International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2021, 11(1), 135-139.

Assessing the Relative Efficiency for Listed Manufacturing Firms in Jordan Using Data Envelopment Analysis

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Received: 29 October 2020 **Accepted:** 03 January 2021 **DOI:** https://doi.org/10.32479/ijefi.10919

ABSTRACT

The purpose of this study is to measure and compare the efficiencies for 35 manufacturing firms listed in Amman Stock exchange (ASE) in Jordan over the period 2009-2017. A panel data was collected for the firms over the 9 years, the data was collected from the annual reports of the firms. The data envelopment analysis (DEA) was used to measure an average efficiency score for each firm, the DEA was also used to find a panel data for efficiency scores, since the data was available for a short period of 9 years the bootstrap technique was used to estimate a confidence interval for the efficiency score for each firm. The linear transformation form of Cobb- Douglas production function with two inputs (capital and labor) and one output (production) was used in DEA. The study revealed that among the 35 firms only 4 firms were efficient, and the rank for the firms' efficiency were also obtained.

Keywords: Data Envelopment Analysis, Efficiency, Manufacturing Firm, Bootstrap Technique, Cobb-Douglas
JEL Classifications: D24, C44

1. INTRODUCTION

Methods used in efficiency measurement can be grouped under three categories: ratio analysis parametric and non parametric. These methods have both advantages and drawbacks when compared with each other (Duzakın and Duzakın, 2007). Parametric and non-parametric procedures differ primarily in the underlying assumptions they use when estimating the efficient frontier. Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are the most employed parametric and non-parametric methods in the literature respectively (Silva et al., 2017). DEA is an optimization method that uses linear programming for assessing the efficiency and productivity of decision making units (DMUs) in term of proportional change in inputs or outputs (Majumdar and Asgari, 2017). Data envelopment analysis method was first introduced by (Charnes et al., 1978), and for this reason it is known as the CCR model, the CCR model assumes constant return of scale production function, then (Banker et al., 1984) modified this model and assumes the variable return to scale (VRS) efficiency measurement model, which is also known as the BCC model according to the names of the authors. The CCR and BCC models can be divided into two terms; the first is the input oriented model; the second is the output oriented model. The input orientation seeks to minimize the usage of inputs given a fixed level of output while the output orientation maximizes the level of output for a given level of inputs (Memon and Tahir, 2012). In this study the constant return to scale, input oriented model was used using Stata software as described by (Ji and Lee, 2010).

According to (Odeck, 2000) the main advantages of DEA are that it allows the simultaneous analysis of multiple outputs and multiple inputs, it doesn't require an explicit a prior determination of a production function, efficiency is measured relative to the highest observed performance rather than against some average, and it doesn't require information on prices. The purpose of DEA is to divide decision making units (DMUs) into two groups: efficient DMUs and inefficient DMUs, based on a given data of multiple inputs and multiple outputs, when the production function is unknown. It also enables an organization to measure the relative efficiency of Decision making unit.

2. LITERATURE REVIEW

DEA technique has been applied to measure productivity/efficiency in different fields includes:
Manufacturing firms, pharmaceutical firms, hospitals, banks, telecommunication firms, petroleum companies, and transportation. The following paragraph includes some examples: (Sengupta, 1998) tested an allocative efficiency model based on data envelopment analysis to evaluate the operational performance of international airlines for a period of 3 years. (Yang and Chang, 2009) used data envelopment analysis (DEA) under constant and variable returns-to-scale to measure Taiwan integrated telecommunication firms' efficiencies over the period 2001-2005, the study used DEA window analysis to increase the number of decision making units. (Memon and Tahir, 2012) used data envelopment analysis to evaluate the efficiency of 49 manufacturing companies in Pakistan over the period of 2008-2010. The study used three inputs variables and two output variables. The authors used input approach of DEA model. They also studied the relationship between firm size and efficiency. In the work of (Zhiyong et al., 2017) the cross-sectional DEA models were extended to time - varying malmquist DEA, results based on a sample of 742 Chinese listed companies observed over 10 years suggested that malmquist DEA offers insights into the competitive position of a company in addition to accurate financial distress predictions based on the DEA efficiency measures. (Majumdar and Asgari, 2017) applied DEA theory to analyze the relative efficiency of 27 listed corporations in the United Arab Emirates, and studied the impact of the financial crisis and the recovery thereafter. They used malmquist productivity Index to study the decomposition of the productivity change for the period (2007-2014). They found that the most efficient industries during the post-crisis period were food and beverages, telecommunication and pharmaceuticals. on the other hand the sectors that were adversely affected by the crisis were services, real estate, construction and cements technical efficiency change and technological change by using the non-parametric malmquist productivity ındex (MPI) over the period from 2007 to 2014.

