Efficiency of Construction Firms in Vietnam

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Efficiency of Construction Firms in Vietnam: Assessment by Parametric and Non-parametric Approaches

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Abstract

This paper uses both parametric and non-parametric approaches to estimate technical efficiency for 2,298 construction firms in Vietnam in the database of the 2002 Economic Census for Enterprises by the General Statistics Office of Vietnam (GSO). It is found that results from both approaches are consistent, and they could help explain the performance efficiency of these firms. Estimates from the non-parametric approach (data envelopment analysis [DEA] model) and the parametric approach (stochastic frontier production function [SFPF] model) indicate that the average pure technical efficiency of these firms was about 60 percent (58.6% and 57.8% for DEA and SFPF, respectively). Models to test the factors influencing efficiency scores in both approaches show relatively similar results that state firms were more efficient than non-state ones, and location in Hanoi and Ho Chi Minh city did have impacts on efficiency scores. However, exploration of the net capital-labor ratio variable show that it did not influence efficiency scores in the DEA model, while it had clear influence in the SFPF model.

Key words: construction firms, data envelopment analysis (DEA), stochastic frontier production function (SFPF), Tobit regression, Vietnam.

JEL Classification: C14, L74

1. Introduction

Since the *Doi moi* (renovation) to transform the country's centrally-planned economy into a market economy, Vietnam has made impressive achievements in both social and economic aspects. The economy recorded a relatively high growth at about 8 percent over the past decade. The economic structure has been changing rapidly, from being predominantly agricultural to having significant contributions from industry and construction. During the period 1995–2003, the construction sector grew at an average rate of 10 percent and contributed 6.3 percent of the country's gross domestic product (GDP) (GSO, 2004). In 2003, the state construction firms employed 486,000 laborers, accounting for 1.5 percent of the labor force (MOLISA, 2004). The non-state construction firms, particularly firms in civil construction, also generated significant employment. These contributions have made construction an important sector that is always taken into account in the social and economic development strategies of the country.

However, according to numerous reports on the operation of the construction sector in general and construction firms in particular with special attention to construction projects, the operation efficiency has been low due to significant extravagance. According to the newspaper *VnExpress* on November 29, 2003, a national inspection report uncovered wasteful construction sites; with figures in parentheses indicating percentage of invested funds wasted, wasteful projects included Binh Trieu bridge (25%), Nguyen Tri Phuong bridge (expanded) (29%), Tuy Hoa General Hospital (36%), and Thanh Yen–Cong Su road in Kien Giang province (approximately 59%). About 20 to 30 percent of state investment was lost. Therefore, a comprehensive assessment of the construction firms' efficiency and associated factors is needed in order to produce appropriate policy recommendations.

Analyzing the data from the 2002 Economic Census for Enterprises by the General Statistics Office of Vietnam (GSO) with both a non-parametric approach (data envelopment analysis [DEA] model) and a parametric approach (stochastic frontier production function [SFPF] model), this paper will assess the construction firms in Vietnam to determine whether they were operating efficiently. It also aims to find the factors associated with these firms' performance efficiency. Both the DEA and SFPF approaches have been applied to Vietnam only recently, and, to the best of our knowledge, there has been no study using DEA and SFPF to analyze the country's construction firms. Thus, this paper might be the first attempt to evaluate the efficiency of the construction firms in Vietnam.

The paper is organized in five sections, including this introductory one. Section 2 will review the literature on evaluating efficiency of construction firms around the world. The methodology and data source will be presented in Section 3 with descriptions of models and variables. Section 4 will discuss the findings and implications. Section 5 will provide conclusions and suggestions for further studies.

2. Measuring Efficiency of Construction Firms: Literature Review

Policy makers in both developed and developing countries have recently paid attention to the performance efficiency of the construction sector in general, and construction firms in particular, because of the significant contribution to social and economic development in terms of GDP share and job creation. One aspect of concern, however, is that the sector may have negative impacts on the economy due to its extravagance in using resources. Numerous countries have been implementing reform programs to improve the sector's operation efficiency, and there is a variety of criteria for assessments and improvements, such as number of houses built and how efficiently the state and non-state firms are operating. In recent years, assessments of the construction firms' operation have focused on their technical efficiency and scale efficiency. Among various methods, DEA and SFPF are the most frequently used.

With the viewpoint that factors associated with performance efficiency of construction projects, particularly construction sites, were linked closely to the efficiency of the construction firm as a whole, Jan (1996) used DEA to evaluate the performance efficiency of 104 construction projects in Sweden in the period 1989–1992 (including 33 office buildings, 40 blocks of flats, and 31 roads and bridges). Output was value added (VA), while inputs were costs of staff, workers, and machines. Estimated results showed a significant difference between efficiency scores of construction sites. To find the causes for this difference, the author used a multi-regression method with results from DEA estimates and direct interviews with the managers of the studied construction sites. It was interesting to see that additional workers due to the customers' requirements, educational level of the workers, hours worked by managers at construction sites, and the participation level of the workers in decision making did not have any influence on the efficiency of any type of construction site. For instance, for office buildings, design and construction time did not influence efficiency, but these factors did have significant impact on efficiency in home decoration. The author also admitted that measuring efficiency was not easy task and gave some suggestions to estimate total factor productivity in the construction industry.

