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Technical Efficiency in the Manufacturing Industries in Bangladesh: A DEA Non-Parametric Analysis

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Abstract

This study aims to evaluate the technical efficiency of Bangladesh's manufacturing industry. We utilized DEA analysis with selected three distinct DEA models: CCR, BCC, and the slack-based model. In this study, the number of firms, labour, salary/wages, industrial and non-industrial costs are considered as inputs variables. However, the gross output value is set as the output variable. We found that common efficient industries are- beverage manufacturing, tobacco manufacturing, ready-made garments, rubber and plastic, transport equipment, recycling, non-metallic mineral products, machinery and equipment, motor vehicles & trailers and repairs of machines & equipment. Using three DEA models explored that, in most circumstances, the manufacture of beverages, tobacco products, of ready-made garments industries remain among the topmost performers in positions of proficiency achievement. This research further suggests that those industries have made significant efficiency improvements, and they have also gained the ability to continue competing in the global marketplace.

Keywords: Technical Efficiency, Manufacturing Industries, DEA Analysis, Non-Parametric Test, Bangladesh

Jel Codes: D20, D22, D24

1. Introduction

Manufacturing is the process of creating items using organic and chemical processes and landing for everyone. However, the mass manufacturing of a product in a factory using mechanical resources, where a significant quantity of raw material is generated, is referred to as manufactured goods production (Kenton Will, 2021). Producing produced items is extremely important in all types of economic systems. Manufactured goods are typically created in a free market economy with the goal of profiting from consumer sales (Spence, M.,1984). The government retains some control over the manufacturing process in a mixed economy. Engineering and industrial design challenges are inseparably linked to the manufacturing business. General Motors, General Electric, Volkswagen, Siemens, and Michelin are major industrial manufacturers in North America. In Europe, Common Motors, General Electric, Volkswagen, Siemens, and Michelin are major industrial producers. Samsung, Toyota, and Bridgestone are among the Asian industrial manufacturers (UNIDO, 2020). So the Manufacture industry is very crucial to every nation. As a south Asian nation, Bangladesh is now trying to overcome its economy through industrialization; though still, the country has some problems with its economic system and policy, we are going to move forward to industrialization (Siddika & Ahmad, 2022). Currently, Bangladesh is a wonder of development. Today, the world recognizes Bangladesh as the most emerging country as it has achieved the desired progress in every sector of the economy. Bangladesh has been successfully included in the list of developing countries from LDC in the recent UN assessment. In the last decade of the present government, significant progress has been made in the industrial sector of Bangladesh. The country's economy has started a fast journey from an agro-based economy and gradually turning to an industrial-based economy (Riaz, Ali; Rahman, Mohammad Sajjadur 2016). According to the Bangladesh Bureau of Statistics, The growth rate in the industrial sector was 33.6 per cent in FY 2016-17 and its contribution increased 34.4% in the FY2018-2019. In the fiscal year 2019-20, the contribution was 34.78%; in the last fiscal year 2020-2021, the contribution to the economy was almost 34.99%, along with the industrial sector (BBS,2019). A review of data from the Economic Survey 2020 published by the Finance Department of the Ministry of Finance shows that the contribution of agriculture to the economy has come down to at least 15 percent. The contribution of the service sector has also decreased in the last five years.

On the other hand, the contribution of the manufacturing industry has been steadily increasing (MOF, 2021). According to the Economic Survey, the manufacturing sector has the most vital position in terms of sector-wise contribution to gross domestic product (GDP). This position has been getting more substantial for the last five financial years. For the first time in FY 2014-15, the sector's contribution to GDP exceeded 20 percent. This study's primary purpose is to analyze the technical efficiency of Bangladeshi industries during a specific time period that the survey done by the Bangladesh bureau of statistics, as well as to determine the input and output variables that are most important in determining firm efficiency in Bangladesh's manufacturing industry. In fact, we use Data Envelopment Analysis (DEA) to assess the technical efficiency of various manufacturing enterprises in 25 industries for the year 2019. Technical efficiency assesses the efficacy of a manufacturing process by determining the most significant output possible given a particular set of inputs and technologies. Likewise, technical efficiency may be described as statistical assessments of efficiency typically expressed as technology distance functions (Chambers et al., 1996). Several parametric and non-parametric methods have been developed to estimate technical efficiency with numerous inputs without imposing functional form limitations and identify the origins of efficiency or inefficiency (Aigner et al., 1977; Charnes et al., 1978). However, understanding the link among variables that contribute to efficiency is necessary. Based on the result, this study tries to figure out how the factors work that contribute to technical efficiency. In its simplest form, technical efficiency examines costs and production frontiers (Farrel, 1957). Therefore, External variables such as firm-specific characteristics, industry-specific elements, or attributes related to the manufacturing environment may influence company efficiency (Page,1980).

The remaining paper is designed in four more sections. After the introduction section, the next part elucidates the literature review. After that, a description of the model, data, methodology and theoretical framework was presented. The following section reviews the results and discusses them. Finally, the last part deals with the conclusion and gives some recommendations.

