 and Model 2 then will be further discussed to explain the efficiency performance as well as the determinants of technical inefficiency in these small firms. Table 5 presents the results of the following hypothesis tests.

[Table 5] Generalized Log-likelihood Ratio Hypothesis Tests

Null Hypothesis	Log-likelihood Value	Test Statistics (λ)	Critical value λ_c at…		Decision
			1 percent	5 percent	
Cobb-Douglas Production Function					
$H_0 : \beta_{LL} = \beta_{KK} = \beta_{LK} = 0$	-9318.268	51.568	10.501	7.045	reject
No technical inefficiency Effects					
$H_0 : \gamma = \mu = \eta = 0$	-9624.013	683.058	10.501	7.045	reject
Time-invariant Technical Inefficiency					
$H_0 : \eta = 0$	-9394.319	224.14	6.63	3.84	reject

Source: Authors' calculations

The first hypothesis test is production function specification. Suppose that these small firms follow the Cobb-Douglas production function. Thus, we have the null hypothesis $H_0(\beta_{LL} = 0; \beta_{KK} = 0; \beta_{LK} = 0)$. The generalized likelihood-ratio test statistic is defined as $\lambda = -2[L(H_0) - L(H_1)]$, in which $L(H_0)$ is the log-likelihood value of a restricted frontier model under the null hypothesis H_0, and $L(H_1)$ is the log-likelihood value of the general frontier model under the alternative hypothesis H_1. This test statistic has an approximately Chi-square (or mixed Chi-square) distribution with degrees of freedom equal to the difference between the parameters involved in the null and alternative hypothesis tests. As can be seen in Table 5, the null hypothesis is rejected at 1% significance level, meaning that the Cobb-Douglas production function is not adequate specification for these small firms. Thus, our estimation will be based on translog production function.

The second test is about technical inefficiency effects. The null hypothesis supposes that there are no technical inefficiency effects, i.e.

$H_0: \gamma = 0; \mu = 0; \eta = 0$. If the null hypothesis is true, there is no frontier parameter in the regression equation, and the estimation becomes OLS estimation. Again, Table 5 shows that the null hypothesis is rejected at the 1% significance level, and this result suggests that the average production function is not an adequate representation for all small firms in our sample data, and such average production function will underestimate the actual frontier due to technical inefficiency effects.

Another interesting question is whether to choose a model of time-invariant technical inefficiency or time-variant technical inefficiency. To answer this question, we conduct the null hypothesis which assumes that technical inefficiency is time-invariant, i.e. $H_0: \eta = 0$. The result in Table 5 also indicates that the null hypothesis H_0 is rejected at 1% significance level for the total sample, meaning that technical inefficiency is time-variant.

2. Estimation by the Stochastic Frontier Production Function (SFPF)

2.1. Estimated Results

The previous section shows that the translog SFPF is the most appropriate model for the available data of this paper.

According to the results in Table 6, the estimated coefficient for the labor input is 0.61, and significantly different from zero at 1% significance level, while the estimated coefficient for the capital input is 0.005, and not significantly different from zero. These estimates indicate that, during the study period, these small firms still largely depended upon labors rather than capitals in their production process.

As mentioned previously, in order to show how technical inefficiency is attributed to the production variance of the small firms in the sample, we introduce $\gamma = \sigma_u^2 / \sigma_v^2$, in which a large γ shows that a large portion of its production variance is attributed to the technical inefficiency error σ_u^2, and a small γ indicates higher production efficiency. Table 6 shows that the estimated values of γ from Model 1 and Model 2 are 0.61 and 0.94, respectively. It is not surprising because, during the period, these small firms had relatively low production efficiency level, at only 49 percent as estimated from SFPF approach. These estimated results are lower than those from Nguyen (2005), which uses data of 32 manufacturing industries in Vietnam and stochastic frontier methodology, and finds that the average efficiency level fluctuates between 60 percent and 70 percent during the period 2000-2002.