Estimating the performance efficiency of the Canadian construction subcontractors by DEA with multi-inputs (such as indirect costs and fixed assets) and multi-outputs (such as revenue and net profit), a study of the Canadian National Steering Committee for Innovation in Construction showed that only 14 percent of subcontractors (or 183 out of 1,310) were efficient, and most of these efficient subcontractors had revenue of less than 10 million Canadian dollars (NSCIC, 2003). Among the rest, only 26 percent were operating above a 75 percent level of efficiency; 26 percent were between 50 and 75 percent, and the remaining 48 percent of the firms had efficiency levels less than 50 percent. In addition, the study also indicated that these firms were poor in innovation in terms of improving labor productivity.

Edvardsen (2004) applied DEA to analyze the performance efficiency of Norwegian construction firms in 2001, and then used the bootstrapping method to test estimated results. Revenue as output in the DEA model was classified based on the type of business, i.e., residential construction, non-residential construction (such as offices and schools), and civil engineering construction (such as roads, harbors, and tunnels). Inputs were labor (number of people), real capital (measured by capital service based on the use of production equipment, machines, etc.), and external expenses (materials, subcontractors, energy, etc.). Estimated results indicated that the sample firms had a relatively high average efficiency score (83.4%). However, in the bootstrapping application, the author showed that the constant returns to scale (CRS) hypothesis was rejected, and only variant returns to scale (VRS) one was appropriate with these construction firms. The model to explain factors associated with efficiency and productivity of the studied firms implied that those with high efficiency scores were influenced by a variety of factors, i.e., high wage per hour, low shares of apprentices, low level of product variety, and high hours worked per employee. Moreover, the estimates also indicated that location in Oslo (the capital and the largest city of Norway) had no impact on efficiency score.

El-Mashaleh *et al.* (n.d.) used a conceptual approach with DEA application to measure and compare construction subcontractor productivity at the firm level. The DEA model included multi-inputs and multi-outputs; resource management was paid much attention. Inputs were categorized into three major expenses: equipment expenses (equipments, depreciation, etc.), labor expenses (e.g., number of hired laborers), and technical staff (expenses on training, salaries, etc.). Each type of work performed by a subcontractor was considered as output of that subcontractor. The authors noted that resources in the construction industry were not allocated proportionally, so that the productivity of construction sites could not reflect that of construction firms. Therefore, according to the authors, adding some other managerial factors to the DEA model could bring more practical results.

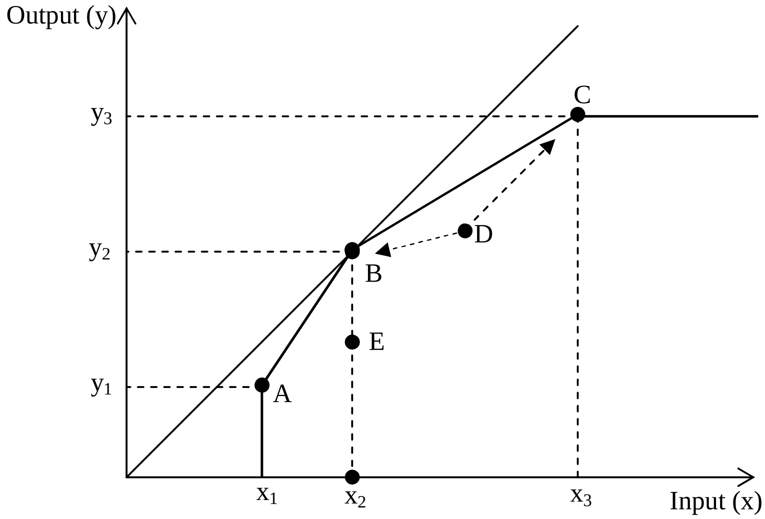
3. Model Specifications and Data Source

3.1. Non-parametric Approach: Data Envelopment Analysis (DEA)

Recently, data envelopment analysis has become the dominant approach to measure the performance of many economic sectors, particularly the public one. One of the attractive characteristics of DEA is that it can deal with multiple outputs easily. In addition, because DEA is a non-parametric approach, it does not require any assumption about the functional form of the production or cost frontier. Therefore, DEA concentrates solely on taking into account and classifying variables, which can be inputs or outputs of the production function.

Technical efficiency may 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 definition. In the figure, there are five points (A–E) associated with different levels of input and output. The line ABC describes the frontier for the production process. Observations A, B, and C are on the frontier, while observations D and E lie below the frontier. There exists a ray from the origin tangent to the frontier at point B, and this ray represents the constant returns to scale of the technology represented by the data of those observations. In this example, observation B depicts the relative technical efficiency, meaning that this firm is purely technically efficient and scale efficient due to its location on the frontier and the property of constant returns to scale.

