

Relative Efficiency Measurement of Enterprises Operating in the Oltu Stone Industry Using Data Envelopment Analysis

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Received: December 29, 2012 Accepted: January 17, 2013 Online Published: February 27, 2013

doi:10.5539/ijbm.v8n6p115

URL: <http://dx.doi.org/10.5539/ijbm.v8n6p115>

Abstract

The city of Erzurum is emerging as one of the most popular jewelry centers in Turkey, principally due to its possession of mines for precious stones, and in particular for Oltu stone. Oltu stone is paramount to the international image of the city, and its contribution to the local and national economy is significant. Although recent studies have underscored the enormous potential of the Oltu stone industry, it is incumbent on the enterprises concerned to use their resources effectively and efficiently in order to reduce their costs, and they are also advised to improve service quality and thus satisfy customer needs more closely. With these aims in mind, Data Envelopment Analysis provides a convenient statistical technique that enables the analyst to measure the relative efficiencies of enterprises. This linear-programming-based technique can be used to identify suggestions for improvement with the goal of achieving greater efficiency. This paper uses Data Envelopment Analysis to perform a relative efficiency analysis of enterprises operating in the Oltu stone industry and presents alternatives whereby inefficient enterprises may become more efficient. The paper makes use of output-oriented CCR and BCC models to specify the scenario by calculating three different efficiency scores.

Keywords: efficiency, Oltu stone industry, data envelopment analysis, operations research

1. Introduction

Oltu stone is a carbon-rich semi-precious gemstone, which scores 3 for hardness and 1.5 for density on Mohs scale of mineral hardness. It was used in manufacturing prayer-beads, holy chests and sculptures during the Middle Ages, and for jewelry manufacturing in the 19th century. Today it is frequently used with silver and gold to manufacture various ornaments, as well as prayer-beads. The Oltu stone industry operates primarily in Erzurum province and Oltu district, and makes a remarkable contribution to employment and livelihood in the region, as well as engendering considerable artistic and artisanal activity (Alparslan, 2010). Unfortunately, however, this valuable industry has not managed to establish a significant competitive advantage for the region, even in today's era of advanced technology, because of ineffective government support programs. Today the Oltu stone industry is coming to a halt, and approximately 110 Oltu stone quarries have shut down due to inactivity and/or economic issues since 1980s. The reasons for this undesirable position can be stated quite briefly: the collapse has been associated with its failure to keep up with the present import conditions, which has seen alternative Georgian stones (known locally as "Russian stones") penetrating the market illegally and out-competing the higher-quality Oltu stone due to their lower costs.

Data Envelopment Analysis (henceforth DEA) was developed early in the process of developing performance evaluation techniques for non-profit decision-making units (henceforth DMUs). Because prices do not actually exist for such units, determination of weights was seen to be essential to evaluating their performance. Hence DEA was used, and continues to be used, for performance comparisons of homogeneous production indicators involving multiple but identical inputs and outputs where classical regression techniques cannot be directly

applied (Yavuz, 2001). DEA works by comparing each DMU with “the best” unit, and differs from central-tendency-based classical statistics methods that consider the “average” DMU option as a reference. This distinctive characteristic makes DEA an extreme point analysis technique, in contrast to other relevant approaches. Although there are various stochastic techniques for making efficiency measurements for different industries, such as the stochastic frontier approach (SFA) and principal component analysis (PCA), these advantages of DEA encourage the authors of this paper to use a DEA methodology that enables ‘relative’ efficiency measurements of the corresponding enterprises with respect to the best unit and efficient frontier approaches.

This paper approaches the performance evaluation of enterprises operating in the Oltu stone industry by using DEA models. To this end, the paper considers multiple and homogeneous inputs and outputs for fifty representative enterprises and determines the relatively most efficient of them. The paper also introduces options for improvement for inefficient enterprises and makes suggestions regarding their sustainability in the competitive Oltu stone market. The paper is organized as follows. Section 2 outlines the conceptual framework of DEA. Section 3 describes the data set and methodology, while Section 4 presents the results of the investigation. Finally, Section 5 discusses the results and concludes.