2. Literature Review

The technique of applying Data Envelopment Analysis (DEA) has been applied on various occasions to evaluate the relative production performance of profit and non-profit Production and service units. Farrell, (1957) presents the relative efficiency notion, which states that a decision-making unit's (DMU) efficiency may be measured by comparing it to the efficiency of other DMUs in the same group. Data Envelopment Analysis was presented by Charnes, Cooper, and Rhodes, (1978) as a linear programming tool for evaluating efficiency (DEA). Since the mid-1980s, Data Envelopment Analysis has become a prominent method for assessing the efficiency of many businesses. The original DEA model, proposed by Charnes et al., (1978), is known as the CCR Model, and it assumes a constant return to scale (CRS), which means that changes in a DMU's outputs are proportional to changes in its inputs. Furthermore, Banker, Charnes, and Cooper, (1984) proposed the BCC model based on the variable returns to scale (VRS) assumption, which states that changes in a DMU's outputs may not occur in the same proportion as increases in its input levels. Fried, Lovell, & Schmidt, (2008) discussed that DEA method had been used extensively in the past to investigate the relative efficiency of homogeneous units. There is also some model nowadays it’s evolved and gained popularity, such as the SBM model, Super efficiency model, Network DEA, multi-stage DEA, bootstrapping model, scale efficiency model etc. Slacks-Based Measure (SBM) models which was introduced by Tone (2001) put aside the assumption of proportionate changes in inputs and outputs and deal with slacks directly. It has three variations, i.e., input-, output-, and non-oriented. The concept of super-efficiency and presented two types of approaches for measuring super-efficiency: radial and non-radial. Super-efficiency measures are widely utilized in DEA applications for many purposes, e.g., ranking efficient DMUs, evaluating the Malmquist productivity index and comparing performances of two groups (Cooper, W.W., Seiford, L.M., Tone, K., 2007). The multi-stage DEA model evaluates both the efficiency score for the stages and overall efficiency of the whole process (Seiford,L M, Zhu J. 1999). Unlike standard DEA, the Network DEA Model does not guarantee the existence of an organizationally efficient DMU. All DMUs under consideration may be organizationally inefficient (Fare R, Grosskopf S., 2000). Scale efficiency can be used to determine how close an observed DMU is to the most productive scale size. It may be calculated as the ratio of the measure of technical efficiency calculated under the assumption of constant returns to scale (CRS) to the measure of technical efficiency calculated under the assumption of variable returns to scale (VRS) (Thanassoulis, E., 2001). The super-efficiency DEA model is the frontier analysis that obtains super-efficiency scores that are greater than one. This method was initially proposed by Anderson & Peterson, (1993), and the Bootstrap method is discussed by Simon & Willson, (2000), which attempts to provide a statistical four DEA model. The bootstrap model is one kind of sampling technique that has been applied in recent decades as a means of sampling the distribution of an estimator. Kundi & Sharma, (2016) said that the DEA technique was primarily used to evaluate the effectiveness of non-profit organizations such as hospitals, educational institutions, and government agencies. Later on, the area of DEA application expanded, and this technique is now being used to analyze the performance of profit-driven enterprises. For example, DEA is used to assess the performance of service sector firms such as banks and software industries and manufacturing industries such as textile and mining industries. Furthermore, DEA is utilized to assess the efficacy of various countries (Goyal et al., 2017).

2.1. DEA Analysis for Manufacture Industry

To create an upgraded super-efficiency DEA model, they combined the standard input-oriented CCR model, the super-efficiency DEA model, and the ideal-DMU-based benchmark sorting model, which was then applied to a real-world problem. After that, they investigated the method on ten well-known domestic energy company subsidiaries to see if it was viable to implement (Li, L et al., 2013). Input-oriented CCR and BCC models were used in their study because they examined the resource of company efficiency. The CCR model was used to determine the overall efficiency values of each decision-making unit based on the years. However, the BCC model was used to calculate the technical efficiency values, and the scale efficiency values were produced by comparing these values to one another. As a result, resource efficiency providers are uncommon among the BIST SME Industrial Index's enterprises, and these companies may attain their present total sales and profitability levels with fewer resources (Buyukkeklik, A. et., 2016). Emran, S. J., & Moniruzzaman, M., (2020) studied and used the output-oriented DEA model to capture the maximum proportional increase in production while maintaining input levels constant. Furthermore, DEA is utilized in this study under two alternative assumptions: constant and variable returns to scale. This study will also examine the dynamics of technical production efficiency in Bangladesh's manufacturing sector using cross-sectional data from the Survey of Manufacturing Industries (SMI) performed in 2006 and 2012. The dynamics of mean efficiency scores across industries were estimated using the Stochastic Frontier Analysis (SFA) method with the Cobb-Douglas model and a half-normal distribution. Khan, A. H., & Farooq, S., (2019) used the technical efficiency of listed spinning enterprises on the Pakistan Stock Exchange as assessed in this study (PSX). The Input Oriented Data Envelopment Analysis technique was used for this, with the Variable Return to Scale (VRS) assumption. For 2011 to 2016, balanced panel data from 55 firms was obtained. According to the study's conclusions, only one out of 55 organizations achieved an efficiency score of one during the course of the six-year study period. Athanassopoulos, A. D., & Ballantine, J. A., (1999) used CCR and BCC in both input and output-oriented data envelopment analyses to address several topics related to corporate performance measurements, such as determining sales efficiency, the effects of economies of scale, measuring a company's performance, and the link between industry groups and performance. Chapelle, K., & Plane, P., (2005) used the Data Envelopment Analysis to evaluate the production frontier technique; they assessed the technical efficiency of Ivorian manufacturing businesses in four industries: textiles and apparel, metal goods, food manufacturing, and timber and furniture. When computing efficiency scores, the external working environment's influence is considered. Khan, M. N. et al., (2018) Used Data Envelopment Analysis; this evaluates the efficiency of listed corporations on the Pakistan Stock Exchange (DEA). The purpose of using and calculating the DEA score is to determine how efficient enterprises are at converting their resources into output (sales/net income). Düzakın, E., & Düzakın, H., (2007) used an Output-oriented super slack-based model in DEA, which meant that the outputs could be negative or not at all. Furthermore, the model can help determine which businesses are the most efficient. People who did this study looked at data from 500 of the most important factories in Turkey to use the Output-oriented method. Ahmed, S. N., (2009), the goal of this study was to examine the "performances" of the Bangladeshi garment sector and to determine the most efficient frontier. The relative scores of the productive efficiency of several apparel manufacturers were determined using input and output-oriented models for both constant and variable return to scale, Scale efficiency, Malmquist Productivity Index and SBM model. The most efficient production periods (months) have been determined based on the efficiency measurement scores.

3. Methodology

3.1. Defining the Variables

a) Output variable: Gross output (production,(Y1): The SMI (Survey of Manufacturing Industries) surveys show the total amount of output which is the main goods, byproducts, and waste that are made. Based on this evidence, they define industrial output by the following components: There are a lot of different ways that businesses make money: (a) by making other people's products, (b) by renting and leasing assets, (c) by renting and leasing equipment, (d) by fixing and setting up other people's machinery, (e) by investing, and (f) by selling raw materials and fuels (BBS, 2019).

b) Input variables:

1. Number of new firms establishment (X1): The survey assessed that the accumulated number of manufacturing establishments (TPE≥10) in the country is 46,110. The most elevated number of the manufacturing industry is discovered, about 23,306 in Small type amongst other three types, namely Micro, Medium and Large scale industries that hold the figure of 16770, 3178 and 2856 respectively (BBS, 2019).

