Technical Efficiency Accounting for Environmental Influence in the Japanese Gas Market

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Abstract: This study measured technical efficiency accounting for environmental influence in the Japanese gas market by stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The results showed that from the viewpoint of fitness, the stochastic frontier production function incorporating an external factor was more appropriate than one without it. The study also found that the distribution of efficiency scores calculated by the DEA model incorporating an external factor was more similar to that by the SFA model incorporating the factor, compared to that by the DEA model without incorporating it. These findings imply that considering the impact of external conditions on technical efficiency is essential for the Japanese gas market.

Keywords: technical efficiency, environmental factor, SBM, SFA

1. Introduction

Until the early 1990s, Japanese gas suppliers operated monopolistically in their respective service areas and did not compete with each other. Taking into consideration that many countries had already introduced competition in the energy sector, in 1995, Japanese government authorized the entry of new players in the market for large-volume gas customers. However, the market for small-volume gas customers, which accounted for about 95 percent of the total, has remained a monopoly until present. Thus, efforts were made to deregulate the Japanese gas business in this restricted market. When multiple gas suppliers exist nationwide, policymakers are able to compare the efficiency and productivity between suppliers across service areas, even if they operate monopolistically. Thus, yardstick competition is expected to work.

At the end of 2010, there were 211 gas suppliers operating in their respective service areas in Japan. While several suppliers, such as the Tokyo Gas Company and the Osaka Gas Company, are large-scale companies operating in urban areas, many others are small-scale companies operating in rural areas, where few large-volume customers exist. Although the costs for charge collection and security services for a small-volume customer are almost the same as those for a large-volume customer, gas suppliers can earn a large amount of revenue from a large-volume customer in a more cost-efficient manner. Thus, the economic environment that may influence the technical efficiency of gas suppliers differs significantly. Although certain environmental conditions could be partially controlled by the supplier, some differences nevertheless remain. Thus, when researchers and policymakers evaluate the technical efficiency of gas suppliers, they need to pay heed to these differences in uncontrollable environmental factors, at least for a short period.

Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) have been used to calculate technical efficiency in a number of fields. Coelli *et al.* (1999) proposed a method to adjust for the differences in environmental factors in SFA. Several DEA studies have proposed a multistage method to measure efficiency accounting for environmental influences. The present study calculates technical efficiency accounting for environmental factors using SFA and DEA in the Japanese gas market, and compares the results of the two methods. The paper is organized as follows. Section 2 provides a survey of the related literature. Sections 3 and 4 explain the models and data used in this study. Section 5 presents the results of the

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calculation. Section 6 provides conclusions.

2. Related Literature

SFA models incorporating environmental factors were proposed by Huang and Liu (1994) and Battese and Coelli (1995).[1] Coelli *et al.* (1999) calculated technical efficiency adjusted under the most favorable conditions using the SFA model proposed by Battese and Coelli (1995). Fried *et al.* (1999, 2002), and Liu and Tone (2008) calculated technical efficiency adjusting external influences using the DEA multistage method. Fried *et al.* (1999) measured the DEA frontier without accounting for external factors, using ordinary inputs and outputs as the first stage. In the second stage, they used the Tobit model to classify the slacks calculated at the first stage into inefficiencies attributable to environmental and other factors, such as management. The third stage concerned adjusting input or output data under the least favorable conditions. In the fourth stage, the DEA model was re-run using the adjusted input and output data. Fried *et al.* (2002) and Liu and Tone (2008) used SFA to adjust inputs or outputs in DEA, while Fried *et al.* (1999) employed the Tobit model. With regard to the energy industry, Tsutsui and Tone (2008) measured the technical efficiency of electric power companies accounting for external factors in the U.S. and Japan. The Cabinet Office ed. (2001) and Asai (2008) have calculated the technical efficiency of Japanese gas suppliers. However, the number of gas suppliers in both studies was small and exogenous influences were not considered.