2. Literature Review

This section presents a literature review, in chronological order, as regards the Oltu stone industry and the areas of application of DEA. Though Oltu stone represents one of the most important sources of income for Erzurum province, and is indeed a symbol for that area and for Turkey as a whole, only a few research studies have concentrated on this valuable stone and its industry. Some of these studies (Özav, 1995; Cengiz & Akkuş, 2012; Bilgili *et al.*, 2012) address the importance of the Oltu stone industry for the economy of Erzurum and Turkey, as well as its tourism potential, while others are interested in the role of Oltu stone with respect to handicrafts (Kılıç, 1996), or its physical properties (Doğanay, 1997; Kalkan *et al.*, 2012).

DEA has been used frequently in recent studies to evaluate the relative efficiencies of various non-profit (e.g. hospitals, post offices, banks, police stations, courts) and for-profit organizations (Yolalan, 1993). Thore, *et al.* (1996) used a DEA approach to rank the efficiency of U.S. computer companies during a ten-year period and confirmed a key relationship between efficiency and the product cycle. Their observations indicated that heavy spending by companies to bring a stream of innovative products on line was generally ineffective. Donthu & Yoo (1998) evaluated store-level retail productivity using DEA and highlighted the potential applications and strengths of DEA in assessing retail productivity. Seifert & Zhu introduced a weighted DEA approach to investigate excesses and deficits in Chinese industrial productivity for the years 1953-1990 and suggested that DEA can be combined with other methods. Tongzon (2001) performed efficiency measurements of selected international airports using DEA, and found the ports of Melbourne, Rotterdam, Yokohama and Osaka to be the most inefficient international airports.

Despotis & Smirlis (2002) developed an alternative numerical approach for dealing with imprecise data in DEA and so formulated another post-DEA model. Zheng *et al.* (2003) investigated the productivity performance of 600 state enterprises from 1980 to 1994 by using DEA and a Malmquist index, and the empirical results revealed the low average technical efficiency of these firms. Düzakın & Düzakın (2007) used a super-slack-based model in DEA to measure the performance of 500 major industrial enterprises in Turkey. Önüt & Soner (2007) conducted an evaluation of energy efficiency in 20 medium-sized companies in Turkey by using DEA, and indicated that there is significant potential to save energy in the companies that are inefficient energy users. Liang *et al.* (2008) recommended alternative secondary goals in cross-efficiency evaluation in DEA and their models are illustrated with examples. Long & Wang (2008) used a Malmquist-DEA model to estimate the dynamic change of the total factor productivity in the household appliance industry from 2002 to 2006 in China and analyzed the scale efficiency of that industry. The results of their study indicated that total factor productivity of the household appliance industry had improved slightly, while pure technical efficiency and scale efficiency were declining. Temur & Bakırcı (2008) analyzed the performance of 846 public hospitals in the years 2003 to 2006 in Turkey and made suggestions for potential improvements.

Liu & Wang (2009) employed the relational two-stage DEA approach for PCB manufacturing firms in Taiwan and found that none of the manufacturing firms performed efficiently in either the stage of production acquisition or the stage of profit earning. Sueyoshi & Goto (2010) investigated a linkage among environmental, operational and financial performance in the Japanese manufacturing industry and observed that large firms have the managerial capabilities to improve their operational and environmental performance. Qureshi & Shaikh (2012) analyzed comparative efficiency in the banking system in Pakistan using two methods, namely impending

ratio analysis and DEA. Sevkli *et al.* (2012) applied the data envelopment analytic hierarchy process (DEAHP) to a well-known Turkish company operating in the appliance industry and aimed to provide a better decision for supplier selection using appropriate quantitative approaches.