Figure 1: Illustration of Technical Efficiency



Although a firm may be technically inefficient in an overall sense, it is possible that it is experiencing inefficiency in scale. This also can be seen in Figure 1. Observations A and C are purely technically efficient because they belong to the frontier, but they exhibit 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 will allow this firm (at point D) to move forward to the frontier between points B and C. Observation E is purely technically inefficient because it lies below the frontier, but it is scale efficient because it produces at input level of x2—the scale-efficient level of input (or the same level of output as observation B).

In this study, we use the DEA approach to construct the best-practice frontier (or find the best-practice construction firm) in a given period (i.e., in 2002). The comparison of an individual construction firm to the best one will give signals of its catching-up process or ability to change production technology.

Let Y be an $(M\times N)$ matrix of outputs of construction firms in the sample, where the element y_{ij} represents the i^{th} output of the j^{th} construction firm. Let X be a $(P\times N)$ matrix of inputs, in which the element x_{kj} represents the k^{th} input of the j^{th} firm and z is an N-vector of weights to be defined. Elements of these vectors denote $z_1, \dots, z_N$. The vector y_j $(M\times 1)$ is the vector of outputs and x_j is the $(P\times 1)$ vector of inputs of the j^{th} firm.

The CRS input-oriented measurement of technical efficiency for the j^{th} construction firm is calculated as the solution to the following mathematical programming problem:

$$\theta_c^j = \min_{\theta,z} \theta, \qquad (1)$$

subject to:

$$y_{ki} \le \sum_{j=1}^{N} y_{kj} z_j \text{ with } k = 1,\dots, P, \text{ and } i = 1,\dots, N$$

$$\sum_{j=1}^{N} x_{ki} z_j \le \theta x_{ki} \text{ with } k = 1,\dots, P, \text{ and } i = 1,\dots, N$$

$z_j \geq 0$ with $j = 1,\ldots, N$.

The scale value λ represents a proportional reduction in all inputs such that $0 \leq \lambda \leq 1$, and λ_c^j is the minimum value of λ so that $\lambda_c^j x^j$ represents the vector of technically efficient inputs for the j^{th} construction firm.

Maximum technical efficiency is achieved when λ_c^j equals unity. In other words, if the DEA gives the outcome $\lambda_c^j = 1$, the construction firm is operating at the best-practice and it is not able to improve its performance any further, given the existing set of observations. If $\lambda_c^j < 1$ then we can conclude that the firm is operating below the best-practice.

The non-increasing returns to scale (NIRS) technical efficiency of j^{th} construction firm is computed as:

$$\theta_n^j = \min_{\theta,z} \theta, \tag{2}$$

subject to:

$$y_{ki} \leq \sum_{j=1}^{N} y_{kj} z_j \text{ with } k = 1,\ldots, P, \text{ and } i = 1,\ldots, N$$

$$\sum_{j=1}^{N} x_{ki} z_j \leq \theta x_{ki} \text{ with } k = 1,\ldots, P, \text{ and } i = 1,\ldots, N$$

$$\sum_{j=1}^{N} z_i \leq 1$$

$z_j \geq 0$ with $j = 1,\ldots, N$.

The VRS technical efficiency for the j^{th} construction firm is computed as:

$$\theta_v^j = \min_{\theta,z} \theta, \tag{3}$$

subject to:

$$y_{ki} \leq \sum_{j=1}^{N} y_{kj} z_j \text{ with } k = 1,\ldots, P, \text{ and } i = 1,\ldots, N$$

$$\sum_{j=1}^{N} x_{ki} z_j \leq \theta x_{ki} \text{ with } k = 1,\ldots, P, \text{ and } i = 1,\ldots, N$$

$$\sum_{j=1}^{N} z_i = 1$$

$z_j \geq 0$ with $j = 1,\ldots, N$.

Given these two estimates of technical efficiency, the input-oriented scale efficiency measure for the j^{th} firm is calculated as the ratio of overall technical efficiency to VRS technical efficiency. This means that:

$$S^j = \theta_c^j / \theta_v^j. \tag{4}$$

If the value of this ratio is equal to unity (i.e., $S^j = 1$), then the construction firm is scale-efficient, meaning that the firm is operating at its optimum size, and hence the productivity of inputs cannot be improved by increasing or decreasing the size of the firm.

If the value of this ratio is less than unity (i.e., $S^j < 1$), then the construction firm is concluded not to be operating at its optimum size.

- If $S^j < 1$ and $\lambda_c^j = \lambda_n^j$ then the scale inefficiency results from increasing returns to scale. In other words, increasing the size of the firm would help to improve its productivity and thereby reduces unit costs.
- If $S^j < 1$ and $\lambda_c^j < \lambda_n^j$ then the scale inefficiency is due to decreasing returns to scale, indicating that the firm can raise its productivity and lessen unit costs by choosing a smaller size.