[Table 6] Maximum Likelihood Estimates for Parameters of the Models

	Model 1			Model 2	
Variables	Parameter	Coefficient	Standard-error	Coefficient	Standard-error
Constant	α_0	3.10509**	0.22997	2.906221**	0.200339
LnL	α_L	0.61330**	0.09763	0.567185**	0.08452
LnK_r	α_K	0.00534	0.06665	0.212678**	0.062068
$(LnL)^2$	β_{LL}	0.00705	0.01576	0.013945	0.013537
$(LnK)^2$	β_{KK}	0.05569**	0.00725	0.041726**	0.00688
$(LnL)(LnK_r)$	β_{LK}	-0.03480*	0.01679	-0.04538**	0.015377
Z_1	δ_1			0.614611*	0.259443
Z_2	δ_2			-1.6168**	0.338189
Z_3	δ_3			1.035779**	0.182227
Z_4	δ_4			-0.12093	0.442974
Z_5	δ_5			-0.59644	0.712294
Z_6	δ_6			1.006579**	0.386471
Z_7	δ_7			0.55234	0.4189
Z_8	δ_8			-2.39353**	0.809485
Z_9	δ_9			-1.61107*	0.675039
Z_{10}	δ_{10}			-0.95632*	0.415027
Z_{11}	δ_{11}			1.293518**	0.445891
Z_{12}	δ_{12}			-0.78134**	0.270854
Z_{13}	δ_{13}			0.835553**	0.188952
Z_{14}	δ_{14}			-0.61345	0.367558
Z_{15}	δ_{15}			-0.05478	0.394171
Z_{16}	δ_{16}			0.605474**	0.167359
sigma squared	σ^2	2.71199	0.10210	9.287189**	1.936482
gamma	γ	0.61705	0.01629	0.941671**	0.011975
	η	-0.20310	0.01307		
Log likelihood	LK	-9282.484		-9110.77	0

Note: Numbers in parentheses are asymptotic t-value. Numbers with (**) or (*) means that the coefficient is significantly different from zero at 1% or 5% significance level, respectively.

Source: Authors' calculations

The average efficiency estimates for sub-industries in the sample are shown in Table 7. An interesting result is that there was not too much heterogeneity among these sub-industries during the study period. For instance, in the year 2000, the efficiency level of the textiles industry (code 17) and the publishing, printing industry (code 22) reached about 53 percent and 61 percent, respectively.

[Table 7] Average Efficiency Level by Sub-manufacturing Industries

Sub-industries	Average Efficiency (TE)				
	2000	2001	2002	2003	Obs
Food products and beverages (15)	0.603	0.340	0.489	0.484	422
Textiles (17)	0.529	0.344	0.482	0.477	29
Wearing apparel (18)	0.583	0.405	0.478	0.496	56
Footwear (19)	0.559	0.449	0.550	0.537	23
Wood and wood-made products (20)	0.542	0.359	0.524	0.520	217
Paper and paper products (21)	0.552	0.394	0.583	0.617	61
Publishing, and printing (22)	0.612	0.448	0.514	0.522	72
Chemicals, and chemical products (24)	0.559	0.416	0.536	0.525	40
Rubber and plastics products (25)	0.575	0.412	0.613	0.607	56
Other non-metallic mineral products (26)	0.557	0.317	0.473	0.496	223
Basic metals (27)	0.557	0.410	0.619	0.620	20
Fabricated metal products, except machinery and equipments (28)	0.573	0.420	0.552	0.563	90
Machinery and equipments (29)	0.569	0.415	0.488	0.512	33
Electrical machinery (31)	0.575	0.410	0.616	0.693	8
Radio and communication equipments, and apparatus (32)	0.532	0.438	0.512	0.450	7
Medical, precision, and optical (33)	0.607	0.434	0.399	0.441	4
Motor vehicles, trailers, and semi-trailers (34)	0.575	0.496	0.529	0.480	29
Other transport equipments (35)	0.594	0.399	0.483	0.489	30
Furniture (36)	0.570	0.401	0.493	0.517	72

Note: The number in parenthesis indicates code of the industry in the dataset. Average numbers are rounded.

Source: Authors' calculations

To investigate the relationship between technical efficiency and firm size on a disaggregated level, we classify firm size by annual employees. The results in Table 8 indicate that the efficiency levels across various size classes are close to each other. This evidence implies that inefficiency was not an intrinsic problem in these small firms during the study period. There were many sub-industries, in which their smaller firms could reach closely to the production frontier. Table 8 also indicates that we could not conclude that there was a positive relationship between efficiency and firm size. In fact, the smallest firms (type one) had an average efficiency of 59 percent in 2000, which was higher than that of all other small firms.