Mahajan et al. (2018) measured the efficiency of Indian pharmaceutical firms and its determinants in the pre- and post-product patent regime. They studied the factors that affect the efficiency in the industry. (Lu et al., 2020) used A three-stage data envelopment analysis (DEA) model to evaluate the total factor productivity of 50 listed Chinese petroleum companies from 2009 to 2018. The study showed that the average annual growth rate of total factor productivity of these companies as 9.05 %, and its efficiency change index and scale efficiency change index were the main driving force for the growth of total factor productivity.

Adams et al. 2020 used data envelopment analysis to measure the efficiency of 110 small-scale vegetable farmers in northern Ghana. The DEA was also used by (Babu and Kulshreshtha, 2014) to measure the efficiency of 34 Indian microfinance institutions. (Charoenrat and Harvie, 2017) applied DEA to measure the technical efficiency of Thai manufacturing small and medium enterprises and examine firm-specific factors contributing to it by using firm-level industrial censuses data in 1997 and 2007.

On the other hand and using a macro level data (Madaeen and Adeinat, 2018) compared between efficiencies of health care sector among 36 middle income countries and ranked their efficiencies using both constant return to scale and variable return to scale versions of DEA.

The nonparametric technique (DEA) was also used in comparison with the parametric (SFA) to measure the efficiency of manufacturing sector (firms), the following are two examples: (Dın et al., 2007) applied both the SFA and DEA to measure the efficiency of the large scale manufacturing sector of Pakistan, they used the data for 101 industries for two periods (1995/1996) and (2000/2001), the results of the two approaches were consistent. On the other hand (Önder et al., 2003) compared between data envelopment analysis and stochastic frontier analysis method in estimating technical efficiency for the manufacturing sector in Turkey. They used a panel data over the period (1990-1998). The study revealed differences in ranking between the two methods.

3. METHODOLOGY AND DATA

In this study the CCR model was used to measure the efficiency for 35 manufacturing firms listed in ASE, a panel data was used for the firms over 9 years (from 2009 to 2017).

Assume that a set of observed decision making units (*DMUs*) is DMU_j, where j =1,2,…n (in this study the decision making unit is firm, and n is the number of firms), and given that:
X: İnput matrix for all DMUs
Y: Output matrix for all DMUs
x_j: İnput vector for DMUj
y_j: output vector for DMUj

Using DEA and in case of cross sectional data the optimization model, the CCR model, that measure the efficiency of a decision making unit j ($DMUj$) is formulated as

$$min_{\theta,\lambda}\ \theta$$

Subject to:

$$\theta x_j - X\lambda \geq 0$$

$$Y\lambda \geq y_j$$

$$\lambda \geq 0$$

Where θ is the input oriented technical efficiency score for firm j

This is an input oriented CRS efficiency model, according to (Ji and Lee, 2010) the goal of the model is to minimize the virtual input relative to a given virtual output, subject to the constraint that no DMU can operate beyond the production possibility set and the constraint relating to nonnegative weight.

In case of a panel data, the DEA can be applied by: (A) averaging the inputs and outputs over the years for each decision making unit (DMU) and applied the DEA on averages inputs and outputs as described in model 1 above or (B) the DEA can be applied for each point of time to get a panel date for efficiency scores and then averaging the efficiency scores for each DMU. If the panel data for efficiency scores have a long period of time the central limit theorem can be used to estimate the efficiency confidence interval of for each DMU. In this study and since the data was available for a short period of time (9 years) which is less than 30 and the central limit theorem can't be applied, we can use the bootstrap methodology to calculate the efficiency confidence interval for each DMU.

Assume that θ_{it} is the efficiency for firm *i* in a period *t* resulted from scenario B above. In order to estimate the confidence intervals for efficiency scores we applied the bootstrap methodology of (Atkinson and Wilson, 1995) which is described in the following steps.