2. Number of labour (X2) & their salary (X3): labour Costs include (monthly wages, salary and social security, pensions, and other relevant expenses.

3. Fixed assets (X4): The value of these assets is called "capital." In the SMI survey, you can find out how much capital things like land, development, and building/infrastructure are worth.

4. Industrial Cost (X5): IC includes the cost of raw materials, packing accessories and replacement parts, and other related materials, the cost of electricity and fuels, wages of temporary works with factory purchases, expenditures for repairs and maintenance, and the cost of goods bought for resale.

5. Non-industrial Cost (X6): NIC includes The cost of excise duty, sales tax, VAT, payments for transportation, insurance, copyright, postage and internet bills,

stationery costs, legal and professional payments, advertising and marketing expenses, interest, other rental costs.

3.2 Sampling Procedure

In 2019, the SMI (Survey of Manufacturing Industries) surveyed 8433 industrial establishments. To ensure that all manufacturing industries were covered, the surveys were done using the company register (manufacturing sector) and stratification according to the size class outlined by the Nationwide Industrial Policy and assigned by the BSIC 4-digit level code. The Bangladesh Standard Industrial Classification (BSIC) 2009 was used to classify manufacturing industries. Although the survey's objective is to estimate aggregated data at the two, three, and four-digit levels, due to the small number of establishments in some industries, some of which have only one, and confidentiality concerns, the results are presented at the two and three-digit levels corresponding to the BSIC and by size class defined in National Industry Policy 2010. To conduct this research, we used data from significant two-digit (BSIC) code-containing sectors; though three-digit code-containing industries exist, due to the taking small sample size, we used a two-digit code-containing 26 industries as sampling data set (BBS SMI, 2019).

3.3 The Model

Based on the survey above, this study focuses on the efficiency of Bangladesh's manufacturing industry. There are two types of DEA: input-oriented and output-oriented. In the case of input-oriented DEA, inputs are decreased while outputs are maintained at their current levels. In contrast, output-oriented DEA tries to capture the most significant gain in production while keeping input levels constant. According to Coelli and Rao, (2003), both methods yield identical scores relative to technical efficiency when using constant returns of scale (CRS) technology; however, the scores differ when using variable returns of scale (VRS) technology. The variable returns to scale (VRS) frontier better matches the data, and efficiency ratings under VRS are predicted to be greater than those using CRS technology in the future. The CCR (Charnes, Cooper, and Rhodes) model is the fundamental DEA model that assumes a constant return to scale. This model is used to calculate total technical efficiency. Only if the DMUs run at their optimal size can the notion of a continuous return to scale be accepted. The CCR model assumes perfect competition. Thus, we use it to see how DMUs perform in the presence of perfect competition. We will also employ the BCC model since manufacturing firms operate in an internationally competitive environment. Their management wants to achieve maximum production with few resources to maintain their current market share. Experts in the manufacturing sector also advocated for using the BCC Model in the manufacturing industry. As a result, in the current situation, it is more realistic to employ both the BCC and CCR models as empirical findings for the comparative DMUs (Khan, M. N., Ahmad, A., & Jehan, N., (2018). Besides, a slack-based measure of efficiency in data envelopment analyzes and measures the scalar efficiency, which deals directly with the input excesses and output shortfalls of the decision-making unit. So after CCR and BCC tests, we also want to test the SBM model to see how inducing slack shows DMUs' decision about efficiency (Tone, K., 2001).

We chose the input-oriented DEA model because we observed that authorities could influence their input variables as survey source. In this study, the input orientation model is favored above the output orientation for several reasons. First, because administrators have greater control over inputs than outcomes, input quantities utilized in the process are the primary decision variable (Akhtar & Asif, 2017; Chapelle & Plane, 2005). Second, input-oriented models are ideal for measuring business resource efficiency (Buyukkeklik, Dumlu, & Evci, 2016). Third, manufacturing industries typically strive to lower their costs (an input) and maximize the use of available resources. As a result, these inputs are a crucial predictor of efficiency, which may be attained by minimizing costs and managing resources efficiently (Akhtar & Asif, 2017; Saranga, 2009).In this regard, the first stage is to use the CCR-I model to identify manufacturing sector efficiency, and the second step is to use the BCC-I model to discover the determinants of the efficiency indicator. Finally, we employ the SBM-I (slack-based) model.

3.3.1. Input Oriented CCR Model

Charnes, Cooper, and Rhodes established the CCR model, which is the first and most basic data envelopment analysis model (1978). In the original model, the efficiency was described as proportional by Charnes Cooper and Rhodes (CCR). The efficiency of any DMU is calculated in the model by maximizing the weighted outputs to the weighted inputs ratio. Each DMU's ratios are organized so that they are less than or equal to one (Kale, 2009). Charnes et al., (1978) proposed the following input-oriented CCR fractional programming model: The DMU's known outputs and inputs are $u_{r,} and\ v_i$, which the weights of the outputs and inputs are. The fractional programming model was linearized using the Charnes-Cooper transformation, yielding the model shown below (Cooper et al., 2011: 9).

Max $\quad z = \sum_{r=1}^{s} u_r y_{rk}$
(Ahuja,2016)
Constraint: $\sum_{i=1}^{m} v x_{ik} = 1$
(Sharif & Abdullah,2013)

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v x_{ij} \ \leq (\, j = 1, \dots \dots, n) \tag{1}$$

$$u_{r,} v_i \geq 0 \qquad (\, r = 1, ., s) \quad (i = 1, \dots .., m) \tag{2}$$

The success of DMU in attaining maximum output with a given mix of inputs is measured in technical efficiency. To assess their effectiveness, a model must be created and solved independently for each DMU. The value of the objective function obtained as a result of the solution provides information about the relevant DMU's Total Technical Efficiency (TTE)cy. DMU is considered to be inactive if the objective function value is less than 1 (*z*<1), and active if it is equal to 1 (*z*=1).