[Table 8] Average Efficiency Level by Firm Size

Size	Obs	TE2000	Obs	TE2001	Obs	TE2002	Obs	TE2003
Less than 5	88	0.598	77	0.368	84	0.479	80	0.449
From 5 to 9	321	0.576	310	0.342	311	0.490	306	0.500
From 10 to 49	750	0.576	759	0.380	734	0.519	734	0.522
From 50 to 199	297	0.565	307	0.383	332	0.518	338	0.531
From 200 to 299	36	0.557	39	0.361	31	0.511	34	0.500
Number of firms	1,492		1,492		1,492		1,492	

Note: TE2000, TE2001, TE2002, and TE2003 are average technical efficiency in 2000, 2001, 2002, and 2003, respectively. Numbers are rounded.

Source: Authors' calculations

[Table 9] Distribution of Efficiency Level of Sample Firms

	TE2000	TE2001	TE2002	TE2003
Mean	0.575	0.372	0.510	0.515
Median	0.576	0.360	0.578	0.587
Maximum	0.787	0.876	0.897	0.894
Minimum	0.243	0.004	0.002	0.002
Observations	1,492	1,492	1,492	1,492

Note: Numbers are rounded.

Source: Authors' calculations

Distribution of production efficiency for the total sample of these small firms in Table 9 shows that the minimum efficiency level in 2000, 2001, 2002, and 2003 were 24.3 percent, 0.4 percent, 0.2 percent, and 0.2 percent, respectively. Also, the maximum efficiency level reached 78.7 percent, 87.6 percent, 89.7 percent, and 89.4 percent, respectively. These results suggest large rooms for efficiency enhancements in the small firms.

The distribution of technical efficiency of these small firms was characterized by the decreasing trend in term of minimum efficiency. As can be seen in Table 10, the efficiency score between the small firms in the three big regions (Region 1 includes 299 observations, Region 7 includes 469 observations, and Region 8 includes 462 observations) indicates that the mean technical efficiency of Region 1 and Region 7 were not too different, and the maximum value of technical efficiency of Region 8 was higher than the others during the study period. The highlight is that the maximum levels of technical efficiency of the firms in Region 8 in 2000, 2001, 2002, and 2003 were relatively higher than those in Region 1 and Region 7.

[Table 10] Distribution of Efficiency Level by Regions

TE	Region 1				Region 7				Region 8			
	2000	2001	2002	2003	2000	2001	2002	2003	2000	2001	2002	2003
Mean	0.571	0.411	0.544	0.549	0.583	0.384	0.541	0.543	0.576	0.33	0.463	0.469
Median	0.571	0.417	0.626	0.627	0.585	0.372	0.602	0.619	0.580	0.32	0.498	0.509
Maximum	0.765	0.791	0.822	0.821	0.786	0.796	0.863	0.865	0.787	0.87	0.897	0.894
Minimum	0.257	0.015	0.003	0.005	0.245	0.006	0.002	0.003	0.283	0.01	0.009	0.002

Note: Numbers are rounded.

Source: Authors' calculations

2.2. Sources of Technical Inefficiency

Table 6 above also reports the results from the maximum likelihood estimation of the inefficiency model. The discussion is focused on the results of overall technical efficiency.

An insignificant relationship between location of Region 1, 2, 5 and sub-industries of fabricated metal products (code 28) and technical inefficiency can be seen from Table 6.

Also, state ownership could not ensure more efficiency as the estimated coefficient is not statistically significant at 1% or 5% significance level.

Sub-industry of food products and beverages (code 15), wood and wood-made products (code 20) are negatively related to technical inefficiency, meaning that they contributed positively to efficiency during the period.

The positive sign of the firm age variable may be due to the fact that age is reflecting the time length for capital accumulation rather than experience of the firm.

The revenue variable is negatively related to technical inefficiency, indicating that the revenue, which is the proxy for firm size, contributed positively to efficiency during the study period. Besides, capital-labor ratio was also positively related to technical inefficiency in the period. These results imply that these small firms were still operating with labor-intensive way of production.

3. Estimation by the Data Envelopment Analysis (DEA)

3.1. Estimated Results

The DEA results are estimated by using the computer program DEAP Version 2.1 by Coelli (1996b) with the same data as in the SFPF approach. Table 11 summarizes technical efficiency estimates for the studied firms during 2000-2003.