3. Model

The present study measures technical efficiency accounting for external influence, using SFA and a slack-based measure (SBM), which is a type of DEA model. An ordinary stochastic frontier production function is formulated by equation (1). This study adopts the time-varying efficiency model proposed by Battese and

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1 Kumbhakar and Lovell (2000) surveyed several models accounting for exogenous influences on technical efficiency in SFA.

Coelli (1992).

$$\ln y_{it} = \alpha_0 + \sum_{k=1}^{m} \alpha_k \ln x_{k,it} + v_{it} - u_{it} \qquad (1)$$

where $u_{it} = \exp\{-\eta(t - T)\}u_i$

The variable y_{it} denotes the output of the i-th firm in the t-th time period. The variable $x_{k,it}$ denotes k input quantities of the i-th firm in the t-th time period. v_{it} is assumed to be independent and identically distributed $N(0, \sigma_v^2)$ random error. u_{it} is assumed to be independent and identically distributed non-negative truncation of the $N(\mu, \sigma_u^2)$ distribution. The observable error term ε_{it} is equal to $v_{it} - u_{it}$, and $\sigma^2 = \sigma_v^2 + \sigma_u^2$, $\gamma = \sigma_u^2/\sigma^2$. γ lies between 0 and 1. T denotes the estimation period. α_0, α_k, and η are parameters to be estimated. If $\eta > 0$, u_{it} decreases as t increases, that is, firms tend to improve their level of efficiency over time. If $\eta = 0$, the level of efficiency remains constant. If $\eta < 0$, u_{it} increases, that is, firms' efficiency tends to deteriorate over time.

According to Battese and Coelli (1995), the stochastic frontier production model accounting for environmental influence on technical efficiency is formulated by equation (2).

$$\ln y_{it} = \alpha_0 + \sum_{k=1}^{m} \alpha_k \ln x_{k,it} + v_{it} - u_{it} \qquad (2)$$

where $u_{it} = \delta_0 + \delta_1 Z_{j,it} + \omega_{it}$, $Z_{j,it}$ is the variable representing environmental factors that may influence technical efficiency of the i-th firm in the t-th time period. ω_{it} is an unobservable random variable, defined by the truncation of the normal distribution with mean zero and variance σ^2, such that u_{it} are non-negative. Technical efficiency (TE) is described by the conditional expectation of $\exp(-u_{it})$, giver observable error term ε_{it}.

$$TE_{it} = E[\exp(-u_{it}|\varepsilon_{it}]$$
$$= \left\{\exp\left[-\mu_{it} + \frac{1}{2}\sigma_*^2\right]\right\} \cdot \left\{\emptyset\left[\frac{\mu_{it}}{\sigma_*} - \sigma_*\right]/\emptyset\left[\frac{\mu_{it}}{\sigma_*}\right]\right\}$$
$$\mu_{it} = (1 - \gamma)[\delta_0 + \delta_1 Z_{it}] - \gamma\varepsilon_{it}$$
$$\sigma_*^2 = \gamma(1 - \gamma)\sigma^2 \qquad (3)$$

where $\emptyset(\cdot)$ denotes the distribution function of the standard normal random variable. When we replace the $\delta_1 Z_{it}$ with max $\delta_1 Z_{it}$ and recalculate efficiency based on equation (3), technical efficiency under the least favorable condition is

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obtained. We refer to equation (1) without the inclusion of external factors as the "SFA 1" model, and equation (2) incorporating them as the "SFA 2" model.