3.3.2. Input Oriented BCC Model

The CCR model that Chernes, Cooper, and Rhodes came up with is based on the idea that there are always equal returns to scale. To get rid of this assumption, Banker, Charnes, and Cooper came up with the BCC model, which looks at how things work when there are different returns to scale, in their study in 1984. Difference: The convexity constraint that was added to the CCR model makes the BCC model different from the CCR model. With this constraint, the linear production limit in the CCR model turns into a piecemeal linear one. Besides the efficiency of DMUs, information about return types (decreasing, constant, or rising with scale) can also be found this way, which is important. Banker, Charnes, and Cooper developed the fractional programming BCC model. It looks like this: (Banker et al., 1984: 1985).The following model is created by converting the input-oriented BCC Fractional programming model into a linear programming model. (Banker et al., 1984: 1985);

$$\text{Max} \quad z = \sum_{r=1}^{s} u_r y_{rk} - u_0 \tag{3}$$

Constraint:

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v x_{ij} - u_0 \leq 0 \quad (j = 1, \ldots \ldots, n) \tag{4}$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1$$

$$u_{r,} v_i \geq 0 \quad (r = 1, \ldots \ldots, s) \quad (i = 1, \ldots, m) \tag{5}$$

u_0 *Sign of unrestricted*

In the results obtained for each DMU as a result of solving the BCC model, if the u_0 value is less than zero ($u_0<0$), DMU is said to have increasing returns to scale, and if it is greater than zero ($u_0>0$), it is said to have decreasing returns to scale. Sometimes BCC model is called Pure Technical Efficiency (STE).STE is a way to measure how far away from efficiency you are because you use too many resources inefficiently when there are different returns to scale (Tutek et al., 2012). The Scale Efficiency (EE) of a DMU is calculated by dividing the TTE that comes from the BCC model by the STE. This shows how far a DMU is from the effective cost limit because of the constant return to scale. A DMU is 100% efficient if the CCR and BCC efficiency values are 100%. It means that the DMU is operating at the most efficient scale size. In DMU, when the PI value is 1, there are no sudden changes in scale. If DMU has BCC efficiency

(STE=1) and the CCR efficiency value is low (TTE=1), it means that DMU is only effective locally because of its size. Because DMU has a low TTE value, it's because it doesn't work well at a large scale. Both CCR and BCC efficiency values are less than 1, meaning that the DMU does not have global and local efficiency.

The improvement rates are calculated using the target values to determine how much the inputs and outputs need to be reduced or increased in order for the inactive DMU to be effective in comparison to its own reference group.

$x_{ij} = \sum_{j=1}^{n} x_i \lambda_j$ (Ahuja,2016)

$$y_{rk} \sum_{j=1}^{n} x_i \lambda_j \quad (6)$$

3.3.3. Slack Based Model (SBM)

The slack-based model (SBM) was proposed as a variation model that represents measurement efficiency. Slacks-Based Measure (SBM) models, which were introduced by (Tone, 2001) and suggested removing the premise of proportional changes in inputs and outputs and dealing directly with slacks. It comes in three types: input-, output-, and non-oriented. The SBM models are intended to fulfill the following two requirements:

1. Units invariant: The measure should be unitless with regard to the data units.

2. Monotone: The measure should decrease monotonically with each slack in input and output.

$$\rho_1^* = min^{\lambda,s^-,s^+}\, 1 - \frac{1}{m}\ \sum_i \frac{s_i^-}{x_{i0}}, \quad (7)$$

$$x_{i0} = \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- \quad (\, i = 1, \dots \dots \dots \dots, m), \quad (8)$$

$$y_{r0} = \sum_{j=1}^{n} \lambda_j x_{rj} - s_i^+ \quad (\, r = 1, \dots \dots \dots \dots, s), \quad (9)$$

$$\lambda_j \geq 0\ (\forall j,\ s_i^- \geq 0\ (\forall i), s_r^+ \geq 0\ (\forall r) \quad (10)$$

Here s_i^- and s_r^+ are slacks, s_i^- is input residuals dan s_r^+ is output lacks. The optimum result of SBM is 1, which can only be accomplished when all the slacks are identical to zero. This is reliable with CCR and BCC models.

4. Results and Discussion

Table 1: Descriptive statistics

	X1	X2	X3	X4	X5	X6	Y1
Mean	1844.4	218606.5	30423940	97961665	2.53E+08	22351842	4.53E+08
Median	383	29315	4511435	25462299	5.6E+07	6911466	1.22E+08
Maximum	12753	3257570	4.85E+08	7.42E+08	2.80E+09	2.75E+08	4.88E+09
Minimum	4	1235	177689	15367	520929	138078	616154
Std. Dev.	3320.21	643003.5	94397447	1.74E+08	5.62E+08	53695224.00	9.76E+08
Skewness	2.139995	4.305035	4.536902	2.624328	3.81674	4.238381	3.82718
Kurtosis	6.501568	20.77739	22.34486	9.379833	17.6533	20.41803	17.72815
Sum	47954.4	5683768	7.91E+08	2.55E+09	6.59E+09	5.81E+08	1.18E+10
Sum Sq. Dev.	2.76E+08	1.03E+13	2.23E+17	7.53E+17	7.90E+18	7.21E+16	2.38E+19

The descriptive statistics of input and output variables including Mean, Standard Deviation, and Minimum and Maximum values are calculated from the values given in the SMI survey of selected firms and are presented in Table 1. On average, the number of manufacturing firms in Bangladesh is 1844 and number of labor they input is 218606.5 and the average salary they get is almost 30423940 Tk. Those manufacturing firms invest on average an amount of 97961665 TK. in Assets with a standard deviation of 5.62E+08. Moreover, the minimum investment in Assets is Tk. 15367, while The maximum investment in Assets is to the tune of Tk. 7.42E+08.The various input cost of firms like Energy cost, Industrial and non-industrial cost on average remains at TK. 2.53E+08, 3.21E+10, 22351842. The maximum amount of Costs are 2.80E+09, 1.78E+11, 2.75E+08 and the minimum costs to produce the goods during sample periods are 520929.0, 94078811,138078. The descriptive results indicate that the average Gross output value is Tk. 4.53E+08 with a maximum 4.88E+09 value of Tk. while the minimum value is 616154 and St. Deviation is 9.76E+08. Since all the variables kurtosis value >3 and skewness is positive so all of the variables is positively skewed and leptokurtic. In statistics, we call the correlation coefficient r, and it measures the strength and direction of a linear relationship between two variables on a scatterplot. The value of r is always between +1 and –1. To interpret its value.

