

## Research Article

# Estimating Performance Efficiency of Mining and Extracting Sectors Using DEA Models: The Case of Jordan

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In this study, we estimated the performance efficiency of the Jordanian mining and extracting sector based on Data Envelopment Analysis (DEA). The utilized dataset includes 6 out of 15 corporations that reflect around 90% of the total market capitalization under the mining and extracting sector in the Amman Stock Exchange (ASE). The sample consists of 126 observations from 2000 to 2020. It should be noted that estimating the efficiency of the sector based on time series for each company is not mentioned in the literature review. Therefore, we applied BCC (Banker–Charnes–Cooper) models to estimate performance efficiency and compared between input and output models under DEA. We also estimated the average performance efficiency of the sector to detect weaknesses/strengths among companies. The market capitalization and the operating revenue are used to evaluate the companies' performance. In addition to the performance variables as output to the DEA models, the current assets, non-current assets, operating expenses, and general administrative expenses are also used as input variables under the DEA models. This study also examined the effect of Gross Domestic Product (GDP) growth and Return on Assets (ROA) on performance efficiency scores for BCC models. In the results, we found that there are differences in performance efficiency across time series in each company based on dynamic BCC models. It is observed that the performance efficiency of NAST Company is better than the other companies based on BCC (Input/output). The GDP growth and ROA reveal the effect on efficiency performance under BCC models. The proposed model can be used to improve the performance efficiency of companies in stock exchange markets.

## 1. Introduction

The mining sector is a central pillar of Jordan's economy. It is considered most significant to the national economy because of its effective contribution in employing local labor, investment, export, and revenue. In 2020, this sector contributed 24.5% of Jordan's GDP and employed 24% of the workforce [1]. Mining and extracting (mostly phosphate and potash) are among the primary industries. The industrial sector contributes to Jordan's financial stability by providing the government with more than JOD 1 billion in direct and indirect taxes each year [2].

The important role of the industrial sector can identify Jordan's position within the Middle East and North Africa (MENA) region, which is supported by a variety of free trade agreements (FTAs) allowing access to 1.5 billion customers across more than 160 countries. The high volume of industrial investment contributes significantly to the strength of the Jordanian Dinar and to the exchange rate's stability by providing the Kingdom's official reserves with foreign currency (more than US\$ 8.0 billion in 2017) [3].

DEA is one of the major and popular techniques employed for analyzing efficiency. Since its introduction through the seminal work of [4], it has seen numerous

developments. Those developments encompass both methodological developments and application developments. Methodological-wise and apart from the basic DEA, several DEA model variations emerge in literature that are dedicated to addressing various technical and modeling issues such as generic DEA models, bootstrap DEA models, network models, multiplier bounds, considerations on the status variables, and data variations. Application-wise, DEA is applied in a wide range of fields for examining and analyzing various aspects of efficiency and productivity. To name but a few, those fields include banking, health care, agriculture and farm, education, transportation, finance, tourism, retailing, fishery, manufacturing, communication, and the list goes on.

From applications perspective [5], survey on DEA application covers the period from 1978 to 2010 that identified banking, health care, agriculture and farm, transportation and education as the top-five industries addressed by DEA. Most recently; [1] a comprehensive survey of DEA-related published articles was conducted that covers the last four decades (1978–2016). This survey includes and analyses all types of articles whether they address theoretical, methodological or real applications. They reported that from 2004 to 2016 the number of DEA-related articles has grown exponentially, with an average of 680 articles per year. In addition, they argued that agriculture, banking, supply chain, transportation, and public policy are the top-five application fields of DEA [1]. References [2, 6] examined the elasticities and casualties of financial performance of the mining and extractive companies listed in the Amman Stock Exchange (ASE) during 2005–2018 period. They applied several models; including Dynamic Ordinary Least Squares (DOLS), Fully Modified Ordinary Least Square (FMOLS), and Pooled Mean Group (PMG). The results showed that company characteristics and GDP growth are most important determinants causing financial performance.

The vast majority of articles, published in the first 20 years of DEA since its development, were purely methodological [5]. However, the accumulated number of application papers exceeds methodological papers starting from 1999 onward. Several authors review and follow the technical and methodological developments as well as application developments of DEA have devoted a considerable endeavor, for example, [7] survey on the developments of DEA from the angle of mathematical programming. Reference [8] tracks the methodological evolutions of DEA over a period of 17 years; from 1978 to 1995. Reference [9] survey analytical models, developed for examining the sensitivity of DEA results to data variations. Over a time period of 30 years, [10] map out the major methodological developments and directions of DEA.

The mining sector is one of the numerous industries where DEA models and techniques can be employed for studying and assessing efficiency. References [3, 11] used bootstrap DEA for assessing the balance of efficiency gains and losses for 33 mining firms in Australia. They tried to identify the behavior of efficiency performance for the 33 firms over the period 2008–2014. Reference [12] employed the DEA models of BCC (Banker, Charnes, and Cooper) and

CCR (Charnes, Cooper, and Rhodes) for measuring, analyzing, and comparing the performance of technical efficiency of 24 major global corporations involved in Phosphate rock mining for the year 2012. They examined whether the efficiency of publicly quoted companies differs significantly from that of state-owned companies. References [4, 13] used the DEA model version of the Malmquist index for studying the growth of efficiency and productivity of the coal mining sector in India over the period 1985–1997. The results show that opencast mining does not have more productivity growth than underground mining. Reference [14] conducted a comparative study on the relative technical efficiency performance of the public coal mining companies in China and the USA. Using CCR and BCC models, they found that the USA companies are relatively much more efficient than the Chinese ones. Using DEA techniques, [15] evaluated and analyzed the safety output efficiency in relation to safety input factors for coal mines. Reference [16] employed DEA bootstrapping for assessing the performance of fifteen strip coal mines in Illinois (USA). The results of this approach indicate significant inefficiencies in the analyzed sample. With the application of DEA and stochastic frontier estimation, [17] found that private international oil companies are more efficient than national oil companies in terms of revenue efficiency. With an emphasis on the potential environmental effects, [18] analyzed the efficiency of the cement industry in 21 countries using DEA and directional distance function. Reference [16] applied DEA along with stochastic frontier analysis (SFA) for assessing the efficiency performance of the Greek Bauxite mining sector over the period 1970–1996. This paper is innovative regarding the utilization of a bootstrapping approach in DEA for aggregated sector data.