1. The efficiency scores were averaged over the years for each firm. The sample firm mean over the years is $\bar{\theta}_{i.}$ which is defined by $\bar{\theta}_{i.} = \frac{\sum_{t=1}^{T}\theta_{it}}{T}$.
2. Calculate $\tilde{\theta}_{it} = \theta_{it}\sqrt{\frac{T}{T-1}} + \bar{\theta}_{i.}\left(1-\sqrt{\frac{T}{T-1}}\right)$,
3. Independently draw T times from the set $\left\{\tilde{y}_{it}\right\}_{t=1}^{T}$ with replacement to obtain $\left\{\theta_{it}^{*}\right\}_{t=1}^{T}$.
4. Calculate $\bar{\theta}_{i.}^{*} = \frac{\sum_{t=1}^{T}\theta_{it}^{*}}{T}$
5. Repeat the last two steps (3 and 4) J times to obtain $\left\{\bar{\theta}_{i.}^{*}(j)\right\}_{t=1}^{T}$.

   Note that J is approximately large in magnitude. (in this study, we choose J = 1000).

This study uses the panel data for 35 manufacturing firms listed in Amman Stock Exchange (ASE) Market over the period 2009-2017. The sample includes firms from different manufacturing sectors, namely; pharmaceutical and medical industries, chemical industries, food and beverages, paper and cardboard, printing and packaging, tobacco and cigarette, textile leather and clothing, engineering and construction.

The data was collected from the annual reports of these firms. Cobb-Douglas production function with two inputs (capital and labor) and one output (production) was used. In order to use the DEA the linear transformation function of Cobb-Douglas was used. The noncurrent assets were used as a proxy for capital input, the number of labors was used as a labor input. And the sales were used as a proxy for output. The same variables were used by (Al-Durgham and Adeinat, 2020).

4. RESULTS

The CCR model of DEA was applied for a set of panel data to measure the efficiency of 35 firms over 9 years, at first and for each firm the values for each of the two inputs (noncurrent asset, labour) was averaged and the values for the output (sales) was averaged over the 9 years, then the DEA was applied on average values. Table 1 shows the results of the DEA technique, from the results it is clear that among the 35 firms only four firms were efficient over the period of the study (these firms have a theta value of 1).

The values of efficiency score (theta) was used to rank the firms according to their efficiencies, in other words as the values of theta increases the efficiency of the firm increase.

In order to calculate the confidence intervals for efficiency scores using the bootstrapping technique it required to have a panel data for efficiency scores, so we applied the DEA for each year separately, and the results are in Table 2 (the same results were obtained when we applied the CCR model, the constant return to scale model, for the panel data). It is clear that the result in Table 2 consists with the results in Table 1 above. The same firms that were efficient using averaging technique above (Table 1), the same firms are efficient using the cross sectional data in each year.

After applying the bootstrapping technique a confidence interval for efficiency score of each firm is shown in Table 3.

The same results are shown in Figure 1 in order to compare between the efficiency confidence intervals over the firms.

Table 1: Efficiency score for average inputs average output

Firm ID	Firm	Rank	Theta
1	DADI	25	0.849755
2	PHIL	9	0.899516
3	HPIC	23	0.857092
4	JPHM	33	0.831873
5	ICAG	17	0.875172
6	JOIC	21	0.864769
7	NATC	27	0.847056
8	JOIR	6	0.922963
9	MBED	11	0.893561
10	IPCH	8	0.907026
11	JPPC	35	0.815572
12	JODA	13	0.884969
13	GENI	26	0.847069
14	UMIC	1	1
15	NATP	22	0.858652
16	AIFF	1	1
17	NDAR	14	0.877144
18	JVOI	5	0.932449
19	EKPC	10	0.895838
20	EICO	1	1
21	UTOB	32	0.838393
22	WIRE	19	0.866852
23	AEIN	18	0.875075
24	UCIC	24	0.855414
25	JOWN	1	1
26	ELZA	20	0.864779
27	ARWU	29	0.844249
28	AALU	31	0.841732
29	NATA	15	0.876957
30	NCCO	12	0.887456
31	JOPI	7	0.912790
32	WOOD	28	0.845050
33	ASPMM	16	0.876839
34	ASAS	34	0.817155
35	RMCC	30	0.843769