Table 2: Correlation Matrix

CORRELATION MATRIX	X1	X2	X3	X4	X5	X6	Y1
X1	1.00	0.57	0.52	0.82	0.65	0.58	0.65
X2	0.57	1.00	0.58	0.89	0.57	0.89	0.48
X3	0.52	0.68	1.00	0.86	0.77	0.79	0.57
X4	0.82	0.76	0.86	1.00	0.81	0.89	0.81
X5	0.65	0.68	0.47	0.52	1.00	0.68	0.88
X6	0.58	0.78	0.67	0.78	0.68	1.00	0.88
Y1	0.65	0.82	0.74	0.83	0.78	0.88	1.00

In the correlation tables, all variables are positively correlated with each other, and maximum show an uphill (positive) linear relationship, and others indicate a moderate uphill (positive) co-relationship. For instance: the number of firms has a strong correlation with energy consumption cost and the lowest co-relationship with salary and wages. Moreover, labour input is correlated with wages, fixed assets, industrial cost, gross outputs, gross value added, the value of other income and wages of the employees is also mildly correlated with labour inputs, non-industrial cost, and gross outputs value-added, the value of other income.

Table 3: Analysis of Technical Efficiency of the Manufacturing Industry in Bangladesh

Serial No.	Industry name	Model = CCR-I		Model= BCC-I		**Model = SBM-I-C**	
No.	DMUs units	Score	Rank	Score	Rank	Score	**Rank**
1	Manufacture of food	0.41	12	1.00	1	0.27	**12**
2	Manufacture of Beverage	1.00	1	1.00	1	1.00	**1**
3	Manufacture of Tobacco	1.00	1	1.00	1	1.00	**1**
4	Manufacture of textiles	0.21	21	0.96	11	0.16	**18**
5	Manufacture of Ready-made garments	0.43	11	1.00	1	0.23	**14**
6	Manufacture of leather products	0.19	22	0.19	25	0.14	**21**
7	Manufacture of wood products	0.21	20	0.26	22	0.11	**24**
8	Manufacture of paper and products	0.23	19	0.26	23	0.15	**19**
9	Printing media	0.17	23	0.22	24	0.11	**23**
10	MF of coke and petroleum products	0.57	9	0.77	14	0.43	**10**
11	Manufacture of chemical products	0.33	15	0.34	19	0.20	**15**
12	MF of Pharmaceutical medical and biotech	0.70	7	0.86	13	0.43	**9**
13	MF of rubber and plastic	1.00	1	1.00	1	1.00	**1**
14	MF non-metallic mineral product	0.27	18	1.00	1	0.20	**16**
15	Manufacture of basic metals	0.68	8	0.69	16	0.50	**8**
16	MF fabricated metal	0.41	13	0.46	18	0.19	**17**
17	MF of computer and electronic	0.85	6	0.86	12	0.52	**7**
18	Manufacture of electric equipment	0.51	10	0.51	17	0.28	**11**
19	MF machinery and equipment	0.87	5	1.00	1	0.63	**6**
20	MF of vehicle & trailers	0.40	14	0.73	15	0.25	**13**
21	Manufacture of transport equipment	1.00	1	1.00	1	1.00	**1**
22	Manufacture of furniture	0.30	17	0.33	20	0.13	**22**
23	Other manufacturing	0.30	16	0.32	21	0.15	**19**
24	Repair of machine & equipment	0.08	24	1.00	1	0.04	**25**
25	Recycling	0.03	25	1.00	1	1.00	**1**

In table:3 Scores, rankings, and links about production efficiency are calculated using the software DEA solver developed by (Coopers, Seiford and Tone). The DEA CCR model implies constant returns to scale, which means that every change in inputs should result in proportional output changes. The average efficiency score earned under CCR (input-oriented) by all sample manufacturing industries was 0.48 in 2019. It is to be noted that out of the 25 sample manufacturing under constant returns to scale in DEA, the 100% efficient industries in 2019, according to the mean efficiency score, are the Manufacture of beverages, Manufacture of tobacco products, Manufacture of rubber and plastics Products, Manufacture of transport equipment. By CCR or constant return to scale model show that there is only 4 industries are fully efficient and 21 industries are inefficient. Moderately efficient DMUs are MF of Pharmaceutical medical and biotech, MF of computer and electronic, and MF machinery and equipment. Therefore, these industries are almost 100% efficient; thus, the organization needs to look forward to controlling their input level and their strategy. Besides, this research provides slack and projection results, so if they follow the slack input, they can be swung back to efficiency. Less efficient DMUs are Repairs of machines & equipment, Recycling, Manufacturing leather products, manufacturing of wood products, and manufacturing of paper and products.

DEA analysis of variable returns to scale. The purpose of this analysis is to The BCC model proposes taking into consideration the fact that the conditions that influence production productivity vary depending on the situation. In other words, the BCC model attempted to interpret the fact that, at different scales, DMUs may have varying productivities and still be considered efficient. Variable returns to scale (VRS) is a frontier scale type employed in data envelopment analysis (DEA). It helps determine whether an increase or reduction in inputs or outputs does not result in a corresponding change in outputs or inputs (Cooper, Seiford, & Zhu, 2011). This strategy incorporates both increasing and declining returns to scale. The average efficiency score under BCC (input-oriented) for all sample manufacturing industries is 0.71 in 2019. Under variable returns to scale in DEA, the 100% efficient industries are the Manufacture of beverages, Manufacture of tobacco products, Manufacture of Ready-made garments, MF of rubber and plastic, Manufacture of transport equipment, Recycling, MF non-metallic mineral product, MF machinery and equipment, manufacture of foods.

Here we use BCC or variable return to scale and we have found that there is 13 industry got 100% efficient score and they, have full control of their production and they are productivity is very good. Thus by the BCC model, we conclude that almost 10 industries are more capable and efficient in long-run production and the other 12 industry are inefficient. Moderately efficient DMUs are the manufacture of textiles, MF of computers and electronics, MF of coke and petroleum products, MF of Pharmaceutical, medical and biotech. Less efficient DMUs are printing media, manufacture of paper and products, manufacture of leather products, and manufacture of wood products.