3. Theoretical Framework of DEA

Efficiency generally refers to using the minimum number of inputs for a given number of outputs, while performance can be defined as an appropriate combination of efficiency and effectiveness (Özcan, 2007). It is essential to make some actual measurements of efficiency if the theoretical arguments as to the relative efficiency of different economic systems are to be subjected to empirical testing. If economic planning is to concern itself with particular industries, it is important to know how far a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources (Farrell, 1957). Moreover, through performance measurement, public and non-profit organizations can become accountable for their results, be more responsive to clients and constituents, improve planning and budgeting programs by exhibiting the existing position, and determine the effectiveness of performance efforts (Berman, 1998).

The production frontier is a function that describes the maximum output a firm can produce using any particular set of inputs (Coelli *et al.*, 2003). The problem of efficient frontier determination and the calculation of radial distances between inefficient points in this efficient frontier and the center have been successfully solved by the non-parametric-based approach embodied in DEA, which has been adopted, along with stochastic methods, as one of the two principal methods to estimate frontiers (Coelli, 1996). DEA is based on an evaluation of technical efficiencies depending on the inputs and outputs of the homogeneous DMUs being observed. In this procedure the structure of the production function comes to prominence, because DEA suggests an efficiency frontier with respect to “the best” combination of multi-input and outputs, where the radial distances to this “reference” frontier represent the original efficiency scores of any DMUs through the application of linear programming (Depren, 2008). As such, DEA does not require explicit specification and permits efficiency to vary over time, and makes no prior assumption about the distribution of inefficiencies around observations, except that undominated observations are fully efficient (Berger & Humphrey, 1997).

This very popular and comparative approach enables researchers to measure the relative performance of multiple and diversely measured DMUs because DEA provides efficiency ratings based on numerical data, and does not use subjective opinions (Tarim, 2001; Ramanathan, 2003). The literature on DEA is broadly speaking characterized as follows: (1) a large amount of application cases in different industries have been implemented, (2) various numerical methods on DEA models and related software have been developed, (3) different DEA models have been proposed and thoroughly discussed, (4) the economic and management background of DEA models and methods have been extensively investigated, and (5) the mathematical theories for DEA research have been discussed (Wei, 2001). Because DEA requires few assumptions, it has also opened up possibilities for use in cases which have been resistant to other complex approaches concerning multiple inputs and multiple outputs (Cooper *et al.*, 2011).

Three assumptions must be in place to construct the production frontier of DEA. Firstly, the production set consists of every observed production plan, which makes DEA a deterministic analysis. Secondly, any unobserved production plan that is weakly dominated by another production plan is also part of the production set, which enables free disposability. The third assumption deals with the issue of combinations of production plans, which often affects the calculated levels of efficiency (Henderson, 2003). In this respect, efficiency evaluation of a DMU involves selection of an appropriate reference plan against which to evaluate and measure performance slack (Bogetoft & Hougaard, 1998).

In DEA, all the organizational DMUs have an opportunity to effect the analysis independently, as well as their weights. Researchers frequently use value judgments to determine the weight restrictions, while these judgments are adopted as the logical structure that reflects the choices of decision makers as regards the evaluation of efficiency (Ulucan, 2001; Allen *et al.*, 1997; Deveci Kocakoc, 2003). However, two constraints must be satisfied in the analysis to overcome one-sided weighting problems. Firstly, the weights of DMUs being used in the analysis must be properly chosen so that none of the efficiencies exceed 100 %, and secondly these weights cannot have a negative value. Consequently, the two constraints function to force the organizational DMUs to become optimal. The results of a DEA approach to performance measurement can be summarized under the following categories (Ulucan, 2001):

- Efficient and inefficient organizational DMUs
- The amount of surplus used by inefficient organizational DMUs

- Existing input and potential improvement levels of inefficient organizational DMUs
- Units which consist of efficient reference sets of inefficient organizational DMUs

DEA has been incorporated into a collection of models with accompanying interpretive possibilities.