Table 2: Efficiency score for panel data

Firm	2009	2010	2011	2012	2013	2014	2015	2016	2017
DADI	0.859605	0.883125	0.856172	0.863652	0.837067	0.848593	0.850468	0.812945	0.802779
PHIL	0.876728	0.860534	0.851947	0.829695	0.912596	0.938109	0.904379	0.867005	0.887543
HPIC	0.837517	0.84437	0.849842	0.864617	0.869946	0.867752	0.84694	0.832888	0.848513
JPHM	0.836802	0.83524	0.833322	0.851292	0.826618	0.831215	0.803442	0.799154	0.829834
ICAG	0.806323	0.918963	0.932473	0.900156	0.88093	0.867427	0.845642	0.814639	0.830522
JOIC	0.892882	0.888481	0.849287	0.856597	0.860676	0.858493	0.86003	0.847365	0.863373
NATC	0.857937	0.856347	0.858196	0.877004	0.870798	0.839932	0.825033	0.789749	0.825926
JOIR	0.956452	0.999428	1	0.99742	0.956325	0.780554	0.823451	0.762732	0.807396
MBED	0.892996	0.897956	0.884684	0.894753	0.90264	0.900296	0.880574	0.873854	0.878001
IPCH	0.856444	0.845786	0.834564	0.84319	0.977077	0.966985	0.798816	0.795404	0.835861
JPPC	0.801039	0.808556	0.815976	0.824722	0.819665	0.819902	0.816021	0.786315	0.791297
JODA	0.882411	0.887892	0.879486	0.892673	0.897327	0.888891	0.889261	0.852232	0.860659
GENI	0.851902	0.862474	0.857505	0.856326	0.838446	0.838564	0.821873	0.810471	0.838085
UMIC	1	1	1	1	1	1	1	0.991168	0.967252
NATP	0.845929	0.869021	0.853944	0.875144	0.860726	0.861476	0.866027	0.823856	0.831435
AIFF	1	1	1	1	1	1	1	1	1
NDAR	0.929756	0.921313	0.891692	0.893153	0.887081	0.810564	0.904991	0.894098	0.897837
JVOI	0.958164	0.926264	0.931177	0.935087	0.932432	0.933511	0.913371	0.903345	0.903108
EKPC	0.870056	0.893001	0.893213	0.89172	0.900374	0.900974	0.886668	0.87601	0.889997
EICO	1	1	1	1	1	1	1	1	1
UTOB	0.859174	0.865787	0.847701	0.858858	0.842742	0.828505	0.823359	0.800262	0.761976
WIRE	0.889996	0.879906	0.869971	0.870227	0.863312	0.863417	0.846964	0.835731	0.850396
AEIN	0.897151	0.880751	0.86148	0.882142	0.89431	0.877652	0.846805	0.802247	0.799465
UCIC	0.759242	0.859202	0.860566	0.855514	0.859031	0.862537	0.856323	0.830637	0.859656
JOWM	1	0.995215	1	1	1	1	1	1	1
ELZA	0.854217	0.867128	0.87123	0.88279	0.863281	0.865819	0.875629	0.828523	0.826986
ARWA	0.842604	0.84956	0.846651	0.845211	0.851447	0.856077	0.834429	0.813118	0.819166
AALU	0.864464	0.892457	0.884194	0.887045	0.873169	0.868525	0.864399	0.842832	0.769672
NATA	0.888676	0.897972	0.887179	0.882204	0.877329	0.874453	0.854595	0.844024	0.852485
NCCO	0.896461	0.900205	0.886665	0.875315	0.875594	0.892611	0.877223	0.863594	0.870791
JOPI	0.934582	0.93168	0.909952	0.904464	0.902238	0.918856	0.991065	0.855914	0.861584
WOOD	0.849154	0.878728	0.833336	0.846044	0.842984	0.843481	0.844428	0.821234	0.823752
ASPMM	0.8818	0.884612	0.883935	0.892162	0.871489	0.880728	0.853352	0.847008	0.856564
ASAS	0.807449	0.814913	0.805269	0.814644	0.824304	0.813902	0.808187	0.805035	0.817252
RMCC	0.85656	0.856353	0.837626	0.841673	0.841347	0.846345	0.828501	0.819418	0.828592