The present study also measures the technical efficiency of Japanese gas suppliers using the SBM proposed by Tone (2001). The SBM deals directly with input excess and output shortfall with respect to slacks, while the traditional DEA models are based on the proportional reduction (enlargement) of input (output) vectors. Japanese gas suppliers have an obligation to provide services regardless of geographic location. Taking this universal service obligation into consideration, this study adopts the input-oriented model that minimizes inputs, while satisfying at least the given level of outputs. The present study adopts the variable returns-to-scale (VRS) model, because increasing returns-to-scale were actually observed in both the SFA 1 and the SFA 2 models. The technical efficiency is obtained using the input-oriented SBM model formulated by (4).

$$\rho = min\left[1 - \frac{1}{m}\sum_{l=1}^{m}\frac{s_l^-}{x_{li}}\right]$$

subject to

$$\mathbf{x}_i = X\mathbf{\lambda} + \mathbf{s}^-$$
$$\mathbf{y}_i = Y\mathbf{\lambda} - \mathbf{s}^+$$
$$\mathbf{e\lambda} = 1$$
$$\mathbf{\lambda} \geq 0, \mathbf{s}^- \geq 0, \mathbf{s}^+ \geq 0 \qquad (4)$$

where m is the number of inputs, and the vectors S$^-$ and S$^+$ denote input excess and output shortfall respectively.

This study accounts for environmental influence through a three-step approach. First, slacks are calculated by ordinary SBM. Second, the obtained slacks (S_{it}) are regressed against the observable environmental variable (Z_{it}) using the Tobit model $S_{it} = f\left(Z_{it}, \delta\right)$, where δ is an estimator. The estimated slack S* is calculated using the values of δ and the variable Z_{it}. Input quantities are adjusted under the least favorable condition by equation (5).

$$x_{it}^{adj} = x_{it} + [Max(S_{it}^*) - S_{it}^*] \qquad (5)$$

Again, technical efficiency is recalculated by (4), using adjusted inputs and output. All gas suppliers are also evaluated under the least favorable environment by SBM. We refer to the variable returns-to-scale model of SBM as "DEA".

4. Data

While 120 of 211 gas suppliers have production facilities and produce gas in-house either fully or partially, the rest do not produce gas themselves and provide customers with gas purchased entirely from a third party. Of the 120 suppliers with production facilities, 89 produced all the gas provided to customers in-house only. We confine our study to these 89 suppliers for the period 2006 to 2010. The observations are 431 gas suppliers.[2]

Output (Y) refers to gas sold in a year and is measured in gigajoules. Labor (L) and capital (K) are the inputs. L is the number of employees. K refers to the facilities for production, distribution, and services. K is deflated by the price index of investment goods of the Corporate Goods Price Index calculated by the Bank of Japan. The material for gas suppliers (M) is fuel, and is measured in gigajoules. Given the characteristics of the gas business, the fuel corresponds with gas sales (Y). Therefore, this study adopts L and K as inputs, while the variable representing material (i.e., fuel) is not used. The variable Z, representing the environmental factor, is the ratio of sales for residential customers to total sales (Y). While residential customers account for about 95 percent of total customers, the ratio of sales to residential customers to total sales (in gigajoules) was only 28 percent on average in 2010. This implies that residential customers are relatively small-volume customers, and that the demand for gas significantly differs between residential customers and other customer types. This study uses the ratio of sales for residential customers to total sales as the environmental factor, because the number of residential customers may influence the technical efficiency, and gas suppliers cannot change this ratio significantly over a short period. The data for Y, L, K, and Z are sourced from the *Annual Report of Gas Business, 2006-2010* edited by Agency for Natural Resources and Energy.

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2 Several of these 89 suppliers purchased gas from a third party for at least one year. Thus, the data used in this paper are unbalanced.

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Table 1 shows the summary of variables. The coefficients of variation for the output and inputs were large, indicating that firm size differed significantly among gas suppliers. The maximum sales ratio for residential customers (Z) was 90.8 percent and the minimum, 1.4 percent. Table 2 shows the correlation coefficients between the variables. The correlation coefficients between sales and inputs (L and K), and between two inputs were more than 0.99, implying that they had very high positive relationship.