The CCR Ratio Model (1978) yields an objective evaluation efficiency and identifies the sources and estimates the amounts of the identified inefficiencies. The BCC Model (1984) distinguishes between technical and scale inefficiencies by estimating pure technical efficiency at the given scale of operation and identifying whether increasing, decreasing or constant returns-to-scale possibilities are present for further exploitation. The Multiplicative Models provide a log-linear envelopment or a piecewise Cobb-Douglas interpretation of the production process. Finally, the Additive Model and the extended additive model relate DEA to earlier inefficiency analyses and in the process also deal with the efficiency results with respect to the economic concept of Pareto optimality (Charnes *et al.*, 1994). The efficiency measurement approach is rooted in duality theory, and the 'value' or dual measures behave like support functions, such as profit, cost and revenue functions. In this case, primal measures are their dual distance functions. Thus, this approach to efficiency measurement yields a natural correspondence between quantity and value measures (Färe & Grosskopf, 2003).

The CCR model was initially proposed by Charnes, Cooper and Rhodes in 1978 and is formulated with row vector \mathbf{v} for input multipliers and row vector \mathbf{u} as output multipliers in the following linear programming problem (LP_0). In addition, the dual problem (DLP_0) is also expressed with a real variable θ and a non-negative vector $\lambda = (\lambda_1, \dots, \lambda_n)^T$ of variables as follows:

$$(LP_0) \quad \max \quad u y_0 \quad (1)$$

$$\text{subject to} \quad v x_0 = 1$$

$$-vX + uY \leq 0$$

$$\mathbf{v} \geq 0, \mathbf{u} \geq 0$$

$$(DLP_0) \quad \min \quad \theta \quad (2)$$

$$\text{subject to} \quad \theta x_0 - X\lambda \geq 0$$

$$Y\lambda \geq y_0$$

$$\lambda \geq 0$$

If an optimal solution $(\theta^*, \lambda^*, S^*, S^{+*})$ of the two linear programming formulas above satisfies $\theta^* = 1$ and is zero-slack ($S^* = 0, S^{+*} = 0$), then DMU_0 is called CCR-efficient, where S^- denotes input excesses and S^+ denotes the output shortfalls (Cooper *et al.*, 2002).

The BCC models were introduced by Banker, Charnes and Cooper in 1984 and offer a separation into technical and scale efficiencies without altering the conditions of the CCR model for use of DEA on observational data. These models identify technical efficiencies with failures to achieve best possible output levels, and/or usage of excessive amounts of inputs. The BCC approach does not require knowledge of the transformation function and does not assume that each DMU will attain the efficiency frontier. The approach simply adjusts the procedures of the CCR model in order to obtain new values $\hat{x}_{ij}, \hat{y}_{rj}$, that are all on the relative efficiency frontier for each of the $j=1, \dots, n$, DMUs, and obtains the following formula:

$$\frac{\sum_{r=1}^s u_r^* \hat{y}_{rj} - u_{0j}^*}{\sum_{i=1}^m v_i^* \hat{x}_{ij}} = 1 \quad (3)$$

where u_0^* denotes repeated applications to provide the relevant identification for each of DMUs (Banker *et al.*, 1984). The ratio form of the variable returns to scale of the BCC is given by

$$\begin{aligned} & \max \quad \frac{uY_0 + \omega}{vX_0} \\ & \text{subject to} \quad \frac{uY_j + \omega}{vX_j} \leq 1, \quad j = 1, \dots, n \\ & \quad u, v \geq 0, \quad \omega \text{ unrestricted.} \end{aligned} \quad (4)$$

Besides this, dual and primal problems are formulated as follows, where ω denotes the weight and μ denotes the output multiplier again (Cook and Zhu, 2005):

$$\begin{aligned} & \max \quad \mu Y_0 + \omega & (5) \\ \text{subject to} \quad & v X_0 = 1 \\ & \mu Y_j + \omega - v X_j \leq 0, j=1, \dots, n \\ & \mu, v \geq 0, \quad \omega \text{ unrestricted} \\ & \text{and} \\ & \min \quad \theta & (6) \end{aligned}$$

$$\begin{aligned} \text{subject to} \\ \theta X_0 - \sum_{j=1}^n \lambda_j X_j & \geq 0 \\ \sum_{j=1}^n \lambda_j Y_j & \leq Y_0 \\ \sum_{j=1}^n \lambda_j & = 1 \\ \lambda_j & \geq 0, j = 1, \dots, n \end{aligned}$$