Table 3 shows that the average efficiency score under SBM (input-oriented) model for all sample manufacturing industries was 0.40 in 2019, which shows the average lowest efficiency score compared to other models. 100% efficient industries by the slack model are the manufacture of beverages, manufacture of tobacco products, Manufacture of rubber and plastics Products, Manufacture of transport equipment, and recycling. By the slack-based model we have found 5 most efficient DMUs as we mentioned their name above. By slack, we got almost the same results as CCR so this result suggests that 5 industries have pure efficiency and production capacity and 20 industries are inefficient. Moderately efficient DMUs are the Manufacture of basic metals, MF machinery and equipment, and MF of computers and electronics. Less efficient DMUs are the repairs of machines & equipment, manufacture of wood products, printing media, manufacture of furniture, manufacture of textiles, Manufacture of paper and products, manufacture of leather products, and Manufacture of chemical products, manufacture of fabricated metal.

Table: 4 Slacks/Potential Improvements Need For the Inefficient Manufacturing Sector by the CCR-I Model

Model = CCR-I

No.	DMU	Score	Rank	X1	X2	X3	X4	X5	**X6**
1	Manufacture of food	0.41	12	1.54	0.00	0.00	0.00	0.00	**0.26**
4	Manufacture of textiles	0.21	21	1.05	0.06	0.00	0.09	0.00	**0.00**
5	Manufacture of Ready-made garments	0.43	11	0.00	3.54	4.32	0.00	2.92	**2.72**
6	Manufacture of leather products	0.19	22	0.07	0.00	0.02	0.00	0.00	**0.04**
7	Manufacture of wood products	0.21	20	0.07	0.01	0.00	0.00	0.00	**0.00**
8	Manufacture of paper products	0.23	19	0.05	0.00	0.01	0.00	0.00	**0.04**
9	Printing media	0.17	23	0.04	0.00	0.00	0.00	0.00	**0.01**
10	products	0.57	9	0.00	0.00	0.00	0.02	0.00	**0.00**
11	Manufacture of chemical products	0.33	15	0.01	0.00	0.04	0.25	0.00	**0.06**
12	MF of Pharma, medical and biotech	0.70	7	0 .00	0.09	0.33	0.00	0.00	**0.35**
14	MF non-metallic mineral product	0.27	18	0.47	0.23	0.03	0.00	0.18	**0.00**
15	Manufacture of basic metals	0.68	8	0.02	0.00	0.01	0.00	0.00	**0.18**
16	MF fabricated metal	0.41	13	0.23	0.02	0.02	0.00	0.00	**0.00**
17	MF of computer and electronic	0.85	6	0.00	0.04	0.06	0.00	0.02	**0.05**
18	Manufacture electric equipment	0.51	10	0.00	0.07	0.12	0.52	0.00	**0.00**
19	MF machinery and equipment	0.87	5	0.04	0.00	0.00	0.00	0.00	**0.00**
20	MF of motor vehicle & trailers	0.40	14	0.01	0.00	0.00	0.02	0.00	**0.00**
22	Manufacture of furniture	0.30	17	0.48	0.06	0.05	0.00	0.00	**0.00**
23	Other manufacturing	0.30	16	0.05	0.00	0.00	0.00	0.00	**0.03**
24	Repair of machine & equipment	0.08	24	0.00	0.00	0.00	0.00	0.00	**0.00**
25	**Recycling**	**0.00**	**25**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

The average input variables slacks 0.1644, 0.1646, 0.2006, 0.036, 0.1247, 0.1502 .Table 4 also presents the potential reduction in inputs. The potential improvement shows those areas of improvement in input-output activity needed to put an inefficient manufacturing capability to the efficient frontier. For getting potential input reduction, consider the case of the important manufacturing sector MF of ready-made garments which is inefficient in the sample. To move on to the efficient frontier need to cut labor, wages, non-industrial cost, and industrial cost by 3.54, 4.32, 2.92, 2.72 percent, respectively.

Table: 5 Slacks/Potential Improvements Need for the Inefficient Manufacturing Sector by The BCC-I Model

Model = BCC-I				**Input reduction%**					
No.	DMU	Score	Rank	X1	X2	X3	X4	X5	**X6**
4	Manufacture of textiles	0.96	11	3.62	0.60	0.00	2.98	0.00	**0.07**
6	Manufacture of leather products	0.19	25	0.07	0.00	0.02	0.00	0.00	**0.04**
7	Manufacture of wood products	0.26	22	0.08	0.01	0.00	0.00	0.00	**0.00**
8	Manufacture of paper products	0.26	23	0.05	0.00	0.01	0.00	0.00	**0.02**
9	Printing media	0.22	24	0.05	0.00	0.00	0.01	0.00	**0.01**
10	MF of coke and petroleum products	0.77	14	0.00	0.00	0.00	0.04	0.01	**0.00**
11	Manufacture of chemical products	0.34	19	0.01	0.00	0.04	0.26	0.00	**0.06**
12	MF of Pharma, medical and biotech	0.86	13	0.00	0.12	0.41	0.33	0.00	**1.05**
15	Manufacture of basic metals	0.69	16	0.02	0.00	0.01	0.00	0.00	**0.18**
16	MF fabricated metal	0.46	18	0.22	0.05	0.04	0.00	0.00	**0.03**
17	MF of computer and electronic	0.86	12	0.00	0.04	0.06	0.00	0.03	**0.04**
18	Manufacture of electric equipment	0.51	17	0.00	0.07	0.12	0.55	0.00	**0.03**
20	MF of motor vehicle & trailers	0.73	15	0.02	0.00	0.00	0.05	0.01	**0.00**
22	Manufacture of furniture	0.33	20	0.49	0.09	0.08	0.00	0.00	**0.04**
23	**Other manufacturing**	**0.32**	**21**	**0.01**	**0.00**	**0.01**	**0.00**	**0.00**	**0.05**

The average input variables slacks are 0.1857, 0.0391, 0.0322, 0.1684, 0.0018, and 0.065. Table: 5 also presents a potential reduction in inputs. The potential improvement shows those areas of improvement in input-output activity needed to put an inefficient manufacturing capability to the efficient frontier.