Several researchers have examined the efficient performance of the mining and extracting sector at the industrial level [19, 20]. Based on the studies, there is a concentration on the efficiency of the mining and extracting sector in developing countries. Reference [19] investigated bootstrap data envelopment analysis to analyze the efficiency performance of 33 mining companies in Australia. They found that most mining companies became more efficient over time in Australia. In addition, there are many researchers have examined the efficiency performance of financial institutions based on traditional DEA [21, 22]. The two-stage network was able to explain more about the variables that affect the efficiency of companies [23–25].

DEA proves to be a common and acceptable tool for studying and analysing various aspects of efficiency and productivity in many sectors and industries, including the mining sector. Different efficiency-related issues in mining industries have been addressed by DEA techniques. Some authors track the efficiency performance of mining sector as a whole over some period of time either on a country-specific level or worldwide, others focus on comparing the efficiency of firms specialized in a specific kind of mining work either in a specific country or globally. Furthermore, some articles try to relate the efficiency of the mining sector to some potential environmental effects [11]. Yet, other papers attempt to relate the efficiency of mining firms to the

type of firms' ownership [19]. In this study, we employ DEA for measuring and analyzing the efficiency of mining sector in Jordan, which is one of the most important industries for the Jordanian economy. In our study, the following are some of the specific contributions:

- (i) We identify the efficiency gaps in Jordanian mining and extracting corporations using BCC models under DEA.
- (ii) We discover how the efficiency performance of mining and extracting corporations has changed from 2000 to 2020 in each corporation.
- (iii) We detect the average performance efficiency level between companies based on BCC models under DEA.
- (iv) We determine the role of internal and external factors on efficiency performance in the mining and extracting sector in Jordan.

The remainder of the study proceeds as follows. Section 2 discusses the mathematical models. Section 3 presents a description of the data. Section 4 highlights the empirical results and discusses the efficiency performance of mining and extracting corporations. Section 4 draws the conclusion.

## 2. Methodological Issues

This section gives a background of the main concepts of DEA models; BCC (input/output).

**2.1. The Efficiency Models.** The efficiency performance at the corporate level has a number of advantages. First, with corporate-level data, we concentrate on a smaller size of data that is more homogenous. Second, with corporate-level analysis, we can explore efficiency performance over years more accurately and discover benchmark years. Third, we can determine both input and output variables more accurately using corporate-level analysis. Fourth, we can identify best practices and benchmarks across comparable firms. Finally, we can decompose the sources of inefficiency into pure technical inefficiency and scale inefficiency based on corporate level. The performance gap between the corporation and the corresponding frontier can be easily assessed using variable returns to scale (BCC) models if the corporation has pure technical inefficiency. The degree to which a corporation operates inefficiently is called scale inefficiency. Constant returns to scale (CRS) efficiency discovers the impact of both scale and pure technical (in) efficiencies. A comparison of efficiency findings from CRS and BCC models can be determined if the cause of inefficiency in the mining and extracting sector is due to pure technical inefficiency.

The measurement of efficiency in the production unit and the identification of sources of their inefficiency are preconditions to improve the performance of any production unit in a competitive environment. The term productive unit refers to a unit producing certain output by spending certain inputs.

In DEA, the organization under study is called a DMU (decision-making unit). Generically, a DMU is regarded as the entity responsible for converting inputs into outputs and whose performances are to be evaluated. In managerial applications, DMUs may include banks, department stores, and supermarkets extending to carmakers, hospitals, schools, public libraries, and so on. Mining and extracting corporations can be treated as production units too. To secure relative comparisons, a group of DMUs is used to evaluate each other with each DMU having a certain degree of managerial freedom in decision making. In general, the group is homogenous units performing the same or similar activities. All inputs and outputs have an impact on the efficient operation of such units, even though some are considered more or less important.

We have a population of  $n$  productive units (companies)  $DMU_1, DMU_2, \dots, DMU_n$ . We write an input matrix  $x_i = (x_{i1}, x_{i2}, \dots, x_{ip})$  and an output matrix  $y_i = (y_{i1}, y_{i2}, \dots, y_{iq})$  of  $DMU_i$ , where  $i = 1, 2, \dots, n$ .  $DMU_0$  is the target of DMU. Also,  $x_0 = (x_{01}, x_{02}, \dots, x_{0p})$  and  $y_0 = (y_{01}, y_{02}, \dots, y_{0q})$  are the input and the output vectors of the target  $DMU_0$ . The efficiency rate of such a unit can be generally expressed as:

$$\begin{aligned} \text{Efficiency rate} &= \frac{\sum_r \text{weighted sum of outputs}}{\sum_i \text{weighted sum of inputs}} \\ &= \frac{\sum_{r=1}^q u_r y_{rj}}{\sum_{i=1}^p v_i x_{ij}}, \end{aligned} \quad (1)$$

where  $v_i, i = 1, 2, \dots, q$ , are weights assigned to  $i$  th input  $u_r, r = 1, 2, \dots, p$ , are weights assigned to  $r$ -th output.

There are several ways to estimate the efficiency rate as defined above, namely multicriteria decision methods and data envelopment analyses (DEA). These approaches differ in how they obtain input and output weights. Multicriterial decision methods usually expect the user to define the weights  $v_i$ , and  $u_r$  upfront, i.e. the user determines the significance of individual inputs and outputs in the analysis. Such an analysis yields the rate of the utility of given units. It reflects the relative importance of inputs and outputs represented by their respective weights. Based on the analysis, units can be ranked from the worst to the best performer. On the other hand, DEA models derive input and output weights by means of an optimizing calculation. Based on that, units can be classified into efficient and inefficient categories. In inefficient units, they tell us the target values of inputs and outputs, which would lead to efficiency.

**2.2. DEA Model.** In DEA model, we evaluate  $n$  productive units, DMUs, where each DMU takes  $p$  different inputs to produce  $q$  different outputs. The essence of the DEA model in measuring the efficiency of a productive unit  $DMU_q$  lies in maximizing its efficiency rate. However, subject to the condition that the efficiency rate of "virtual output" versus "virtual input" should not exceed 1 for every DMU. The objective is to obtain the ratio of the weighted output to the

weighted input weights. By virtue of the constraints, the optimal objective value  $\theta^*$  is at most 1. Mathematically, the non-negativity constraint is not sufficient for the fractional terms to have a positive value. We do not treat this assumption in the explicit mathematical form at this time. Instead, we put this in managerial terms by assuming that all outputs and inputs have some nonzero worth and this is to be reflected in the weights  $v$  and  $u$  being assigned some positive value. DMU<sub>0</sub> is CCR-efficient if  $\theta^* = 1$  and there exists at least one optimal  $u^* > 0$  and  $v^* > 0$ . The fractional model is initially proposed by [8].

$$\begin{aligned} & \text{Maximize :} \\ & \theta = \frac{v^T y_0}{u^T x_0}, \\ & \text{Subject to :} \\ & v^T y_j \leq u^T x_j, \quad j = 1, 2, \dots, n \\ & u_r \geq \varepsilon > 0 \quad r = 1, 2, \dots, p \\ & v_i \geq \varepsilon > 0 \quad i = 1, 2, \dots, q, \end{aligned} \quad (2)$$

where  $\theta$  is the efficiency ratio,  $\varepsilon$  is a constant greater than zero that is called a non-Archimedean element defined to be smaller than any positive real number. It is normally pitched at  $10^{-6}$  or  $10^{-8}$ .