Figure 1: Efficiency confidence intervals for firms

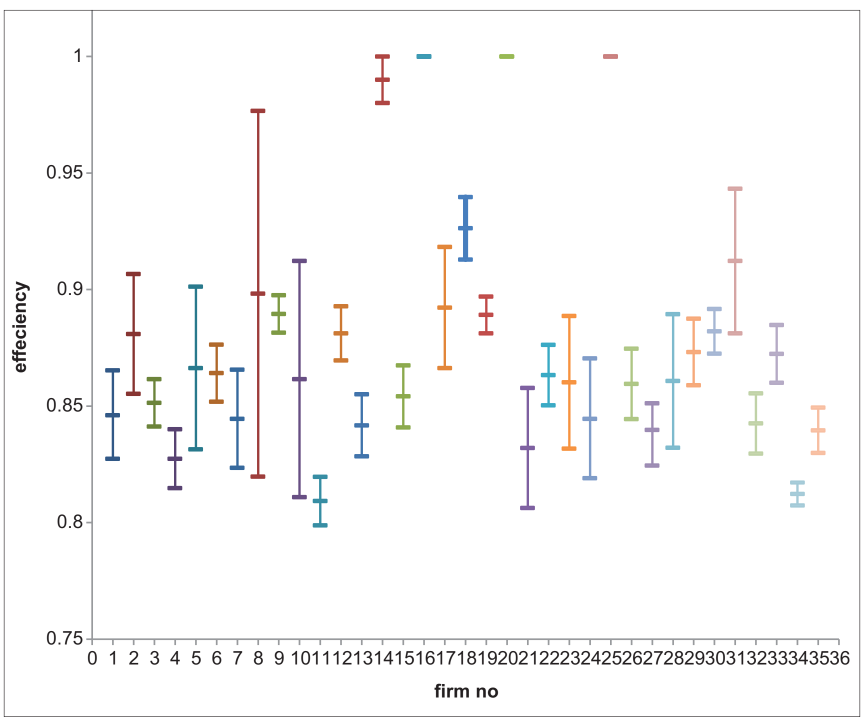

Table 3: Efficiency confidence intervals for firms

Firm no	Firm ID	Mean	std error	Lower	Upper
1	DADI	0.846045	0.008371	0.82741	0.865349
2	PHIL	0.880948	0.011154	0.855226	0.906671
3	HPIC	0.851376	0.004412	0.841202	0.86155
4	HPHM	0.827435	0.005463	0.814838	0.840033
5	ICAG	0.866342	0.015132	0.831447	0.901237
6	JOIC	0.864132	0.005321	0.85186	0.876403
7	NATC	0.844547	0.009128	0.823498	0.865596
8	JOIR	0.898195	0.034004	0.819782	0.976609
9	MBED	0.889528	0.003497	0.881464	0.897592
10	IPCH	0.86157	0.021977	0.810892	0.912248
11	JPPC	0.809277	0.004516	0.798823	0.819692
12	JODA	0.881204	0.005036	0.86959	0.892817
13	GENI	0.841738	0.005775	0.828421	0.855056
14	UMIC	0.99538	0.003648	0.986967	1.003793
15	NATP	0.854173	0.005775	0.840856	0.86749
16	AIFF	1		1	1
17	NDAR	0.892276	0.011272	0.866282	0.91827
18	JVOI	0.926273	0.005819	0.912855	0.939692
19	EKPC	0.889113	0.003432	0.881199	0.897026
20	EICO	1		1	1
21	UTOB	0.83204	0.011156	0.806315	0.857766
22	WIRE	0.863324	0.00562	0.850364	0.876285
23	AEIN	0.860223	0.012341	0.831764	0.888681
24	UCIC	0.844475	0.011157	0.819018	0.870473
25	JOWN	1		1	1
26	ELZA	0.859511	0.006559	0.844387	0.874636
27	ARWA	0.839807	0.004925	0.824497	0.851164
28	AALU	0.860751	0.012419	0.832113	0.889389
29	NATA	0.873213	0.006208	0.858898	0.887529
30	NCCO	0.882051	0.004163	0.872451	0.891651
31	JOPI	0.91226	0.013457	0.881228	0.943291
32	WOOD	0.842571	0.005605	0.829646	0.855496
33	ASPMM	0.872406	0.005387	0.859983	0.884829
34	ASAS	0.812328	0.002128	0.80742	0.817236
35	RMCC	0.839602	0.004211	0.829891	0.849312

5. CONCLUSION

In this study the DEA was used to measure the efficiency for 35 listed manufacturing firm in Amman Stock Market, the study shows that among the 35 firms only four firms were efficient (having an efficiency score of 1), these firms are (UMIC, AIFF, EICO, JOWN), other firms in the sample are inefficient with an efficiency score <1. The study revealed that the inefficient firms has an opportunity to utilize their inputs without affect their output. The study also ranked the firms according to their efficiency scores.

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