Technical efficiency refers to a DMU’s ability to achieve maximum output given its set of inputs and varies between 0 and 1. Here, a value of 1 indicates full efficiency and that operations are on the production frontier, while a value less than 1 reflects operations under the frontier, the wedge between 1 and the value being observed thus representing technical efficiency. The corresponding evaluation is denominated an output-oriented technical efficiency measurement. Furthermore, input-oriented technical efficiency has an effect on the degree to which a DMU, which must produce at a particular output level, could proportionally reduce its use of inputs while maintaining a feasible production set (Coelli *et al.*, 2003). Technical efficiency assumes clear-cut objectives, complete decision making and implementation control by management, and that technical efficiency problems arise from causes within the firm such as the differential capacities of management (Leibenstein, 1977). Firms need to choose a technology that can produce at minimum cost in order to eliminate technical inefficiency and then adjust the mix of factor inputs, such as labor, capital, materials (Anandalingam & Kulatilaka, 1987).

The ratio of CCR efficiency to BCC efficiency gives “scale efficiency” (Banker *et al.* 1984; Kao and Liu, 2011). The function

$$S_o(x^j, u^j) = \frac{F_o(x^j, u^j \setminus C, S)}{F_o(x^j, u^j \setminus V, S)}, \quad j= 1, 2, \dots, J \tag{7}$$

refers to the output scale efficiency measure, and observation j is output-scale efficient if $S_o(x^j, u^j) = 1$, or if it is equally technical efficient relative to the (C,S) and (V,S) output sets (Färe *et al.*, 1994). The combined technical and scale inefficiency of the j_0 th DMU can be interpreted by the following formula, where $\lambda_j \geq 0$ and m' and m denote inputs (Banker & Morey, 1986):

$$\sum_{j=1}^N \lambda_j x_{ij} + s_i^- - x_{ij_0} \sum_{j=1}^N \lambda_j = 0, \quad i = m' + 1, \dots, m; \quad j = 1, 2, \dots, N \tag{8}$$

Here, the potential improvements approach refers to $g^{PI}(x) \propto x - x^*$ and $s^{PI}(x) = x - e(x, L, g^{PI}(x))g^{PI}(x)$, where L denotes the input set, g^{PI} denotes the reference direction and S^{PI} denotes the reference plan (Bogetoft & Hougaard, 1998). In other words, percentile potential improvements of inputs and outputs can be calculated as follows (Özden, 2008):

$$PI = \frac{(\text{Objective} - \text{Observed})}{\text{Observed}} \times 100 \tag{9}$$

The input- or output-oriented model choice of DEA depends on the judicial discretion of decision makers. There is no doubt that the structure of the existing data also has a significant impact on model choice. Very often, analysts prefer output-oriented models because the input use is generally accepted as a primary factor. In several industries, enterprises aim to obtain maximum outputs with constant production factors, which means that for them output-oriented model selection would be the more appropriate analysis procedure. The CCR models usually concentrate on total efficiency results of DMUs and assume constant returns to scale, while the BCC models consider technical efficiency and are also applied under the assumption of efficient scale (Lorcu, 2008).

4. Methodology & Data Set

This paper applies DEA to the efficiency evaluation of enterprises operating in the Oltu stone industry. The Turkish Statistical System is in the process of transition to the European Union Classification System, so as to be in accord with both international and European systems, ensure data comparability and at the same time to respond to data requests at the national level (Turkish Statistical Institute, 2012). The survey reported in this paper considers the NACE Rev 1.1 classification of the Turkish Statistical Institute, which distinguishes 157 enterprises in the Oltu stone industry by retail and/or wholesale; in addition, this survey also addresses relative efficiency measurements for 50 representative DMUs (in this survey they are all enterprises) via face-to-face interview. Table 1 sets out the input and output variables of the study in 2009.