**2.3. CCR Model.** In 1978, this model was developed to measure the technical efficiency of a given observed decision-making unit (DMU) assuming constant returns to scale (CRS). In other words, the change in inputs has a constant effect on the outputs if moved from one point to another point on the frontier curve. CCR model is considered as a global pure technical efficiency. The linear programming formulation allowed multiple inputs and multiple outputs. However, the CCR model is divided into input-oriented (CCR-I) and output-oriented (CCR-O).

**2.3.1. Input-Oriented (CCR-I) Model.** This model assumes that the inefficient units can become efficient if they reduce their input while maintaining the same level of production. In other words, they try to find out how to improve the input characteristics of the unit concerned for it to become efficient. In addition, the above fractional program (1) is replaced by the *equivalent* linear program (2). The CCR-I model maximizes the numerator and considers the constant denominator as shown in Table 1.

The dual model (b) in Table 1 has a feasible the solution  $\theta^* = 1$ ,  $\lambda_0^* = 1$ ,  $\lambda_j^* = 1$  ( $j \neq 0$ ). Hence, the optimal value  $\theta^*$  is not greater than 1 [4, 26]. The optimal solution,  $\theta^*$ , yields an efficiency score for a particular DMU. The process is repeated for each DMU<sub>*j*</sub>,  $j = 1, 2, \dots, n$ . DMUs for which  $\theta^* < 1$  are inefficient, while DMUs for which  $\theta^* = 1$  are boundary points. Some boundary points may be “weakly efficient” because we have nonzero slacks. This may appear

to be worrisome because alternate optima may have nonzero slacks in some solutions, but not in others. However, we can avoid being worried even in such cases by invoking the following linear program in which the slacks are taken to their maximal values. In Table 1, we also note that choices of  $s_i^-$  and  $s_r^+$  do not affect the optimal  $\theta^*$ , which is determined from model (b). Where  $s_i^-$  and  $s_r^+$  are slack variables used to convert the inequalities in (b) in Table 1 to equivalent equations. This is equivalent to solving (b) in Table 1 in two stages by first minimizing  $\theta$  and then fixing  $\theta = \theta^*$  as in (c) in Table 1, where the slacks are to be maximized without altering the previously determined value of  $\theta = \theta^*$ .

These developments based on the “relative efficiency” lead to the following. First, the performance of DMU<sub>0</sub> is fully (100%) efficient if we do not have ability to decrease inputs ( $s_i^- = 0$ ), increase outputs ( $s_r^+ = 0$ ), and set efficiency ratio  $\theta^* = 1$ . Second, the performance of DMU<sub>0</sub> is weakly efficient if we have ability to decrease inputs ( $s_i^- \neq 0$ ), increase outputs ( $s_r^+ \neq 0$ ), and set efficiency ratio  $\theta^* = 1$ . Finally, the inefficiency ratio is.  $\theta < 1$ .

**2.3.2. Output-Oriented (CCR-O) Model.** CCR-O model assumes that the inefficient units can become efficient if they increase their output while maintaining the same level of input. In other words, they try to find out how to improve the output characteristics of the unit concerned for it to become efficient. In addition, CCR-O model minimizes the denominator and considers the constant numerator (a) in Table 2:

The models in Table 2 assume output-oriented CCR. In equation (b) in Table 2, we use the dual equation to solve equation (a) in Table 2. In equations (c) and (d) in Table 2, we use slacks.

The aim of DEA analysis is not only to determine the efficiency rate of the units reviewed, but in particular to find target values for inputs  $X'q$  and outputs  $Y'q$  for an inefficient unit. After reaching these values, the unit would arrive at the threshold of efficiency. Target values are calculated with the following [4]:

- (i) The productive unit vectors: ( $X'_q = \lambda X^*$  and  $Y'_q = \lambda Y^*$ ), where  $\lambda^*$  is the vector of optimal variable values.
- (ii) The efficiency rate and values of additional variables  $s^-$  and  $s^+$ : input-oriented CCR model ( $X'_q = \theta X - s^-$  and  $Y'_q = Y_q + s^+$ ) and Output-oriented CCR model ( $X'_q = X_q - s^-$  and  $Y'_q = \phi Y_q + s^+$ ), where  $\theta$  is the efficiency rate in the input-oriented model and  $\phi$  is the efficiency rate in the output-oriented model.

**2.4. BCC Models.** BCC models extend the CCR model to allow variable returns to scale [16]. They are developed to measure the technical efficiency of a given observed decision-making unit (DMU) assuming variable returns to scale (VRS). This model considers a local pure technical efficiency. The BCC model is divided into input-oriented (BCC-I) and output-oriented (BCC-O)[27].

TABLE 1: Input-oriented CCR model.

(a)	(b)	(c)	(d)
<b>Maximize:</b> $\theta = v^T y_0$	<b>Minimize:</b> $\theta = v^T y_0$	<b>Maximize:</b> $\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+$	<b>Minimize:</b> $\theta - \varepsilon (\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+)$
<b>Subject to:</b> $u^T x_0 = 1$ $v^T y_j - u^T x_j \leq 0,$ $j = 1, 2, \dots, n$ $u, v \geq \varepsilon > 0$	<b>Subject to:</b> $\sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{i0}$ $\sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}$ $\lambda_j \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$	<b>Subject to:</b> $\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = \theta^* x_{i0}$ $\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = y_{r0},$ $\lambda_j, s_i^-, s_r^+ \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$	<b>Subject to:</b> $\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = \theta x_{i0}$ $\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = y_{r0},$ $\lambda_j, s_i^-, s_r^+ \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$

TABLE 2: Output-oriented CCR model.