Rearranging equation (4), we have the overall technical efficiency being the product of VRS technical efficiency and scale efficiency:

$$\theta_c^j = \theta_v^j S^j . \tag{5}$$

Note that λ_v^j is also the pure technical efficiency, or the technical efficiency of the j^{th} construction firm, less the inefficiencies due to scale.

Equation (5) shows two sources of technical inefficiency: scale inefficiency ($1 - S^j$) and pure technical inefficiency ($1 - \lambda_v^j$). In the absence of environmental differences (i.e., local government policies and other unspecified variables) and measurement errors of inputs and outputs, the pure technical inefficiency would reflect departures from the management of the best-practice construction firm. Eliminating the latter source of inefficiency requires forming a benchmarking partnership with relevant best-practice firms for identifying and then emulating their management practices.

The output of DEA thereby includes measures of each construction firm's scale efficiency, pure technical efficiency, overall technical efficiency, and the identification of its best-practice benchmark. The best-practice benchmark provides the potential benchmark partners associated with their respective contribution to the best-practice benchmark.

3.2. Parametric Approach: Stochastic Frontier Production Function (SFPF)

Unlike the non-parametric approach, which is based on linear programming without functional forms (and therefore does not guarantee statistical appropriateness), the parametric approach is based on parameter estimation with given functional forms[1]. Parametric estimates were initiated by Aigner and Chu (1968), Afriat (1972), and Richmond (1974) with the Cobb-Douglas form. There were some crucial complement studies in this field, such as Schmidt (1976, 1980) and Green (1980). All studies focused on estimating at best the classical production function, i.e., concave (or at least semi-concave), increasing return, and decreasing marginal productivity.

Under the given technology, most production functions focus on maximizing outputs with given inputs. All maximized production points will create a production frontier. It is worth noting, however, that not all firms can reach the production frontier: some firms lie below the frontier, and therefore the distance for them to the frontier indicates their level of production inefficiency.

The question to be addressed is which approach is appropriate to measure production inefficiency. So far, most studies have used parametric estimates, commonly known as the

[1] In practice, it is impossible to apply one technology for all different industries, or even to do so for all firms within an industry. Thus, identifying an appropriate technology for each industry/firm is also difficult. Most studies have used certain production functions, such as Cobb-Douglas, constant elasticity of substitution (CES), and translog.

stochastic frontier production function, to measure technical inefficiency of each firm (such as Battese and Coelli, 1995). In this paper, we use this approach to estimate the relative technical efficiency of construction firms in the sample.

Suppose that $X_i(x_{i1}, x_{i2}, ..., x_{in})$ is the input vector of the construction firm *i* with output Y_i,[2] and also assume that production function $f(.)$ is a classical one. Therefore, $f(.)$ is continuous, concave, differentiable, and non-decreasing, i.e., $f(.)$ satisfies:

$$f(.) > 0; \frac{\partial f(.)}{\partial x} > 0; \frac{\partial^2 f(.)}{\partial x^2} < 0 . \tag{6}$$

After the estimation, the real production levels are represented by production function, inefficiency factor, and random factor as:

$$Y_i = f(X_i)\exp(-V_i + U_i) . \tag{7}$$

In equation (7), residuals V_i and U_i need to be estimated, and their distribution functions are given. Residual U_i is considered random, and it may be positive or negative. Residual U_i usually follows a given distribution function such as Gamma or normal distribution[3] with E = 0. Residual V_i represents technical inefficiency of the construction firm and is always positive. Most studies on V_i indicate that it follows positively normal distribution, and is truncated at 0. Thus, technical efficiency of a construction firm can be estimated as:

$$\frac{Y_i}{f(X_i)} = \frac{f(X_i)E[\exp(-V_i + U_i)]}{f(X_i)} = \exp(-V_i) = \frac{1}{\exp(\mathrm{V_i})} . \tag{8}$$

Equation (8) can be rearranged as:

$$\ln(Y_i) - \ln(f(X_i)) = -V_i . \tag{9}$$

The remaining task is to identify the production function. As mentioned earlier, it is difficult to identify a production function because we are not sure which is the best one. In this paper, we apply translog production function, so the production function in equation (7) can be identified as:

$$\ln Y_i = \ln f(X_i) = \sum \alpha_j \ln x_j + \sum \beta_j (\ln x_j)^2 + \sum \gamma_{jh} (\ln x_j) \ln(x_h) - V_i + U_i , \tag{10}$$

where Y and X are output and input, respectively; α, β, and γ are parameters that need to be estimated in the model; residual U_i is randomly distributed with E = 0; and residual V_i represents the technical inefficiency of the firm *i*, and follows positively normal distribution and is truncated at 0.