Table 1　Sample Summary

	Sales	Labor	Capital	Ratio
Average	5,264,414	116	8,920	44.3
Maximum	379,127,422	5,541	517,458	90.8
Minimum	12,714	4	42	1.4
Std. Dev.	38,041,976	591.1	53,924.6	17.0
C.V.	7.226	5.098	6.045	0.3836

Std. Dev. Standard Deviation, C.V. Coefficient of Variation

Unit: Sales (gigajoule), Labor (person), Capital (million yen), Ratio (%)

Table 2　Correlation Coefficients

	Sales	Labor	Capital	Ratio
Sales	1.0000			
Labor	0.9906	1.0000		
Capital	0.9939	0.9973	1.0000	
Ratio	−0.1453	−0.1640	−0.1596	1.0000

5. Results

The present study did not adopt the translog production function including cross terms and squared terms, because the correlation relationship between the variables was very high, as shown in Table 2. Table 3 reports the results of the Cobb-Douglas production frontier models estimated by equations (1) and (2).

The values of γ in the SFA 1 and SFA 2 models were positive at the 1 percent significance level, implying that the stochastic frontier function estimated by the maximum likelihood method was more appropriate than the ordinary

production function estimated by ordinary least squares (OLS) method. The total values of α_1 and α_2 exceeded 1 for the two models.

With regard to SFA 1, the value of η was positive, implying that suppliers have improved efficiency over time. However, the value was near 0 and the null hypothesis was not rejected. With regard to SFA 2, the value of δ_1 was significantly positive at the 1 percent significance level, implying that the higher ratio of sales to residential customers deteriorated technical efficiency. Judging from the values of the log likelihood and the Akaike information criterion (AIC), SFA 2 accounting for environmental influence was more appropriate than SFA 1 without it.

Table 3　Estimation Results

	SFA 1	SFA 2
α_0 (constant)	7.1232 (0.1964)***	9.0956 (0.1167)***
α_1 (labor)	0.5794 (0.0678)***	0.8848 (0.0495)***
α_2 (capital)	0.5939 (0.0520)***	0.3545 (0.0399)***
δ_0 (constant)		0.0953 (0.1548)
δ_1 (ratio)		0.6114 (0.0516)***
σ^2	0.3313 (0.0561)***	0.1730 (0.0141)***
γ	0.6613 (0.0367)***	0.9999 (0.0007)***
μ	0.9361 (0.1327)***	
η	0.0020 (0.0156)	
L.L	−260.971	−227.845
AIC	1.2296	1.0805

*** 1%, L.L: Log likelihood Standard errors are in parentheses.

Table 4 reports the technical efficiency calculated by the SFA and DEA models. The "SFA 2 before" model denotes the efficiency calculated under the environment surrounding each supplier by equation (2), while the "SFA 2 after" model denotes the efficiency calculated under the least favorable conditions, by replacing $\delta_1 Z_{it}$ with max $\delta_1 Z_{it}$ in equation (3). The "DEA before" model denotes the efficiency calculated without incorporating an external factor using ordinary SBM, while the "DEA after" model denotes the efficiency calculated under the least favorable condition by (4) and (5).

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With regard to SFA 2 before and after models, the difference in the scores of efficiency between the two SFA models depends on the value of $1 - \gamma$ in equation (3), and the gap between the supplier's ratio of sales to residential customers and the highest ratio. The change in μ corresponding to the changes in ratios of sales to residential customers (Z_{it}) was significantly small in equation (3), because the value of $1 - \gamma$ was very small at 0.0001. As a result, the averages of efficiency scores in the SFA 2 before and the SFA 2 after models were almost the same. In summary, although high sales ratios to residential customers deteriorated technical efficiency, the impact of the difference in the ratios on technical efficiency was very small.