(a)	(b)	(c)	(d)
<b>Maximize:</b> $\theta = u^T x_0$	<b>Minimize:</b> $\theta = u^T x_0$	<b>Maximize:</b> $\sum_{i=1}^p s_i^- + \sum_{r=1}^q s_r^+$	<b>Minimize:</b> $\theta - \varepsilon (\sum_{i=1}^p s_i^- + \sum_{r=1}^q s_r^+)$
<b>Subject to:</b> $v^T y_0 = 1$ $u^T x_j - v^T y_j \geq 0,$ $j = 1, 2, \dots, n$ $u, v \geq \varepsilon > 0$	<b>Subject to:</b> $\sum_{j=1}^n \lambda_j x_{ij} \leq x_{i0}$ $\sum_{j=1}^n \lambda_j y_{rj} \geq \theta y_{r0}$ $\lambda_j \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$	<b>Subject to:</b> $\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = x_{i0}$ $\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = \phi^* y_{r0},$ $\lambda_j, s_i^-, s_r^+ \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$	<b>Subject to:</b> $\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = x_{i0}$ $\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = \phi y_{r0},$ $\lambda_j, s_i^-, s_r^+ \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$

TABLE 3: Input-oriented BCC model.

(a)	(b)	(c)	(d)
<b>Maximize:</b> $\theta = v^T y_0 - v_0$	<b>Minimize:</b> $\theta = v^T y_0 - v_0$	<b>Maximize:</b> $\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+$	<b>Minimize:</b> $\theta - \varepsilon (\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+)$
<b>Subject to:</b> $u^T x_0 = 1$ $v^T y_j - u^T x_j \leq 0,$ $j = 1, 2, \dots, n$ $u, v \geq \varepsilon > 0$	<b>Subject to:</b> $\sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{i0}$ $\sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}$ $\sum_{j=1}^n \lambda_j = 1$ $\lambda_j \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$	<b>Subject to:</b> $\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = \theta^* x_{i0}$ $\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = y_{r0},$ $\sum_{j=1}^n \lambda_j = 1$ $\lambda_j, s_i^-, s_r^+ \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$	<b>Subject to:</b> $\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = \theta x_{i0}$ $\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = y_{r0},$ $\sum_{j=1}^n \lambda_j = 1$ $\lambda_j, s_i^-, s_r^+ \geq 0$ $j = 1, 2, \dots, n$ $i = 1, 2, \dots, p$ $r = 1, 2, \dots, q$

**2.4.1. Input-Oriented (BCC-I) Model.** The difference between BCC-I model and CCR-I model is presented in free variable  $v_0$  in equation (a) in Table 3, which is the dual variable (b) in Table 3 associated with the constraint  $\sum_{j=1}^n \lambda_j = 1$  that also does not appear in the CRR model. The performance of  $DM U_0$  is fully (100%) efficient in BCC if we cannot decrease inputs ( $s_i^- = 0$ ), increase outputs ( $s_r^+ = 0$ ), and set efficiency ratio  $\theta^* = 1$ . The BCC-I model is explained in Table 3.

**2.4.2. Output-Oriented (BCC-O) Model.** The difference between the BCC-O model and the CCR-O model is presented in free variable  $u_0$  in equation (a) in Table 4, which is

the dual variable (b) in Table 4 associated with the constraint  $\sum_{j=1}^n \lambda_j = 1$  that also does not appear in the CRR model. The BCC-O model is explained in Table 4.

**2.5. Tobit Model.** The Tobit model is a statistical model proposed by Tobin to describe the relationship between a non-negative dependent variable  $y_i$  and an independent variable  $x_i$  [28]. The benefit of the Tobit model is to draw the relationship between the relative efficiency scores of companies and some of the factors that may affect companies' efficiency. The model supposes that there is a latent (i.e. unobservable) variable  $y_i$ . This variable linearly depends on  $x_i$  via a parameter (vector)  $\beta$  which determines the

TABLE 4: Output-oriented BCC model.

(a)	(b)	(c)	(d)
<b>Maximize:</b>	<b>Minimize:</b>	<b>Maximize:</b>	<b>Minimize:</b>
$\theta = u^T x_0 - u_0$	$\theta = u^T x_0 - u_0$	$\sum_{i=1}^p s_i^- + \sum_{r=1}^q s_r^+$	$\theta - \varepsilon (\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+)$
<b>Subject to:</b>	<b>Subject to:</b>	<b>Subject to:</b>	<b>Subject to:</b>
$v^T y_0 = 1$	$\sum_{j=1}^n \lambda_j x_{ij} \leq x_{i0}$	$\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = x_{i0}$	$\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = x_{i0}$
$u^T x_j - v^T y_j \geq 0,$	$\sum_{j=1}^n \lambda_r y_{rj} \geq \theta y_{r0}$	$\sum_{y=1}^n y_{rj} \lambda_j - s_r^+ = \phi^* y_{r0},$	$\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = \phi y_{r0},$
$u, v \geq \varepsilon > 0$	$\sum_{j=1}^n \lambda_j = 1$	$\sum_{j=1}^n \lambda_j = 1$	$\sum_{j=1}^n \lambda_j = 1$
$j = 1, 2, \dots, n$	$\lambda_j \geq 0$	$\lambda_j, s_i^-, s_r^+ \geq 0$	$\lambda_j, s_i^-, s_r^+ \geq 0$
	$j = 1, 2, \dots, n$	$j = 1, 2, \dots, n$	$j = 1, 2, \dots, n$
	$i = 1, 2, \dots, p$	$i = 1, 2, \dots, p$	$i = 1, 2, \dots, p$
	$r = 1, 2, \dots, q$	$r = 1, 2, \dots, q$	$r = 1, 2, \dots, q$

relationship between the independent variable (or vector)  $x_i$  and the latent variable  $y_i$  (just as in a linear model). In addition, there is a normally distributed error term  $u_i$  to capture random influences on this relationship. When the dependent variable  $y_i$  is limited to the interval  $[0, 1]$ , it may be described by the following general model [29, 30]:  $Y_i^* = \beta x_i + \varepsilon_i^*$ , where the  $\varepsilon_i^* \sim N(0, \sigma^2)$  and  $i = 1, \dots, n$ . However, we measure  $Y_i = Y_i^*$  only if  $Y_i^* > L$  and  $Y_i^* < U$  for some cutpoints  $L$  and  $U$ . Otherwise we let  $Y_i = L$  or  $Y_i = U$ , whatever is closer. The Tobit model is thus a multiple linear regression but with censored responses, if it is below or above certain cut points.