It is shown that, on average, the mean and minimum levels of *crste* for these small firms were about 35.5 percent and 6.8 percent, respectively. We also get the mean values for other technical efficiency components for these firms, i.e. VRS technical efficiency (or *vrste*), and scale efficiency (or *scale*). In the period 2000-2003, *scale* and *vrste* were 90 percent and 39.9 percent, respectively. If all small firms had applied the same technology, we would have expected a style of increasing returns to scale for the firms with a relatively low output level, and a style of decreasing returns to scale for the firms with a relatively high output level.

[Table 11] Technical Efficiency Scores from Input-oriented DEA

	crste	scale	vrste
Mean	0.355	0.900	0.399
Median	0.293	0.960	0.336
Maximum	1.000	1.000	1.000
Minimum	0.068	0.233	0.070
Std. Dev.	0.205	0.137	0.219
Observations	1,492	1,492	1,492

Note: crste is technical efficiency from CRS DEA, vrste is technical efficiency from VRS DEA, and scale is scale efficiency (= crste/vrste). Numbers are rounded.

Source: Authors' calculations

[Table 12] Frequency Distribution of Technical Efficiency Measures from DEA

Range	crste			scale			vrste		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
[0, 0.2)	0.160	0.025	336				0.167	0.023	263
[0.2, 0.4)	0.285	0.056	711	0.295	0.056	9	0.293	0.055	648
[0.4, 0.6)	0.487	0.058	254	0.516	0.054	76	0.488	0.055	318
[0.6, 0.8)	0.694	0.060	111	0.713	0.055	172	0.689	0.060	151
[0.8, 1)	0.902	0.056	68	0.953	0.049	1202	0.892	0.060	83
[1, 1.2)	1.000	0.000	12	1.000	0.000	33	1.000	0.000	29
All	0.355	0.205	1,492	0.900	0.137	1,492	0.399	0.219	1,492

Note: Numbers are rounded.

Source: Authors' calculations

Table 12 summarizes the frequency distribution of the various efficiency measures for these small firms. By CRS DEA estimates, the number of small firms laid in the technical efficiency interval from 20 percent to 40 percent was 771, while that laid in the technical efficiency interval from 80 percent to 100 percent was only 68.

3.2. Relationship between Industry Profit and Efficiency Measures and Regional Factor

Profit is one of the most important signs for the firm's production efficiency. Therefore, we conduct a regression to analyze the relationship between this indicator and all efficiency measures from DEA approach and regional factor.

[Table 13] Relationship between Profits and Efficiency Measures and Regions

$$
\begin{array}{llllllll}
profit=0.596+ & 0.258crste & -\ 0.200vrste & -\ 0.134scale & +\ 0.036Re1 & +\ 0.029R7 & -\ 0.0208R8 \\
t\ \ (8.48)^{***} & (1.93)^{*} & (-1.60)^{*} & (-1.79)^{*} & (3.21)^{***} & (2.878)^{**} & (-1.97)^{*}
\end{array}
$$

$R^2=0.037$, $\sqrt{R^2}=0.193$

Note: Numbers with (***), (**) and (*) denote that the coefficient is significantly different from zero at 1%, 5%, and 10% significance level, respectively. Numbers in parentheses are asymptotic t-values.

Source: Authors' calculations

Table 13 shows the relationship between profit and *crste*, *vrste*, *scale* efficiency, Region 1, Region 7, and Region 8 during the study period.

Linear correlation between profit and efficiency measures and regions is evaluated by using squared-root of the R^2. The results in Table 13 show a positive and statically significant relationship between profit and *crste*, Region 1 and Region 7, while it indicates a negative and statistically significant relationship between profit and *vrste*, *scale*, and Region 8.

4. Comparing the Estimated Results from SFPF and DEA

In order to measure level of technical efficiency for the small and medium manufacturing firms in Vietnam, this paper has used a parametric approach (based on SFPF) and a non-parametric approach (based on DEA). It is expected that efficiency scores estimated from the DEA frontier would be lower than those obtained from SFPF because DEA attributes any deviation from the frontier to inefficiency.