Table 1. Input and output variables employed in the survey

<i>Input Variables</i>	<i>Output Variables</i>
Total expenditure of enterprise (TL*)	Cash value of products (TL)
The amount of Oltu stone used (kg)	The amount of sales sold by retail and wholesales (TL)
The number of workdays of employees (person/day)	Net profit of enterprise (TL)

* TL = Turkish Lira

The input variables of the survey are selected in order to provide interpretations regarding the use of resources for the 50 DMUs, while the output variables focus on the benefits deriving from these resources. This paper employs output-oriented DEA modeling, which identifies the maximum potential output for constant input without additional resources by using the computer package program Frontier Analyst Professional. Table 2 sets out the descriptive statistics for the input and output variables used in this survey.

Table 2. Descriptive statistics for the input and output variables

<i>Input-Output Variables</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean</i>	<i>Standard Deviation</i>
Inputs				
Total expenditure (TL)	3130	170000	31025	39845
Amount of Oltu stone used (kg)	5	500	69.06	72.64
Number of persons/day	210	3164	604.56	479.85
Outputs				
Cash amount (TL)	2800	237600	29127	47713.27
Amount of sales (TL)	3600	175800	35027.2	8961.5
Net profit (TL)	25	30000	8961.5	6854.95

The survey then investigates the correlation coefficient between input and output variables. As Table 3 shows, all these coefficients are positive, even though both high and low correlations are observed, where any of the output variables are generally highly correlated.

Table 3. Correlation analysis of input and output variables

Input-Output Variables	Total expenditure (TL)	Amount of Oltu stone (kg)	Number of persons/day	Cash amount (TL)	Amount of sales (TL)	Net Profit (TL)
Total expenditure (TL)	1.00					
Amount of Oltu stone (kg)	0.41	1.00				
Number of persons/day	0.61	0.16	1.00			
Cash amount (TL)	0.84	0.49	0.67	1.00		
Amount of sales (TL)	0.90	0.44	0.72	0.88	1.00	
Net profit (TL)	0.80	0.31	0.61	0.74	0.86	1.00

5. Results

The main concern of this survey lies with the efficiency measurement of DMUs by output-oriented BCC and CCR models as illustrated in Table 4, which also comprises average efficiency measures for both models.

Table 4. Relative efficiency scores of Oltu stone enterprises

DMU	Efficiency Scores				
	CCR Input	BCC Input	CCR Output	BCC Output	Average
1	81.91	82.77	81.81	86.99	83.37
2	100.00	100.00	100.00	100.00	100.00
3	57.49	64.07	57.49	78.00	64.26
4	93.49	99.71	93.49	99.79	96.62
5	73.50	100.00	73.50	100.00	86.75
6	36.55	36.70	36.55	73.12	45.73
7	86.77	87.20	86.77	90.84	87.90
8	53.64	55.77	53.64	72.55	58.90
9	100.00	100.00	100.00	100.00	100.00
10	78.27	78.93	78.27	79.62	78.77
11	85.91	87.89	85.91	85.96	86.42
12	64.12	84.67	64.12	92.54	76.36
13	75.45	76.07	75.45	86.09	78.27
14	59.07	59.11	59.07	73.42	62.67
15	76.05	87.44	76.05	83.92	80.86
16	100.00	100.00	100.00	100.00	100.00
17	81.83	87.27	81.83	81.93	83.22
18	83.39	100.00	83.39	100.00	91.70
19	88.43	100.00	88.43	100.00	94.22
20	60.76	69.86	60.76	62.67	63.51
21	46.90	47.10	46.90	54.95	48.96
22	100.00	100.00	100.00	100.00	100.00
23	100.00	100.00	100.00	100.00	100.00
24	46.15	48.89	46.15	85.63	56.71
25	100.00	100.00	100.00	100.00	100.00
26	51.11	51.36	51.11	71.69	56.31