Table: 6 Slacks/Potential Improvements Need For the Inefficient Manufacturing Sector By The SBM-I Model

	Model = SBM-I-C			**Input reduction %**					
No.	DMU	Score	Rank	X1	X2	X3	X4	X5	**X6**
1	Manufacture of food	0.27	12	4.66	0.77	0.73	1.50	2.52	**1.82**
4	Manufacture of textiles	0.16	18	6.48	2.43	1.94	4.36	2.40	**2.23**
5	Manufacture of Ready-made garments	0.23	14	2.52	12.47	13.87	4.17	9.71	**10.77**
6	Manufacture of leather products	0.14	21	0.67	0.42	0.49	0.77	0.48	**0.66**
7	Manufacture of wood products	0.11	24	0.35	0.06	0.05	0.03	0.03	**0.05**
8	Manufacture of paper products	0.15	19	0.26	0.09	0.12	0.17	0.11	**0.26**
9	Printing media	0.11	23	0.26	0.06	0.07	0.08	0.04	**0.10**
10	MF of coke and petroleum products	0.43	10	0.00	0.00	0.01	0.08	0.05	**0.05**
11	Manufacture of chemical products	0.20	15	0.09	0.09	0.21	1.09	0.20	**0.55**
12	MF of Pharma, medical and biotech	0.43	9	0.00	0.13	0.48	0.52	0.22	**1.34**
14	MF non-metallic mineral product	0.20	16	2.81	2.16	1.23	1.85	2.10	**0.98**
15	Manufacture of basic metals	0.50	8	0.09	0.00	0.05	0.16	0.52	**0.37**
16	MF fabricated metal	0.19	17	0.62	0.16	0.15	0.05	0.13	**0.17**
17	MF of computer and electronic	0.52	7	0.00	0.05	0.08	0.07	0.08	**0.16**
18	Manufacture of electric equipment	0.28	11	0.02	0.14	0.29	1.52	0.49	**0.58**
19	MF machinery and equipment	0.63	6	0.05	0.01	0.01	0.00	0.02	**0.01**
20	MF of motor vehicles & trailers	0.25	13	0.02	0.00	0.01	0.08	0.04	**0.03**
22	Manufacture of furniture	0.13	22	1.74	0.40	0.36	0.14	0.25	**0.30**
23	Other manufacturing	0.15	19	0.22	0.10	0.11	0.06	0.13	**0.27**
24	**Repair of machine & equipment**	**0.04**	**25**	**0.04**	**0.01**	**0.01**	**0.01**	**0.00**	**0.01**

The average input variables slacks are 0.8358, 0.7823, 0.8103, 0.6686, 0.7814, and 0.8284. Table 6 also presents the potential reduction in inputs. The potential improvement shows those areas of improvement in input-output activity needed to put an inefficient manufacturing capability to the efficient frontier. For getting potential input reduction and output addition, consider the case of the critical manufacturing sector MF of ready-made garments, which is inefficient in the sample. To move on to the efficient frontier need to reduce the of firms and cut the cost of labour, wages, fixed assets, non-industrial cost, and industrial costs and reduce the number of firms by 2.52, 12.47, 13.87, 4.17, 9.71, 10.77 percent respectively.

5. Conclusion and Policy Implications

Through digital transformation, the industry turns manufacturing, production, and operation into a process that creates value. Even though Bangladesh is an agricultural country, the manufacturing sector is now the main source of income for the country. Bangladesh was one of the lowliest places in the world when it got its independence in 1971. At that time, there were no major industries. Bangladesh now has to deal with the global business environment of the 21st century, especially in the ready-made garment (RMG) sector. The main purpose of this study was to test the efficiency of the manufacturing industry in Bangladesh. The results of the research give us the information that currently, the most skilled industries are tobacco, beverages, rubber and plastic and ready-made garments. Although the different models have given different results, the beverage, tobacco and ready-made garments industries are the most efficient industry according to the variable return to scale model. However, even though some other industries have increased their production efficiency, we have identified some of the three industries that have played a major role in the production of Bangladesh. However, it is not good news for us to be efficient in the tobacco industry because tobacco cultivation is as harmful to the land as it is to the health. However, the industry has gained a lot of expertise due to the popularity of tobacco cultivation and the availability of tobacco leaves at low prices. And if we talk about the garments industry, then the most popular industry in Bangladesh is ready-made garments and this industry has easily gained skills due to cheap labor. However, the test result also revealed that a maximum of the industries are inefficient, so we want to give some recommendations on how they can improve their production level. As we use an input-oriented model, all models suggest that, at first, the organizer needs to reduce their variable cost, fixed cost, and average and marginal cost. Besides some guidelines, we can give that firstly, formulation of a trade policy that encompasses industrial, investment, and commercial concerns because the policy lacking industries suffer extra cost and taxation burden. Secondly, establishing new power plants for industrial units can reduce fuel and consumption costs. Thirdly concentrate public spending on infrastructure, energy, and technology and develop a differentiated indirect tax regime for SMBs. Fourthly, monitoring domestic and international markets and making them competitive. The oligopolistic behaviour of the market structure makes the firm inefficient in production. Moreover, Facilitates SME entry to imported inputs that can reduce the inputs cost of the firms. Lastly, Establish Special Economic Zones (SEZs) to attract foreign direct investment (FDI) in new industries such as light engineering (bicycles and electronic devices), IT products, medicines, and shipbuilding because inefficient industries can be shut down so we need to focus on current market emerging industry which is become efficient so quickly. So the research proves that the industry of Bangladesh is currently moving towards efficiency. Some industries are still inefficient but have increased the efficiency score of this country's manufacturing industry.

Reference

Ahmed, S. N. (2009). Productivity modeling in the apparel industry of Bangladesh: an application of data envelopment analysis (DEA) technique.

Ahuja, H. L. (2016). Macroeconomic Theory and Policy (19th ed.). New Delhi: S. Chand & Co. Ltd. .

Ahn, H., & Le, M. H. (2014). An insight into the specification of the input-output set for DEA-based bank efficiency measurement. *Management Review Quarterly, 64*(1), 3-37.

Athanassopoulos, A. D., & Ballantine, J. A. (1995). Ratio and frontier analysis for assessing corporate performance: evidence from the grocery industry in the UK. *Journal of the Operational Research Society, 46*(4), 427-440.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science, 30*(9), 1078-1092.

Banker, R. D., Cooper, W. W., Seiford, L. M., Thrall, R. M., & Zhu, J. (2004). Returns to scale in different DEA models. *European Journal of Operational Research, 154*(2), 345-362.

Basso, A., & Funari, S. (2001). A data envelopment analysis approach to measure the mutual fund performance. *European Journal of Operational Research, 135*(3), 477-492.