After the technical efficiency indices are identified, we also need to identify the factors influencing these indices. They will be found by regression methods.

$$TE = \mathrm{R}(\varphi_0 + \sum \varphi_l s_l) , \tag{11}$$

where TE is technical efficiency of the construction firm; s_l represents socio-economic factors that influence the production efficiency of the construction firm; φ_0 and φ_1 are parameters that

[2] Suppose that we have *k* construction firms, and each firm uses *n* input units to produce one unit of output.
[3] Examples include the study of Richmond (1974) on Gamma distribution and the studies of Kumbhakar (1987, 1988, 1990) on normal distribution.

need to be estimated, and R is regression type. *TE* in equation (11) of the SFPF model is *1/exp(V)*, as in equation (8).

3.3. Model of Factors Influencing Efficiency Scores

As mentioned above, after estimating efficiency score (TE) in both the DEA and SFPF models, we will identify the model of factors that could influence TE in the study year. This step is important because it can help us to point out appropriate policy implications to improve performance efficiency of the construction firms. The following is the model of these factors.

$$TE = \alpha_0 + \alpha_1 krl + \alpha_2 r + \alpha_3 r^2 + \alpha_4 loc + \alpha_5 dnnn + \varepsilon, \qquad (12)$$

where *TE* is efficiency score and α_i (I = 1, 2, 3, 4, 5) is the respective coefficient of the following independent variables: *krl*, which is net capital-labor ratio of each construction firm; *r* and r^2, which are net revenue and squared net revenue, respectively, and represent the firm size; the dummy variable *loc* (which is 1 if the firm is located in Hanoi or Ho Chi Minh city (HCMC), and 0 otherwise); *dnnn* (which is 1 if the firm is a state firm[4], and 0 otherwise); and ε, which is random error.

Since TE is upper-bounded by 1, we will apply Tobit regression for this model. A statistical summary for the independent variables is in Table 1.

Table 1: Statistical Summary of Factors Influencing Technical Efficiency

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
krl	2,298	75.19465	161.2229	0.8607	4,941.728
r	2,298	11081.66	30485.03	305	748,185
r^2	2,298	1.05e+09	1.37e+10	93,025	5.60e+11
loc	2,298	0.1845083	0.3879826	0	1
dnnn	2,298	0.6366406	0.4810718	0	1

Source: Authors' estimates

Theoretically, *krl* and *r* are crucial and determinant variables of technical efficiency of the construction firms. Firstly, net capital-labor ratio (*krl* = Kr/L) represents technical intensification of the worker, and it indirectly reflects whether the construction firm is labor-intensive or capital-intensive. Secondly, net revenue shows the firm's performance and reinvestment capacity, particularly technological investment. Moreover, the estimated coefficients of *r* and r^2, if statistically significant, will tell us whether there existed an efficient construction firm with the smallest or largest size.

Dummy variable *loc* represents the business location of the firm in Hanoi, HCMC, and other provinces, and it indicates how the business environment could influence efficiency of the studied firms. It is expected that the firms located in these two central cities could have better efficiency performances than their counterparts in other parts of the country.

Dummy variable *dnnn* is used to identify the impact of ownership on the technical efficiency of the construction firm. Some studies show that non-state firms are usually more efficient than the state ones because they can use resources, such as labor and capital, more efficiently. This is why we integrate ownership structure into the model to test whether the above argument is appropriate in Vietnam's context. In the sample, the state firms are large in terms of inputs and outputs, so testing this dummy variable is also important.

[4] State firms include central government-managed (code 01), local government-managed (code 02), joint stock with more than 50% capital contributed by the state-affiliated agencies (code 07), and joint stock companies between state and foreign investors (code 10).

As mentioned earlier, there are many other variables that might influence the efficiency performance of the construction firms, such as management capacity and labor costs. Due to data limitations, however, we could not put these variables into the model. This is one of the limitations of our paper.

3.4. Description of Data

Data used in this paper include inputs and outputs at firm level, which are from the 2002 Economic Census for Enterprises by the GSO. There were 3,400 observations (or 3,400 construction firms). However, in order to avoid outliers, we eliminated the firms with total revenue of less than 100 VND million per year and total labor of less than 10 people; these firms were considered too small in this industry. The remaining observations for this paper, therefore, were 2,298 firms. Due to the different characteristics of construction firms in operation, we use the following variables as inputs and output(s). Net revenue (*r*) is considered as output. It is calculated by subtracting required contributions from the total revenue (measured in VND million). Inputs for both models include labor (*l*), which is average number of laborers in the year, and net capital (*kr*), which is measured by subtracting depreciation from the total capital (measured in VND million). A statistical summary of inputs and output is in Table 2.

Table 2: Statistical Summary of Inputs and Output

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
r	2,298	11,081.66	30,485.03	305	748,185
l	2,298	170.9038	390,4281	10	8,152
kr	2,298	13,011.61	41,435.06	15	1,304,653

Source: Authors' estimates

Significant differences were found between construction firms in the sample. For instance, net revenue per year ranged from 305 to 748,185 VND million. Labor ranged from 10 to 8,152 people, and net capital ranged widely from 15 to 1,304,653 VND million.