Table 4 Technical Efficiency

	SFA1	SFA2		DEA	
		Before	After	Before	After
Ave	0.3996	0.1156	0.1155	0.3104	0.2451
Max	0.9382	0.9989	0.9954	1.0000	1.0000
Min	0.1318	0.0120	0.0120	0.0741	0.0997
S.D.	0.1625	0.1046	0.1043	0.1859	0.1726
E=1	0	0	0	6	5

Ave = average, S.D. = Standard Deviation

E = 1: The number of observations that the efficiency score equals one

Table 5(a) reports the correlation coefficients between the efficiency scores calculated by the five models, while Table 5(b) reports the rank correlation coefficients between them. SFA 1 is correspondent to DEA before in the sense that the two models do not incorporate environmental influence. SFA 2 after is correspondent to DEA after in the sense that efficiency scores were adjusted under the least favorable condition. The correlation coefficient between efficiency scores calculated by SFA 1 and DEA before was 0.5738 and the rank correlation was 0.4555, while the correlation coefficients between SFA 1 and DEA after calculated under different conditions were smaller at 0.5219 and 0.3599, respectively. The correlation coefficients between the SFA 2 before and SFA 2 after models were nearly 1, as shown in Tables 5(a) and 5(b), because the

difference in efficiency scores between the two models was very small.

Table 5 Correlation between Technical Efficiency

(a) Efficiency	SFA 1	SFA 2	SFA 2	DEA	DEA
		Before	After	Before	After
SFA 1	1.0000				
SFA 2 Before	0.6327	1.0000			
SFA 2 After	0.6330	0.9999	1.0000		
DEA Before	0.5738	0.5589	0.5590	1.0000	
DEA After	0.5219	0.6586	0.6586	0.6420	1.0000
(b) Rank	SFA 1	SFA 2	SFA 2	DEA	DEA
		Before	After	Before	After
SFA 1	1.0000				
SFA 2 Before	0.8120	1.0000			
SFA 2 After	0.8121	0.9999	1.0000		
DEA Before	0.4555	0.4706	0.4709	1.0000	
DEA After	0.3599	0.4558	0.4561	0.6097	1.0000

Figures 1 to 5 show the histogram of efficiency scores calculated by SFA 1, SFA 2 before, SFA 2 after, DEA before, and DEA after, respectively. The histograms of efficiency scores differed significantly between Figures 1 and 2, and between Figures 1 and 3, although all the three models were SFA models. One reason the distribution of efficiency scores between Figure 1 and Figure 2 and between Figure 1 and Figure 3 differed is that the SFA 1 model (Figure 1) did not use an environmental factor as variable, while the SFA 2 before (Figure 2) and the SFA 2 after (Figure 3) models did. Another reason seems to be the problem of fitness of SFA 1. The distributions of efficiency in Figures 2 and 3 were similar, because the changes in efficiency scores caused by adjustment for an environmental factor were very small. The histogram of the DEA after model adjusting for the external factor (Figure 5) was more similar to that of the SFA 2 after model adjusting for the factor (Figure 3), compared with that of DEA before without the adjustment (Figure 4). Thus, the equivalence in the environmental condition brought the

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distribution of technical efficiency closer, although the approach to measuring efficiency differs between SFA and DEA.

6. Conclusions

The present study measured technical efficiency accounting for environmental influence in the Japanese gas market using SFA and DEA, formulated five models, and compared the efficiency scores among them. The findings obtained from the calculations are as follows. First, with regard to SFA, the fitness of a model incorporating the environmental factor was better than that of a model without it. Thus, it is important to consider the impact of the external factor on the technical efficiency of gas suppliers. Second, operating in service areas with few large-volume customers deteriorated technical efficiency. However, the difference in efficiency scores between the SFA 2 before and the SFA 2 after models was very small, implying that the impact of the difference in the ratios of sales to residential customers on technical efficiency was not large. Third, the distribution of DEA efficiency scores calculated under the least favorable condition (DEA after model) was closer to the distribution of SFA efficiency scores calculated under the same condition (SFA 2 after model), compared to that of the DEA before model without accounting for the external condition. It seems that the technical efficiency scores calculated by two different approaches became similar after adjusting the external condition.