### 3. Results and Discussion

The source of research data for this study is from financial statements of corporations, listed on the Amman Stock Exchange (ASE) in Jordan. This article studies 6 out of 15 corporations that reflect around 90% of the total market capitalization under the mining and extracting sector from 2000 to 2020. The selected corporations are namely; Arab Aluminum Industry (AALU), National Steel Industry (NAST), Jordan Phosphate Mines (JOPH), The Arab Potash (APOT), Jordan Steel (JOST), and National Aluminum Industrial (NATA). The market capitalization and the operating revenue are used to evaluate companies' performance. The performance variables are used as output in Data Envelopment Analysis models [12, 19]. In addition, the current assets, non-current assets, operating expenses, and general administrative expenses are used as input in DEA models. In order to examine the factors that affect the efficiency performance of the mining and extracting sector in Jordan, the Tobit model has been used. This section will discuss the results of the DEA models and Tobit model. Package "deaR" in R-program is used in the analysis of BCC models [13, 20, 31].

Table 5 shows the descriptive statistics of input/output variables. The mean and standard deviation of current assets are 116096738 and 170279405, respectively. The skewness and kurtosis are 1.413 and 0.681, respectively. In addition, the mean and standard deviation of non-current assets are 154095030 and 238863286, respectively. The skewness and kurtosis are 1.535 and 1.025, respectively. Furthermore, the

mean and standard deviation of operating expenses are 124276270 and 174729427, respectively. The skewness and kurtosis are 1.478 and 0.967, respectively. Moreover, the mean and standard deviation of general administration expenses are 14477754 and 24463219, respectively. The skewness and kurtosis are 2.193 and 5.150, respectively. However, the mean and standard deviation of operating revenue are 171383507 and 245544797, respectively. The skewness and kurtosis are 1.376 and 0.481, respectively. In addition, the mean and standard deviation of market capitalization are 396254882 and 820977697, respectively. The skewness and kurtosis are 2.646 and 6.787, respectively.

*3.1. Comparative Analysis of CCR and BCC Models.* The DEA models' assumptions have been applied before running CCR and BCC models. First, the input/output variable selected is greater than or equal to zero. Second, there are significant positive correlation between inputs and outputs greater than 50%. Third, homogeneity DMUs refer to identical used input/output variables for DMUs. Four, the sample size selected (sample = 126) is greater than or equal to the multiply of input (4 variables) with output (2 variables). Five, also the sample size selected (sample = 126) is greater than or equal to the multiplied by (3 \* input \* output). Finally, the full efficiency rate (100%) for DMUs is not greater than or equal to third sample size ((1/3) \* 126 = 42). The CCR and BCC models is applied after the above conditions.

The comparison between CCR and BCC models is explained in Table 6. We can observe that the performance of DMU is better in BCC models compared to CCR models for several reasons: (i) we find that mining and extracting corporations could improve their performance from a minimum of 0.47 in CCR-I to a minimum of 0.53 in BCC-I. Furthermore, the corporations could improve their performance from a maximum of 2.12 in CCR-O to a maximum of 1.97 in BCC-O. The output-oriented DEA models give the DMUs score values from 1 to infinity. In other words, the DMUs lay on the efficiency frontier if scores go to 1, otherwise it is inefficient. (ii) The number of efficient DMUs in BCC models is more than in CCR models. (iii) We find that the BCC models are better than CCR models because they

TABLE 5: Descriptive statistic for input and output variables.

Variables	N	Mean	Std. deviation	Skewness		Kurtosis	
				Statistic	Std. error	Statistic	Std. error
Current assets	126	116096738	170279405	1.413	0.216	0.681	0.428
Non-current assets	126	154095030	238863286	1.535	0.216	1.025	0.428
Operating expenses	126	124276270	174729427	1.478	0.216	0.967	0.428
General administration expenses	126	14477754	24463219	2.193	0.216	5.150	0.428
Operating revenue	126	171383507	245544797	1.376	0.216	0.481	0.428
Market capitalization	126	396254882	820977697	2.646	0.216	6.787	0.428

TABLE 6: Comparison between CCR and BCC models.

Models	No. of DMU	Efficient	Non-efficient	Average score	Max	Min	S.D
CCR-I	126	13	113	0.7865	1	0.4710	0.1279
CCR-O	126	13	113	1.3071	2.1231	1	0.2270
BCC-I	126	23	103	0.8428	1	0.5297	0.1229
BCC-O	126	23	103	1.2274	1.9784	1	0.2040

TABLE 7: The average efficiency rate and slacks for BCC-I during 2000–2020.

Models	Corporations	Efficiency rate	Rank	Current assets ( $s^-$ )	Non-current assets ( $s^-$ )	Operating expenses ( $s^-$ )	General adm. expenses ( $s^-$ )
BCC-I	AALU	0.7185	6	0.0000	4305.9293	0.0000	13382621.4783
	NAST	0.9590	1	68809.9091	2282.5163	0.0000	1190421.0986
	JOPH	0.8055	5	7353350.0924	12033450.8901	0.0000	430138786.3599
	APOT	0.8218	4	0.0000	12877691.8722	215931.5630	119493303.9384
	JOST	0.8808	2	0.0000	0.0000	0.0000	20666331.5067
	NATA	0.8674	3	0.0000	0.0000	0.0000	4981090.9670

use the VRS rather than CRS. This result is consistent with [3, 11]. For this reason, we will select BCC-I and BCC-O in our study.

**3.2. The Input-Oriented DEA Model.** The average efficiency and slacks for input-oriented in BCC-I models from 2000 to 2020 are shown in Table 7. The corporations should decrease the input variables to approximate the performance efficiency to 100%. For instance, NAST should reduce, on average, current assets to 68809.91 JD, Non-current assets to 2282.52 JD, Operating expenses to 0.00 JD, and general administrative expenses to 1190421.10 JD if we assume BCC. In addition, NAST is the best efficiency performance on average from 2000 to 2020 and AALU is the lowest efficiency performance on average during the same period based on rank in BCC-I. Indeed, the input-oriented DEA model considered a good efficiency performance if the efficiency rate is close to one.