In terms of business type, there were 67 firms operating on construction site preparation (accounting for 2.91% of the sample), 2,184 firms operating on building and civil engineering construction (95.03%), and 47 firms operating on construction installation and completion (2.06%). Therefore, most of the observed construction firms were working on building and civil engineering construction, and this might be a factor significantly influencing the average technical efficiency of the studied firms.

Table 3: Statistical Summary of Firms by Ownership

State Firms					
Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
r	485	38,471.69	56,783.4	430	748,185
l	485	559.7546	696.1336	11	8,152
kr	485	46,993.49	79,375.16	114	1,304,653
loshare (%)	485	72,66871	23,59213	1,152	116,219
Non-State Firms					
Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
r	1,813	3,754.484	7,893.828	305	163,484
l	1,813	66.88141	111.7824	10	1,925
kr	1,813	3,921.037	10,086.54	15	249,640
loshare (%)	1,813	23.24586	15.44946	.1	110,25

Source: Authors' estimates

In addition, in terms of ownership, Table 3 shows that there were 485 state firms in the sample, accounting for 21 percent. The remaining was non-state firms with different types and sizes. Also, in terms of labor, capital, and revenue, the state firms were much larger than the non-state ones. The variable *loshare* represents the ratio between the borrowed capital and the net capital of the observed firms. The average ratio of the state firms (72.66%) was much higher than that of the non-state ones (23.24%), and this reflected the fact that the state firms could access financial resources more easily than could the non-state firms. This was advantage of the state firms in terms of business size.

Table 4: Statistical Data for Firms in Hanoi and Ho Chi Minh City

Hanoi					
Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
r	199	28,591.99	44,386.26	330	315,225
l	199	410.8392	587.0365	10	3,806
kr	199	31,685.61	52,656.11	87	328,709
HCMC					
Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
r	226	1,7803.5	38,498.88	386	333,636
l	226	254.677	481.9554	10	3,600
kr	226	20,243.6	44,399.27	105	407,330

Source: Authors' estimates

Table 4 summarizes the statistical data for the firms operating in Hanoi and HCMC. These firms were clearly larger than those outside these areas in terms of net revenue, labor, and net capital.

4. Estimated Results and Analysis

In order to estimate efficiency scores for the observed construction firms, we will use program DEAP Version 2.1 by Coelli (1996b). The DEA model will measure efficiency scores with CRS technology (or overall technical efficiency, or *crste*) and VRS technology (or pure technical efficiency, or *vrste*). Finally, scale efficiency (or *scale*) represents the level of inputs used in the construction firms. In the parametric approach, we will use the program FRONTIER Version 4.1 by Coelli (1996a) to estimate the technical inefficiency of the construction firms (or *te-est*).

It is noted that pure technical efficiency (*vrste*) from the DEA model is equivalent to the technical efficiency estimate (*te-est*) from SFPF. Therefore, in the model that tests the factors influencing the efficiency performance of the studied construction firms, we will use these two results for comparison.

4.1. Estimated Results from DEA and SFPF

From the DEA model, we estimate efficiency scores for all the construction firms in the sample with *crste* (overall technical efficiency), *vrste* (pure technical efficiency), and *scale* (scale efficiency). We have efficiency scores in the SFPF model as *te-est*. Estimated results from both the DEA and SFPF models are shown in Table 5.

In the DEA model, on average, the overall technical efficiency (*crste*) was 57.6 percent, the pure technical efficiency (*vrste*) was 58.6 percent, and the scale efficiency (*scale*) was high, at 98.3 percent. There were, however, only 3 firms operating with overall technical efficiency, meaning that they reached both pure and scale technical efficiencies. There were 22 firms reaching pure technical efficiency, of which 3 firms reached scale efficiency; the remaining 19 firms could not achieve scale efficiency. This implies that these 19 firms were operating on the production frontier, but the level of inputs was not optimal. The estimated results for the 2,298 firms in the sample also show that there were 101 firms operating with CRS technology (accounting for 4.39% of the sample); 2,067 firms operating with decreasing returns to scale (DRS) technology, a popular technology in manufacturing industries (accounting for 89.94%), meaning that the current level of inputs was still high; and the remaining 130 firms operating with IRS technology (accounting for 5.67%), implying that the current level of inputs was low. These results indicate that, in order to improve production efficiency, the 2,076 firms with DRS should reduce the level of inputs and/or avoid wasteful and extravagant use of inputs, and the 130 firms with IRS should increase their operation size to increase efficiency.

In the SFPF model, the estimated results show that the average pure technical efficiency of these construction firms was 57.8 percent. This was consistent with the results of the DEA model, where *vrste* = 58.6 percent. The consistency between the two models was also expressed by efficiency gaps among the observed firms, i.e., [0.291; 1] in DEA and [0.297; 0.999] in SFPF. This also implies that there were few outliers in the sample.