In SFA, the estimated values of γ and the calculated efficiency scores depend on the assumption for the distribution of the error term. Compared to DEA, a limited number of studies employing SFA have incorporated an external influence. Therefore, in the future, the effectiveness and reliability of adjustment for external factors in SFA would need to be confirmed through empirical studies. On the other hand, although researchers can select the best model among several SFA models, based on the log likelihood or AIC, there is no objective criterion for selecting the best model in DEA. Comparing the efficiency scores calculated by several models in both SFA and DEA is the

only way to select the best model among DEA models.

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Series: SFA1	
Sample 1 431	
Observations 431	
Mean	0.399593
Median	0.375389
Maximum	0.938173
Minimum	0.131761
Std. Dev.	0.162462
Skewness	1.214678
Kurtosis	4.547569
Jarque-Bera	148.9957
Probability	0.000000
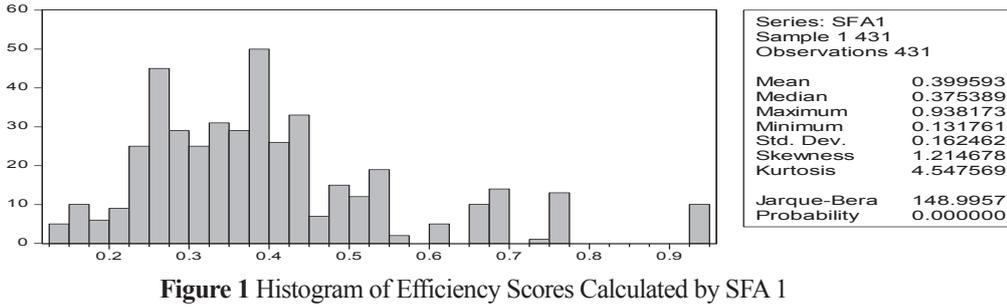
Figure 1 Histogram of Efficiency Scores Calculated by SFA 1

Series: SFA2BEFORE	
Sample 1 431	
Observations 431	
Mean	0.115619
Median	0.091353
Maximum	0.998930
Minimum	0.011980
Std. Dev.	0.104617
Skewness	5.522764
Kurtosis	41.44644
Jarque-Bera	28735.72
Probability	0.000000
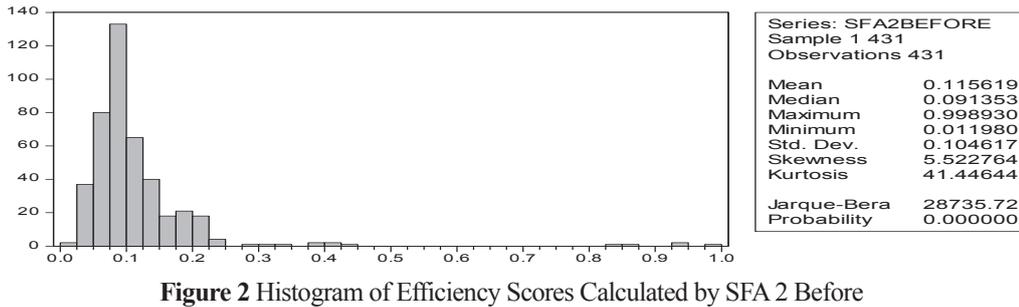
Figure 2 Histogram of Efficiency Scores Calculated by SFA 2 Before