27	79.63	83.70	79.63	81.88	81.21
28	100.00	100.00	100.00	100.00	100.00
29	35.56	39.73	35.56	46.34	39.30
30	52.15	61.89	52.15	52.94	54.78
31	41.98	45.75	41.98	45.26	43.74
32	44.42	48.35	44.42	49.89	46.77
33	91.18	99.73	91.18	99.70	95.45
34	37.86	42.02	37.86	82.96	50.18
35	72.47	83.94	72.47	88.38	79.31
36	77.29	93.30	77.29	96.93	86.20
37	100.00	100.00	100.00	100.00	100.00
38	93.60	96.40	93.60	96.97	95.14
39	100.00	100.00	100.00	100.00	100.00
40	100.00	100.00	100.00	100.00	100.00
41	61.40	62.88	61.40	75.21	65.22
42	100.00	100.00	100.00	100.00	100.00
43	100.00	100.00	100.00	100.00	100.00
44	100.00	100.00	100.00	100.00	100.00
45	100.00	100.00	100.00	100.00	100.00
46	47.86	53.36	47.86	49.65	49.68
47	51.51	71.53	51.51	51.59	56.54
48	34.13	49.03	34.13	92.16	52.36
49	74.30	100.00	74.30	100.00	87.15
50	79.02	82.73	79.02	80.27	80.26

Table 5 summarizes descriptive information concerning the BCC and CCR results of the survey. As shown in Table 4, the number of efficient DMUs enclose 14 observations and the 48th DMU is the least efficient one for both input and output CCR models with a 34.13 % efficiency score. Otherwise, the number of efficient DMUs is 18, while the lowest efficiency score belongs to the 6th DMU with 36.70 % for the output-oriented BCC model, and similarly the 31st DMU has the lowest score with 45.26 for the output-oriented CCR model. When all of the models being observed are taken into consideration, the 29th DMU has the lowest relative efficiency score with 39.3 %. Besides this, the BCC models encompass more relatively efficient DMUs than the CCR models, because the latter models evaluate both technical and scale efficiency scores and manifest an overall efficiency score under constant returns, while the former models consider only technical efficiency outcomes under variable returns.

Table 5. Summary of efficiency results

	CCR Output	BCC Output	CCR Output	BCC Output	Average
Efficient DMUs	14	18	14	18	14
Inefficient DMUs	36	32	36	32	36
Minimum Efficiency Score	34.13	36.70	34.13	45.26	39.30
Maximum Efficiency Score	100	100	100	100	100
Average Efficiency Score	75.10	80.38	75.10	85.00	78.90
Standard Deviation	22.13	21.40	22.13	17.41	19.93

In this section, the survey will seek to interpret scale efficiencies of DMUs for output-oriented BCC and CCR

models in order to clarify results. As mentioned earlier, technical efficiency is based on the expression $SE = TE_{CRS}/TE_{VRS}$, where TE_{CRS} denotes technical efficiency under constant returns to scale and TE_{VRS} denotes variable returns to scale. When scale efficiency is equal to 1, this means that there is no observed deviation caused by scale for the corresponding DMU. According to the results in Table 5, the average scale efficiency score is 93.1 %. 15 DMUs are scale efficient and 14 DMUs are very close to scale efficiency, meaning that an increase of outputs does not have a significant effect. This observation clearly does not apply to the 48th DMU, which is sensitive to scale efficiency. In addition, the efficiency scores of the 18th DMU vary with respect to the BCC and CCR models. Consequently, potential improvements are also illustrated with respect to the efficiency scores illustrated in Table 6.