Some studies compare technical efficiency estimates from SFPF and DEA models, and most of them have mixed results. Ferrier and Lovell (1990), in the analysis of U.S banks, show higher technical, but lower economic efficiency in the SFPF model than those from DEA frontier. Based on the sample farms in Bangladesh, Wadud (2003) finds that levels of all efficiency measurements based on *crste* and *vrste* DEA frontiers are higher than those based on SFPF models. The study by Kalaitzandonakes and Dunn (1995) shows a significant higher level of mean technical efficiency under CRS DEA frontier than under the stochastic frontier production function (SFPF).

In this paper, the estimated results show that the average efficiency level based on VRS DEA model (39.9 percent) is lower than that based on SFPF model (49.7 percent).

[Table 14] Spearman rank correlations of efficiency rankings based on SFPF and DEA estimates

Year	2000	2001	2002	2003
Spearman rank correlation (ρ)	0.767	0.137	0.033	0.021
Probability	0.000	0.000	0.205	0.413

Source: Authors' calculations

To further examine the match between the two applied approaches, we compute the Spearman rank correlation coefficients between the efficiency rankings of small firms. The estimated results are presented in Table 14, which shows that rank correlations in 2000 and 2001 are positive and highly significant, while rank correlations in 2002 and 2003 are positive and insignificant.

Why were the outcomes of these approaches somewhat different? Since we used similar data, the major difference might be derived from the applied techniques. We only would expect these two approaches to yield comparable results in case of no effects of uncontrollable environment variables and measurement errors due to the differences in business management, and no problems on aggregate technology as well as functional form describing the technology of these firms. Ferrier and Lovell (1990) and Drake and Weyman-Jones (1996) produce insignificant rank correlation coefficients between the estimated efficiencies from these two approaches. Sharma *et al.* (1999) also find that the estimated mean technical and economic efficiencies obtained from the parametric technique are higher than those from DEA for *crste* efficiency, but quite similar for *vrste* efficiency, while allocative efficiencies were generally higher in DEA. Therefore, these above disagreements in the empirical studies on the comparison of two approaches might be mainly attributed to differences in the characteristics of the available data, choices of input and output variables, measurement and specification errors, and estimation procedures.

V. CONCLUDING REMARKS

To study productive efficiency of the small and medium manufacturing firms in Vietnam, this paper employed a parametric approach (based on SFPF), and a non-parametric approach (based on DEA) with the panel data for 1,492 firms during the period 2000-2003. The hypothesis tests confirmed that the translog SFPF model is appropriate for analyzing productive efficiency of these small firms.

The results obtained from DEA showed that, during the period, the average efficiency of these small firms only reached 39.9 percent, and it was lower than the average efficiency obtained from SFPF, at 49.7 percent.

Regression analysis allowed us to identify some determinants of firm's efficiency. Among them, ownership characteristics were not significantly related to efficiency.

One of the important results derived from our analysis was the existence of slightly heterogeneous efficiency levels among sub-industries and regions. Even if we controlled some sub-industries, these were still variations in efficiency. In terms of policy implications, this evidence showed that traditional resource reallocation might not be the best way to increase efficiency or productivity. It would be better to design intervention strategies targeted at some specific sub-industries.

Our results also suggest that there were several factors that could be affected by the current public policy options. These factors were related to the capital-labor ratio. According to this, government policies should aim at increasing and improving accessibility of the small firms to capital markets. A higher quantity of financial sources would allow them to increase investments in both physical and human capital, and thus technological innovations. This kind of policy might be crucial in order to increase efficiency and productivity of the small firms.

Because of low technical efficiency levels of these firms, and the narrow gap of production efficiency between regions, we believe that there would be still a large room for the studied firms in this paper to improve and get more profits than their present achievements. Moreover, small firms have played a key role in the national economy, so that efficiency improvement become more indispensable, and it requires proper attention from the government through appropriate adjustments and policies.

Finally, despite the firm-level data, we believe that both parametric and non-parametric approaches could provide an overall picture and many pieces of important information on technical efficiency of small and medium manufacturing firms in Vietnam. The estimated results suggested that low technical efficiency might be originated from the lack of information and capital input. Other possible sources of inefficiency might also be derived from low capacity of workers to adapt new technology, or inappropriate business strategies of the inefficient firms in a rapidly growing and competitive economy.

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