Figure 1 shows the dynamic BCC-I efficiency performance of each corporation over the years from 2000 to 2020. The AALU has a full efficiency performance of 100% in all years except the following cases; the increase in general administration expenses is reduced efficiency performance in 2004, and the increase in current assets reduced efficiency performance in 2007. The increase in non-current assets and operating expenses reduced efficiency performance in 2008, the increase in non-current

assets reduced efficiency performance in 2010, and the increase in current assets and operating expenses reduced efficiency performance in 2012. Moreover, the effect of economic crises from 2007 to 2010 reduced the efficiency performance. The NAST also has full efficiency performance of 100% in all years except the following cases; the increase in non-current assets and general administration expenses reduced efficiency performance in (2002, 2003, 2006–2007), the increase in non-current assets is reduced efficiency performance in 2009, the increase in current assets and operating expenses are reduced efficiency performance in 2010 and 2012. The increase in current assets and non-current assets reduced efficiency performance in 2017. The JOPH also has full efficiency performance of 100% in all years except the following cases; the increase in operating expenses is reduced efficiency performance in (2000, 2010, 2012 : 2014, and 2016 : 2020), and the increase in general administration expenses is reduced efficiency performance in (2012 : 2014, 2015, and 2016). The APOT also has full efficiency performance of 100% in all years except the following cases; the increase in current assets is reduced efficiency performance in 2002, the increase in current assets and general administration expenses is reduced efficiency performance in 2009, the increase in non-current assets, operating expenses, and general administrative expenses are reduced efficiency performance in 2013 to 2020. The JOST has also a full efficiency performance of 100% in all years except the

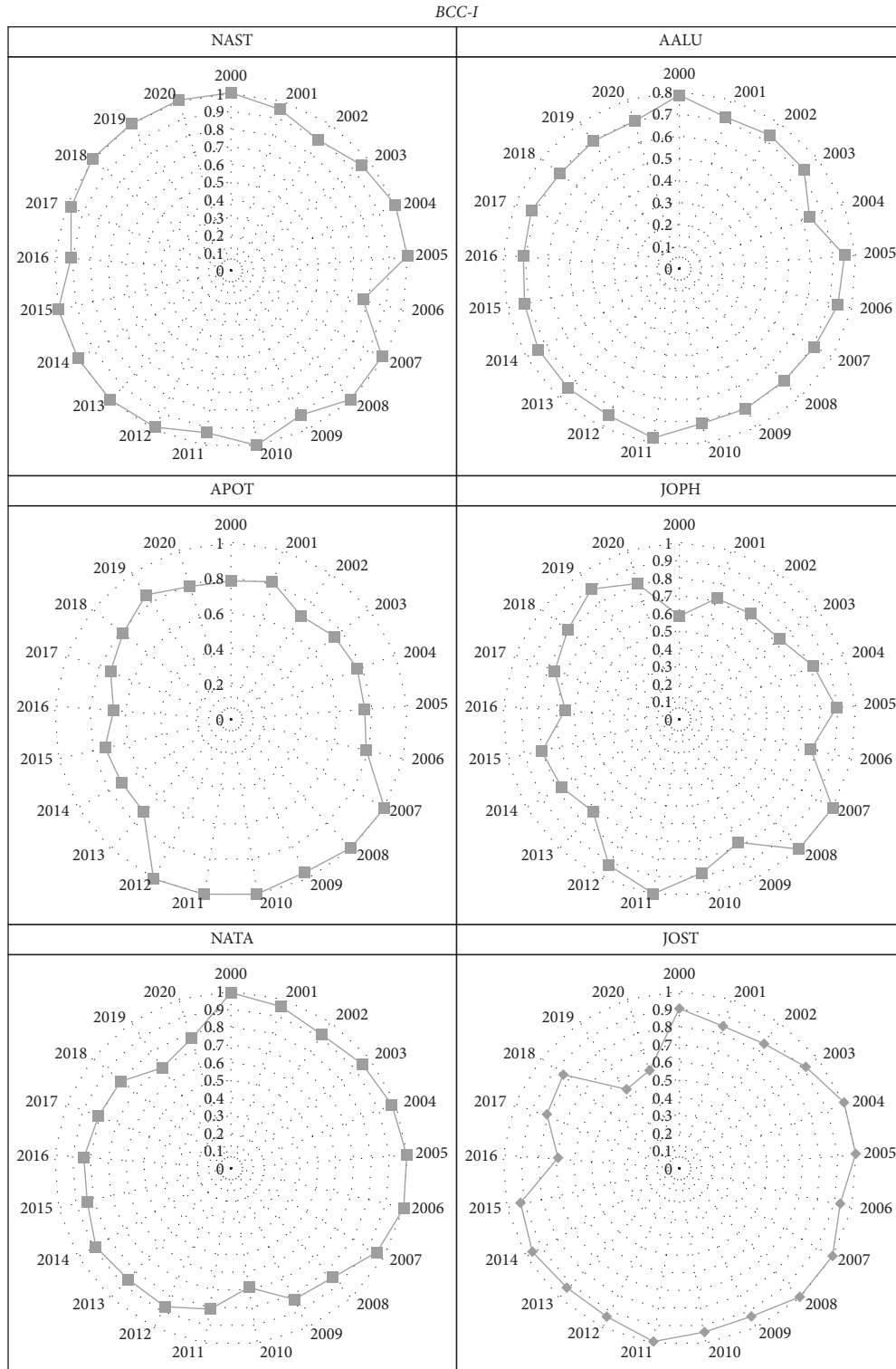


FIGURE 1: The efficiency rate for each company of BCC-I model during 2000–2020.

following cases; the increase in current assets reduced efficiency performance in (2002, 2010, 2016, 2017, and 2019), the increase in non-current assets is reduced efficiency performance in (2001, 2002, 2010, 2012 : 2013, and 2015 : 2019), the increase in general administration expenses is reduced efficiency performance in (2001, 2002,

2006, 2016, and 2019). The NATA also has full efficiency performance of 100% in all years except the following cases; the increase in current assets is reduced efficiency performance in (2008, 2013, 2014, and 2017). The increase in non-current assets is reduced efficiency performance in 2002, the increase in operating expenses is reduced



TABLE 8: The average slacks for output-oriented in BCC models during 2000–2020.

Models	Corporations	Efficiency rate	Rank	Operating revenue ( $s^+$ )	Market capitalization ( $s^+$ )
BCC-O	AALU	1.44024	6	0.00000	21885185.75731
	NAST	1.07258	1	0.00000	1765157.58978
	JOPH	1.24070	5	0.00000	541679987.51728
	APOT	1.22811	4	433577.65242	165482653.94463
	JOST	1.18573	2	0.00000	27123503.81740
	NATA	1.20444	3	0.00000	8506632.47749

efficiency performance in 2008, the increase in general administration expenses is reduced efficiency performance in (2015, 2017, and 2018).