Table 6. Scale efficiencies of DMUs

DMU	Overall	Technical	Scale	DMU	Overall	Technical	Scale
	Efficiency	Efficiency	Efficiency		Efficiency	Efficiency	Efficiency
	TECRS	TEVRS	SE		TECRS	TEVRS	SE
1	0.82	0.83	0.99	26	0.51	0.51	0.99
2	1.00	1.00	1.00	27	0.80	0.84	0.95
3	0.57	0.64	0.90	28	1.00	1.00	1.00
4	0.93	1.00	0.94	29	0.36	0.40	0.90
5	0.74	1.00	1.00	30	0.52	0.62	0.84
6	0.37	0.37	0.99	31	0.42	0.46	0.92
7	0.87	0.87	0.99	32	0.44	0.48	0.92
8	0.54	0.56	0.96	33	0.91	0.99	0.91
9	1.00	1.00	1.00	34	0.38	0.42	0.90
10	0.78	0.79	0.99	35	0.72	0.84	0.86
11	0.86	0.88	0.98	36	0.77	0.93	0.83
12	0.64	0.85	0.76	37	1.00	1.00	1.00
13	0.75	0.76	0.99	38	0.94	0.96	0.97
14	0.59	0.59	0.99	39	1.00	1.00	1.00
15	0.76	0.87	0.87	40	1.00	1.00	1.00
16	1.00	1.00	1.00	41	0.61	0.63	0.98
17	0.82	0.87	0.94	42	1.00	1.00	1.00
18	0.83	1.00	0.83	43	1.00	1.00	1.00
19	0.88	1.00	0.88	44	1.00	1.00	1.00
20	0.61	0.70	0.87	45	1.00	1.00	1.00
21	0.47	0.47	0.99	46	0.48	0.53	0.90
22	1.00	1.00	1.00	47	0.52	0.72	0.72
23	1.00	1.00	1.00	48	0.34	0.49	0.70
24	0.46	0.49	0.94	49	0.74	1.00	0.74
25	1.00	1.00	1.00	50	0.79	0.83	0.96

6. Discussion and Conclusion

The purpose of DEA is to determine the efficient DMUs, namely those which achieve maximum outputs using the minimum input combination. DEA offers a relative efficiency frontier as a reference and evaluates the efficiency measurement for DMUs in respect of distances to this reference frontier. The most important advantage of the DEA approach here adopted is the potential improvement which the analysis suggests that inefficient DMUs can

achieve with respect to efficiency gains. This paper identifies 14 efficient DMUs according to the output-oriented CCR model under constant returns to scale. These efficient DMUs are the 2nd, 9th, 16th, 22nd, 23rd, 25th, 28th, 37th, 39th, 40th, 42nd, 43rd, 44th and 45th enterprises operating in the Oltu stone industry. The inefficient DMUs of the survey are the 6th, 21st, 24th, 29th, 31st, 32nd, 34th, 46th and 48th enterprises. The average efficiency score of the output-oriented CCR approach is observed to be 75.10 %.

Additional efficient DMUs for the output-oriented BCC model are the 5th, 18th, 19th and 49th enterprises, while the inefficient DMUs are analogous to those of the CCR model except for the 46th enterprise, where the average technical efficiency score is 80.38 %. As the overall efficiency comprises both technical and scale efficiency, the overall scores suffice to reach technical efficiency scores numerically. Scale efficiency scores identify 15 efficient DMUs, and additionally the 5th enterprise also reaches the efficiency frontier; however, the 12th, 47th, 48th and 49th enterprises have scale efficiency scores under 80 %. The average scale efficiency is 93.1 %. The authors of this paper suggest that inefficient enterprises operating in the Oltu stone industry decrease their input variables and increase their output variables simultaneously within the framework of potential improvements and in line with the nature of the output-oriented models. For instance, inefficient DMUs should compare their efficiency scores with the 14 most efficient units which have average efficiency scores of 100 %. As well as this, the correlation analysis of input and output variables representing the net profit variable is the most notable indicator affecting efficiency, with the highest correlation coefficients considered numerically. In this context, inefficient DMUs should increase their net profit, and so increase their efficiency scores and reach the maximum efficiency frontier.

Inefficient enterprises may benefit from all these results to struggle against their competitors within the Oltu stone industry, where the competitive environment possesses dynamic, ever-changing and complex characteristics. Within these circumstances, concentrating on internal factors will be more advantageous than monitoring external indicators. Therefore, enterprises should focus on increasing efficiency by using their resources effectively and establishing a good balance of decreasing costs and increasing quality. In this respect, decision makers should determine the existing positions of their enterprises by stochastic frontier analyses such as DEA and should improve scarce resource management through developing administrative strategies and programs while providing accurate information flows about idle inputs and insufficient outputs to eliminate extravagancy in resource use.

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