Series: SFA2AFTER	
Sample 1 431	
Observations 431	
Mean	0.115507
Median	0.091302
Maximum	0.995419
Minimum	0.011999
Std. Dev.	0.104320
Skewness	5.517145
Kurtosis	41.38387
Jarque-Bera	28644.93
Probability	0.000000
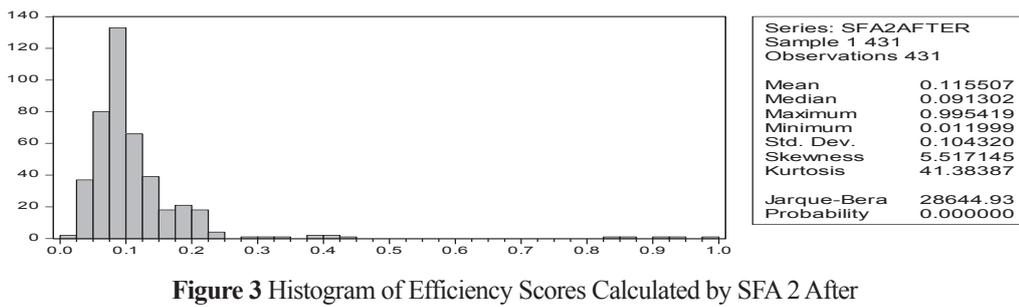
Figure 3 Histogram of Efficiency Scores Calculated by SFA 2 After

Series: DEABEFORE	
Sample 1 431	
Observations 431	
Mean	0.310414
Median	0.255787
Maximum	1.000000
Minimum	0.074083
Std. Dev.	0.185901
Skewness	1.954865
Kurtosis	6.941698
Jarque-Bera	553.5291
Probability	0.000000
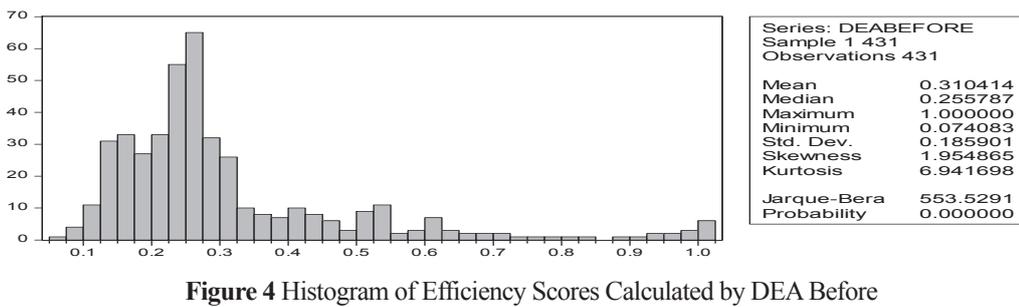
Figure 4 Histogram of Efficiency Scores Calculated by DEA Before

| Series: DEAAFTER	
Sample 1 431	
Observations 431	
Mean	0.245103
Median	0.192089
Maximum	1.000000
Minimum	0.099725
Std. Dev.	0.172588
Skewness	3.008948
Kurtosis	11.83772
Jarque-Bera	2053.004
Probability	0.000000
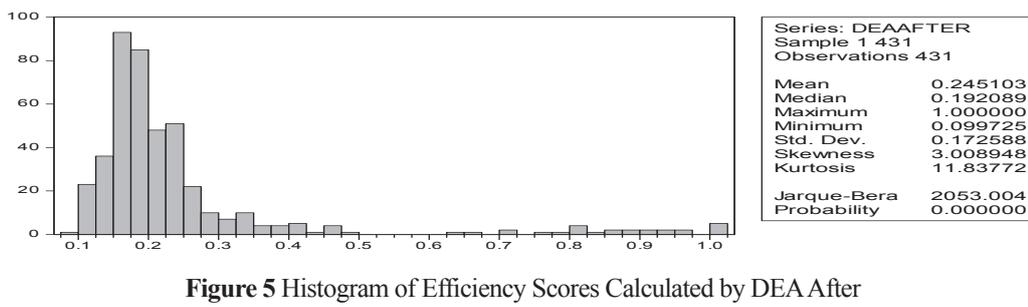
Figure 5 Histogram of Efficiency Scores Calculated by DEA After

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