Bayyurt, N., & Yılmaz, S. (2012). The impacts of governance and education on agricultural efficiency: an international analysis. *Procedia-Social and Behavioral Sciences, 58*, 1158-1165.

BBS. (2019). Survey of Manufacturing Industries (SMI) 2019 .

Buyukkeklik, A., Dumlu, H., & Evci, S. (2016). Measuring the efficiency of turkish SMEs: A data envelopment analysis approach. *International Journal of Economics and Finance, 8*(6), 190-200.

Carrillo, M., & Jorge, J. M. (2017). DEA-like efficiency ranking of regional health systems in Spain. *Social Indicators Research, 133*(3), 1133-1149.

Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. *Management science, 27*(6), 668-697.

Cook, P. (2001). Finance and small and medium-sized enterprise in developing countries. *Journal of Developmental Entrepreneurship, 6*(1), 17.

Din, M.-u., Ghani, E., & Mahmood, T. (2007). Technical efficiency of Pakistan's manufacturing sector: A stochastic frontier and data envelopment analysis. *The Pakistan Development Review*, 1-18.

Düzakın, E., & Düzakın, H. (2007). Measuring the performance of manufacturing firms with super slacks based model of data envelopment analysis: An application of 500 major industrial enterprises in Turkey. *European Journal of Operational Research, 182*(3), 1412-1432.

Emran, S. J., & Moniruzzaman, M. (2020). The Dynamics and Sources of Technical Efficiency of the Manufacturing Industries in Bangladesh.

Farrell, M. The Measurement of Productive EfficiencyJournal of the Royal Statistical Society. Series A (General), 1957. In.

Frija, A., Chebil, A., Speelman, S., Buysse, J., & Van Huylenbroeck, G. (2009). Water use and technical efficiencies in horticultural greenhouses in Tunisia. *Agricultural Water Management, 96*(11), 1509-1516.

Gökgöz, F. (2010). Measuring the financial efficiencies and performances of Turkish funds. *Acta Oeconomica, 60*(3), 295-320.

Index, E. (2010). Finance division, Ministry of Finance, Government of the People Republic of Bangladesh. In.

Kassam, A. (2017). Efficiency analysis of healthcare sector. *Engineering and Technology Journal, 35*(5 Part A), 509-515.

Khan, A. H., & Farooq, S. (2019). Evaluating Technical Efficiency of Textile Firms in Pakistan: An Application of Data Envelopment Analysis (DEA) Approach. *Paradigms, 13*(2), 160-169.

Khan, M. F. Z. (2014). The Social and Financial Performance of Conventional and Islamic Microfinance Institutions in Pakistan. *Al-Idah, 28*(1), 17-34.

Khan, M. M. N., Ahmad, A., & Jehan, N. (2018). Pakistani Firms' Efficiency: An Empirical Study of Pakistani Listed Firms through Data Envelopment Analysis. *Global Social Sciences Review (GSSR), 3*, 158-174.

Li, L., Li, M., & Wu, C. (2013). Production efficiency evaluation of energy companies based on the improved super-efficiency data envelopment analysis considering undesirable outputs. *Mathematical and Computer Modelling, 58*(5-6), 1057-1067.

Mogha, S. K., Yadav, S. P., & Singh, S. P. (2014). New slack model based efficiency assessment of public sector hospitals of Uttarakhand: State of India. *International Journal of System Assurance Engineering and Management, 5*(1), 32-42.

MOF, BD. (2021). Bangladesh Economic Review.

Njikam, O. (2003). *Trade reform and efficiency in Cameroon's manufacturing industries*: AERC.

Pille, P., & Paradi, J. C. (2002). Financial performance analysis of Ontario (Canada) Credit Unions: An application of DEA in the regulatory environment. *European Journal of Operational Research, 139*(2), 339-350.

Raheli, H., Rezaei, R. M., Jadidi, M. R., & Mobtaker, H. G. (2017). A two-stage DEA model to evaluate sustainability and energy efficiency of tomato production. *Information Processing in Agriculture, 4*(4), 342-350.

Si, L.-B., & Qiao, H.-Y. (2017). Performance of Financial Expenditure in China's basic science and math education: Panel Data Analysis Based on CCR Model and BBC Model. *EURASIA Journal of Mathematics, Science and Technology Education, 13*(8), 5217-5224.

Staub, R. B., e Souza, G. d. S., & Tabak, B. M. (2010). Evolution of bank efficiency in Brazil: A DEA approach. *European Journal of Operational Research, 202*(1), 204-213.

Sharif, T., & Abdullah, J. A., Shibly. (2013). Human Resource Development and Economic Growth in Bangladesh: An Econometric Analysis. European Journal of Business and Management, 5(7), 133-144.

Siddika, R., & Ahmad, S. (2022). CSR Failures in Bangladeshi Apparel Industry: An Agency Theory Perspective. International Journal of Supply Chain Management.

Spence, M. (1984). oCost Reduction. Competition, and Industry Performance, p Econometrica, 52(1).

Taymaz, E., & Saatci, G. (1997). Technical change and efficiency in Turkish manufacturing industries. *Journal of Productivity Analysis, 8*(4), 461-475.

Thanassoulis, E. (2001). *Introduction to the theory and application of data envelopment analysis*: Springer.

Titko, J., Stankevičienė, J., & Lāce, N. (2014). Measuring bank efficiency: DEA application. *Technological and economic development of economy, 20*(4), 739-757.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 130*(3), 498-509.

Wang, Y., Pan, J.-f., Pei, R.-m., Yi, B.-W., & Yang, G.-l. (2020). Assessing the technological innovation efficiency of China's high-tech industries with a two-stage network DEA approach. *Socio-Economic Planning Sciences, 71*, 100810.

Wei, C.-K., Chen, L.-C., Li, R.-K., & Tsai, C.-H. (2011). Exploration of efficiency underestimation of CCR model: Based on medical sectors with DEA-R model. *Expert systems with applications, 38*(4), 3155-3160.

Yadava, A. K., & Komaraiah, J. B. (2021). Benchmarking the performance of organic farming in India. *Journal of Public Affairs, 21*(2), e2208.

Zamanian, G. R., Shahabinejad, V., & Yaghoubi, M. (2013). Application of DEA and SFA on the Measurement of Agricultural Technical Efficiency in MENA Countries.

Zhu, J. (2015). *Data Envelopment Analysis a Handbook of Models and Methods*: Springer.