**3.3. The Output-Oriented DEA Model.** The average efficiency and slacks for output-oriented in BCC models from 2000 to 2020 are shown in Table 8. The corporations should increase the following outputs to get to the efficiency performance of 100%. For instance, NAST should increase, on average, operating revenue to 0.00 JD, and market capitalization to 1765157.59 JD in BCC. In addition, the table shows that NAST is the best efficiency performance on average from 2000 to 2020 and AALU is the lowest efficiency performance on average during the same period based on rank in BCC-O. Indeed, the output-oriented in DEA models is considered a good efficiency performance if the efficiency rate is close to one.

Figure 2 shows the dynamic BCC-O efficiency performance of each corporation over the years from 2000 to 2020. The AALU has full efficiency performance at one in all years except the following cases; the over increase in market capitalization makes efficiency performance become more 100% in (2004, 2007 : 2010, and 2012). The NAST has full efficiency performance also 100% in all years except the following cases; the over increase in operating revenue and market capitalization together make efficiency performance become more 100% in (2002 : 2003, 2007, 2010, and 2012), the over increase in only market capitalization makes efficiency performance become more 100% in (2006, 2009, and 2017). The JOPH has full efficiency performance also 100% in all years except the following cases; the over increase in operating revenue and market capitalization together make efficiency performance become more 100% in (2000, 2010, and 2012 : 2017). The APOT has full efficiency performance also 100% in all years except the following cases; the over increase in operating revenue and market capitalization together make efficiency performance become more 100% in (2000 : 2006 and 2013 : 2020). The JOST has full efficiency performance also 100% in all years except the following cases; the over increase in operating revenue and market capitalization together make efficiency performance become more 100% in (2001 : 2002, 2006, 2010, and 2019). The over increase in market capitalization only make efficiency performance become more 100% in (2015 and 2016 : 2018). The NATA has full efficiency performance also 100% in all years except the following cases; the over increase in operating revenue and market capitalization together make efficiency performance become more 100% in (2008, 2014, and 2018).

The over increase in market capitalization only make efficiency performance become more 100% in 2013, 2015, and 2017.

**3.4. Tobit Model.** The Tobit model proposed by James Tobin in 1958 reference to describe the relationship between a non-negative dependent variable (efficient ratios) and an independent variable (financial ratios). In this section, we will run the Tobit model, using the VGLM function of the VGAM library in the R-package to find the financial ratios that affect the efficient performance in DEA models. The upper cutpoints in input-oriented equals ( $L = 1$ ) and the upper cutpoints in output-oriented equals ( $U = 2.5$ ) in our analysis.

Table 9 shows the efficient performance of CCR-I as a dependent variable. The return on assets (ROA) and Growth gross domestic product (GDP) are independent variables. The table shows that there is a significant positive relationship between ROA and efficient rate at  $p$  value less than 1%. In other words, The ROA value of 0.7269 affects the efficiency rate for corporations. In addition, there is significant positive relationship between GDP growth and the efficient ratio at  $p$  value less than 1%. Moreover, the GDP growth value of 1.2916 affects the efficient rate for corporations under CCR-I. Furthermore, the GDP growth and ROA explain about 26.99% (R-square is 0.2699) of efficiency performance under the CCR-I model. The intercept 1 is constant for the model. Moreover, intercept 2 is an ancillary statistic if we exponentiate this value as  $e^{-2.13411} = 0.1183$ , we get a statistic that is analogous to the square root of the residual variance in OLS regression. The intercept 2 is described as  $\ln(\sigma)$ . However, the result in Table 9 shows the efficient performance of BCC-I as dependent variable. The return on assets (ROA) and Growth gross domestic product (GDP) are independent variables. The table shows that there is a significant positive relationship between ROA and efficiency performance at  $p$  value less than 1%. In other words, the ROA value 0.6003 affects the efficiency performance rate for corporations. In addition, there is a significant positive relationship between GDP growth and efficient performance at  $p$  value less than 5%. Moreover, the GDP growth value of 1.0851 affects the efficient rate for corporations under BCC-I. Furthermore, the GDP growth and ROA explain about 14.93% (R-square is 0.1493) of efficiency performance under the BCC-I model. The intercept 1 is constant for the model. Moreover, the intercept 2 is an ancillary statistic if we exponentiate this value as  $e^{-2.02410} = 0.1321$ , we get a statistic that is analogous to the square root of the residual