Table 5: Statistical Summary of Efficiency Scores in DEA and SFPF

Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***	***No. of Efficient Firms***
DEA						
crste	2,298	0.5761079	0.1931614	0.29	1	3
vrste	**2,298**	**0.5861336**	**0.1945986**	**0.291**	**1**	**22**
scale	2,298	0.9831519	0.0417821	0.386	1	57
No. of CRS firms: 101; No. of DRS firms: 2,067; No. of IRS firms: 130						
SFPF						
te-est	**2,298**	**0.5785486**	**0.1946858**	**0.297178**	**0.9999592**	

Source: Authors' estimates

In order to have more concrete analysis, we classify the studied firms by ownership types (state and non-state), and by business types (construction site preparation, building and civil engineering construction, and construction installation and completion). Tables 6 and 7 summarize the estimated results of the efficiency scores for the studied construction firms by ownership types and business types, respectively.

Table 6: Efficiency Scores by Ownership

State Construction Firms						
Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***	***No. of Efficient Firms***
DEA						
crste	485	0.6554639	0.1861833	0.31	0.996	0
vrste	**485**	**0.6654062**	**0.185782**	**0314**	**1**	**5**
scale	485	0.9843485	0.0374882	0.547	1	11
SFPF						
te-est	**485**	**0.6599663**	**0.1874313**	**0.311262**	**0.998321**	
Non-state Construction Firms						
Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***	***No. of Efficient Firms***
DEA						
crste	1,813	0.5551634	0.1898074	0.29	1	4
vrste	**1,813**	**0.5652092**	**0.1917618**	**0.291**	**1**	**17**
scale	1,813	0.9828361	0.0428751	0.386	1	47

SFPF						
te-est	**1,813**	**0.5567684**	**0.1908272**	**0.297178**	**0.9999592**	

Source: Authors' estimates

Table 7: Efficiency Scores by Business Types

Construction Site Preparation						
DEA						
Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***	***No. of Efficient Firms***
crste	67	0.6133582	0.2079011	0.32	1	1
vrste	**67**	**0.6258657**	**0.203723**	**0.326**	**1**	**3**
scale	67	0.9768657	0.0545674	0.659	1	2
No. of CRS firms: 4; No. of DRS firms: 59; No. of IRS firms: 4						
SFPF						
te-est	**67**	**0.6149996**	**0.2092914**	**0.30458**	**0.9958654**	
Buildings						
DEA						
Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***	***No. of Efficient Firms***
crste	2,184	0.5743951	0.1933532	0	1	3
vrste	**2,184**	**0.5842143**	**0.1949604**	**0**	**1**	**19**
scale	2,184	0.9830801	0.046097	0	1	55
No. of CRS firms: 90; No. of DRS firms: 1,970; No. of IRS firms: 124						
SFPF						
te-est	**2184**	**0.5769035**	**0.1943036**	**0.297178**	**0.9999592**	
Construction Installation and Completion						
DEA						
Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***	***No. of Efficient Firms***
crste	47	0.6017447	0.1869482	0.306	0.968	0
vrste	**47**	**0.6175319**	**0.1871355**	**0.317**	**0.976**	**0**
scale	47	0.9747021	0.0542742	0.707	1	1
No. of CRS firms: 7; No. of DRS firms: 38; No. of IRS firms: 2						
SFPF						
te-est	**47**	**0.6030299**	**0.1863083**	**0.3056225**	**0.9823263**	

Source: Authors' estimates

In the DEA estimates, the state firms were clearly more efficient than the non-state ones; particularly their average overall and pure technical efficiencies were 10 percent higher than those of the non-state ones. This result reflected that the state firms may be invested with better resources than the non-state ones; state firms might have the advantages of better infrastructure and easier access to financial resources. In addition, 1,813 non-state firms had low average efficiency scores, so many of them were operating at very low efficiency. The estimated results from the SFPF model once again show that both DEA and SFPF provided consistent estimates. The average efficiency scores were nearly equal (56.52% for DEA and 55.67% for SFPF), and efficiency range was also approximated ([0.291; 1] for DEA and [0.297; 0.999] for SFPF).

Even though the number of construction firms by business types were significantly different (only 67 firms operating in construction site preparation, 47 firms operating in construction installation and completion, and 2,184 firms operating in buildings), their technical efficiency and scale efficiency were relatively similar. There are two interesting findings in the above estimated results. First, the number of efficient firms (technical and scale) in all types of business was low, particularly for the firms operating in buildings. Second, most of the observed firms that were operating with DRS technology, so their performance efficiencies were low partly because they utilized inputs wastefully or extravagantly. The estimated results in Table 7 show the consistency between DEA and SFPF in estimating efficiency scores of the construction firms in the sample.