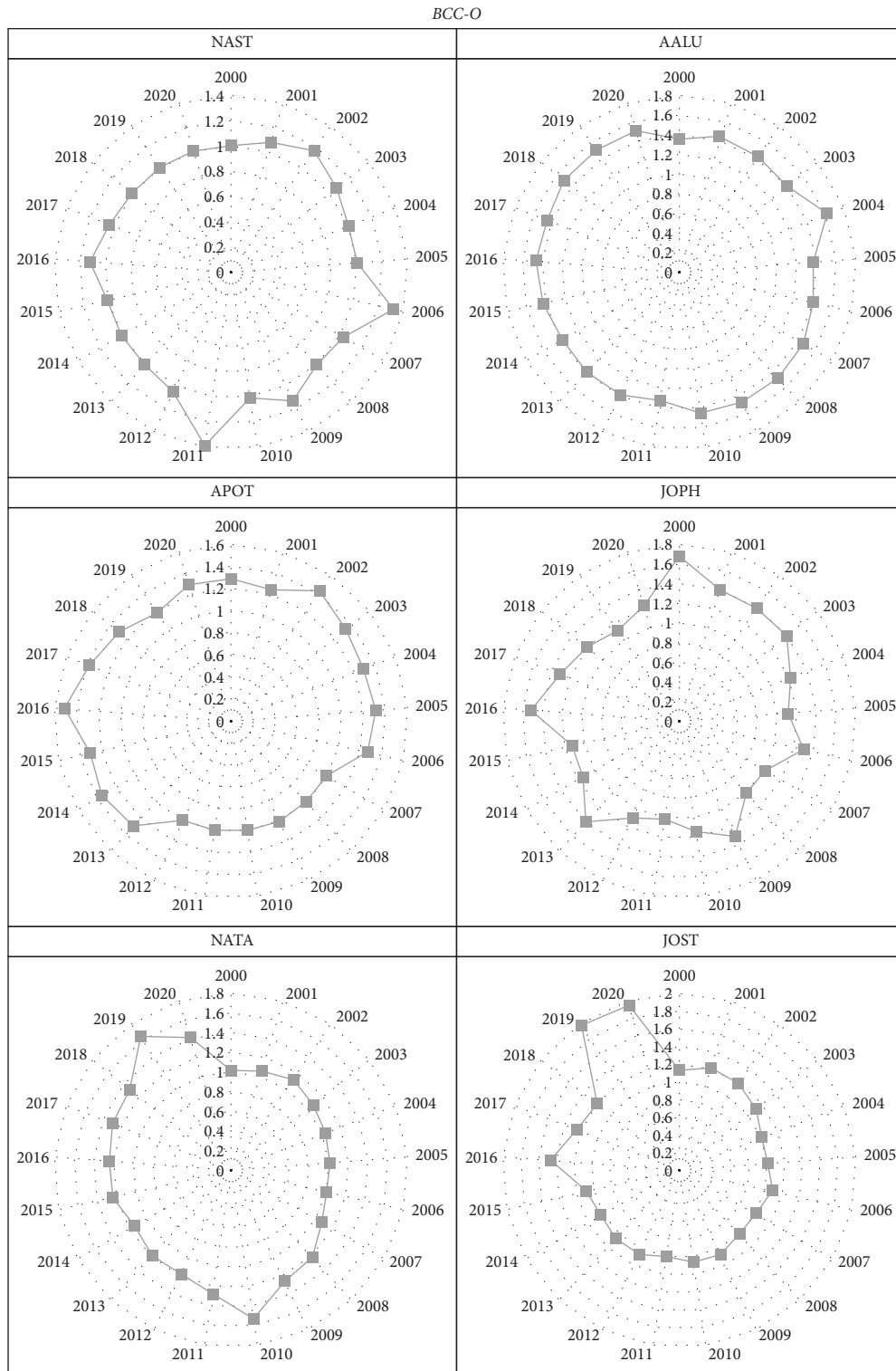


FIGURE 2: The efficiency rate for each company of BCC-O model during 2000–2020.

variance in OLS regression. The intercept 2 is described as  $\ln(\sigma)$ . Indeed, the GDP growth and ROA explain affect on efficiency performance under BCC-I less than CCR-I.

Table 9 also highlights the efficient performance of CCR-O as a dependent variable. The return on assets (ROA) and Growth gross domestic product (GDP) are independent

variables. The table shows a significant negative relationship between ROA and efficient ratio at  $p$  value of less than 1%. In other words, the ROA value of  $-1.049$  affects the efficient performance rate for corporations. In addition, there is significant negative relationship between GDP growth and efficient performance at  $p$  value of less than 1%. Moreover,

TABLE 9: Tobit model.

		Estimate	Std. error	Z-value	Pr ( $> z $ )	Criteria	Statistic
BCC-I	(Intercept): 1	0.78331	0.02253	34.763	$<2e-16^{***}$	R-squared	0.149387
	(Intercept): 2	-2.02410	0.07129	-28.392	$<2e-16^{***}$	Log-likelihood	40.171
	GDP growth	1.08513	0.45445	2.388	0.0169**	Number of iterations	7
	ROA	0.60033	0.14238	4.216	$2.48e-05^{***}$	Degree of freedom	248
BCC-O	(Intercept): 1	1.32919	0.03069	43.310	$<2e-16^{***}$	R-squared	0.1822066
	(Intercept): 2	-1.69405	0.06299	-26.892	$<2e-16^{***}$	Log-likelihood	34.6641
	GDP growth	-1.51748	0.61798	-2.456	0.0141**	Number of iterations	5
	ROA	-0.78873	0.18354	-4.297	$1.73e-05^{***}$	Degree of freedom	248

Signif. codes: 0.01 “\*\*\*” 0.05 “\*\*” 0.1 “\*”.

the GDP growth value of  $-2.2718$  affects the efficient rate for corporations under CCR-O. Furthermore, the GDP growth and ROA explain about 27.90% (R-square is 0.2790) of efficiency performance under the CCR-O model. The intercept 1 is constant for the model. Moreover, intercept 2 is an ancillary statistic if we exponentiate this value as  $e^{-1.65042} = 0.1920$ , we get a statistic that is analogous to the square root of the residual variance in OLS regression. The intercept 2 is described as  $\ln(\sigma)$ . However, the result in the table below shows the efficient performance of BCC-O as dependent variable. The return on assets (ROA) and Growth gross domestic product (GDP) are independent variables. The table shows that there is a significant negative relationship between ROA and efficiency performance at  $p$  value less than 1%. In other words, the ROA value  $-0.7887$  affects the efficiency performance rate for corporations. In addition, there is a significant negative relationship between GDP growth and efficient performance at  $p$  value of less than 1%. Moreover, the GDP growth value  $-1.5175$  affects the efficient rate for corporations under BCC-O. Furthermore, the GDP growth and ROA explain about 18.22% (R-square is 0.1822) from efficiency performance under the BCC-O model. The intercept 1 is constant for the model. Moreover, the intercept 2 is an ancillary statistic that if we exponentiate this value as  $e^{-1.69405} = 0.1838$ , we get a statistic that is analogous to the square root of the residual variance in OLS regression. The intercept 2 is described as  $\ln(\sigma)$ . Indeed, the GDP growth and ROA explain the affect on efficiency performance under BCC-O less than CCR-O.

#### 4. Conclusion

In this study, we have proposed successfully an estimation of performance efficiency for mining and extracting corporations in Jordan. This paper selected those mining and extracting corporations that reflect 90% of the total market capitalization in the Amman Stock Exchange (ASE) from 2000 to 2020. The DEA models (CCR (input/output) and BCC (input/output)) are used to analyse the performance efficiency based on the average efficiency ratio of the sector. In addition, the role of internal and external factors on performance efficiency in mining and extracting sector is determined based on the Tobit model. The results show that the performance of DMU is better in BCC models compared to CCR models for several reasons; the sector could improve its performance from a minimum of 0.47 in CCR-I to a

minimum of 0.53 in BCC-I, the sector could improve its performance from a maximum of 2.12 in CCR-O to a maximum of 1.97. In BCC-O, the number of efficient *DM Us* in BCC models is more than in CCR models and the BCC models are better than CCR models because they use VRS rather than CRS. This result is consistent with References [3, 4]. However, the average of NAST’s performance efficiency is higher than that of other companies based on BCC (Input/Output). Moreover, the performance efficiency ratio variety is based on company level from 2000 to 2020. Finally, GDP growth and ROA have affected BCC’s efficiency performance rate based on the Tobit model. In future work, we will use another dynamic DEA models and compare with our study. Managerial implications for enhancing decision-making are expected to contribute to management policies. This study asks mining and extracting companies to take the indicator results to improve their efficiency performance.

#### Data Availability

The datasets analyzed during the current study are available in the Amman Stock Exchange (ASE) repository, <https://www.ase.com.jo/>.

#### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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