4.2. Estimated Results for the Factors that Influenced Efficiency Scores

As stated earlier, efficiency from the SFPF model (*te-est*) is equivalent to pure technical efficiency (*vrste*) in the DEA model. Thus, we will use Tobit regression for equation (12), in which *te-est* from the SFPF model and *vrste* from the DEA model will be dependent variables. Tables 8 and 9 summarize our findings from both DEA and SFPF.

Table 8: Factors Influencing Efficiency Scores, DEA Model

Log likelihood = 1081.5995			Number of Obs. = 2298		
Pseudo R2 = -1.1779			LR chi2(5) = 1169.96		
vrste	Coef.	Std. Err.	P>t	[90% Conf. Interval]	
krl	-.0070607	.0085126	0.407	-.0210683	.0069469
r	-3.18e-07	2.09e-07	0.128	-6.61e-07	2.60e-08
r2	2.32e-13	4.15e-13	0.576	-4.51e-13	9.14e-13
loc	.2005164	.008249	0.000	.1869424	.2140903
dnnn	.2488571	.0099895	0.000	.265295	.2324192
_cons	.6194602	.018479	0.000	.5890527	.6498678

Source: Authors' estimates

Table 9: Factors Influencing Efficiency Scores, SFPF Model

Log likelihood = 598.24665			Number of Obs. = 2298		
Pseudo R2 = -0.2016			LR chi2(5) = 200.74		
te-est	Coef.	Std. Err.	P>t	[90% Conf. Interval]	
krl	.0897294	.0105055	0.000	.0724424	.1070164
r	2.45e-07	2.58e-07	0.341	-1.79e-07	6.69e-07
r2	9.99e-14	5.12e-13	0.845	-7.42e-13	9.42e-13
loc	.044403	.0101801	0.000	.0276514	.0611546
dnnn	.1209283	.0123257	0.000	.1006461	.1412105
_cons	.3590961	.0228053	0.000	.3215696	.3966226

Source: Authors' estimates

In the DEA model, at significance level of 10 percent, the dummy variables *krl*, *r*, and r^2 did not influence *vrste*. This means that the firm size and technical intensification of the worker had no impact on the pure technical efficiency of the construction firms in Vietnam in the study time.

The coefficient of variable *loc* is positive and is significantly different from 0, implying that location in Hanoi and HCMC influenced pure technical efficiency. This finding could be supported by the fact that the construction firms located in these central cities may have better business conditions, such as financial resources, technical improvements, and human resources. In addition, the coefficient of variable *dnnn* is also positive and is significantly different from 0, meaning that the firms under state ownership had better efficiency levels than did the non-state firms. This estimate is confirmed by the estimates from both the DEA and SFPF models in the previous section, and it is also proved by the fact that the state firms in this industry are usually larger than the non-state firms in terms of both capital and labor.

In the SFPF model, the estimated results are relatively consistent with those of the DEA model, except regarding the variable *krl*. At a significance level of 10 percent, it was found that the dummy variables *r* and r^2 had no influence on *te-est*, indicating that firm size had no impact on the technical efficiency of the construction firms. In addition, the coefficients of both variables *loc* and *dnnn* are positive and significantly different from 0, and they could provide the same interpretations as in the DEA model. Conversely to the finding in the DEA model, variable *krl* in the SFPF model has a positive coefficient that is significantly different from 0. This means that technical intensification of the worker had no impact on the efficiency of the construction firms in the study time. It also means that these construction firms would have been able to improve their efficiency performance if their workers had been equipped with more capital.

5. Concluding Remarks and Suggestions for Further Studies

This study used both parametric and non-parametric approaches to estimate technical efficiency of 2,298 construction firms in Vietnam by using data from the 2002 Economic Census for Enterprises by the General Statistical Office of Vietnam (GSO). It was found that results from both approaches were relatively consistent, and they could help explain the efficiency performance of these firms. Estimates from data envelopment analysis (DEA, the non-parametric approach) and stochastic frontier production function (SFPF, the parametric approach) indicated that the average pure technical efficiency of these firms was about 60 percent (58.6% and 57.8% for DEA and SFPF, respectively). In terms of business type, building and civil engineering construction firms usually had the lowest efficiency scores, which reflected the fact that they were operating with many inputs, and construction time was usually long. Moreover, it was shown that state firms were more efficient than non-state ones, possibly because these firms could invest more capital and have better technical capacity. Also, business location in Hanoi and Ho Chi Minh city had significant influence on these firms' efficiency scores, and the result could be explained by easier access to resources, such as labor and capital, in these cities. One different finding between the two approaches was that the variable capital-labor ratio had no impact on the efficiency performance of the studied firms in the DEA model, while it had obvious influence in the SFPF model.

This paper could not avoid some limitations. These limitations are derived not only from a shortage of data, which made it impossible to reflect the business performance of a typical construction firm, but also from the models. They did not take into account some typical criteria in the construction industry, such as management expenses, workers at different skill levels, and many other unobserved variables. Thus, policy implications could not indicate all necessary aspects of the industry. The findings of the paper need to be complemented by more comprehensive evaluation approaches.

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