Measuring technical efficiency and productive slacks of Tunisian manufacturing industry: A comparative analysis between the traditional and the bootstrap Data Envelopment Analysis

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Abstract

This research investigates technical efficiency score that focuses on productivity, and helps in establishing a decision-support system to slack industrial performance evaluation especially in the post revolution Tunisian economy using Data Envelopment Analysis (DEA) and Malmquist productivity index (MPI) methodologies.

The Data for this study were collected from the Tunisian National Institute of Statistics (TNIS) over the period 1961 and 2016. Our investigation led us to conclude that the traditional-DEA cannot determine the true efficiency score. We therefore applied the bootstrapping method using the MPI to determinate the efficiency changes over time. Our findings indicate an ambiguous impact of the manufacturing sectors on efficiency levels.

Keys-words**:** Technical efficiency, DEA-traditional, DEA-Bootstrap, Malmquist index

The used Method

A quick glance at the literature related to manufacturing efficiency score allows us to remark a huge discrepancy. In fact, while this topic has been extensively discussed in relation with developed countries, it still suffers a huge shortage if not a total absence of information when it comes to the developing nations. This is what motivated us to carry out this research work on Tunisia, one of the developing countries that go through several economic difficulties during the post revolution era.

The method used in this article relies heavily on the previous works of Koopmans (1951), Debreu (1951) and Farell (1957). Farrell introduced the term of decision making unit (DMU) when using a linear programming consisting of creation of inputs and outputs to vary the entities for which the efficiency scores can be calculated. Also, he presents the distance function as a derived frontier, which indicates the maximum possible efficiency and can after wards easily determine the score for each DMU.

In this case, the DEA model is among the robust non-parametric methods to calculate the technical efficiency estimation and also productivity. Over time, the DEA tried to involve the solution of a linear programming problem through using many kinds of models. First, the DEA-CCR proposed by Charnes, Cooper and Rhodes model (1978) presented in the form of maximization program and can be written as follows:

$$Max\phi + \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$$

$$\text{Subject to} \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = x_{i0} \\ \sum_{j=1}^{n} \lambda_j x_{ij} - S_i^+ = \phi y_{r0} \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases} \quad (1)$$

This model is based on the constant return of scale (CRS) which CRS indicates that every increase or decrease of the quantity of inputs in the production can also change the output. But, this type is not capable of providing information in regards to the degree to which the identified inefficiency may be due to technical inefficiency or scale efficiency. Therefore, Banker, Charnes and Cooper (1984) created the DEA-BCC model based on the variable returns to scale (VRS), which either increases or decreases returns to scale by adding an unconstrained scalar variable θ.

$$Min\theta - \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$$

$$\text{Subject to} \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = \theta x_{i0} \\ \sum_{j=1}^{n} \lambda_j x_{ij} - S_i^+ = y_{r0} \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases} \quad (2)$$

In the BCC-DEA, the production frontier indicates three levels: the segment with increasing returns to scale ($\theta > 0$), the segment of constant returns to scale ($\theta = 0$), and the segment with decreasing returns to scale ($\theta < 0$).

Nonetheless, these traditional models of DEA have some disadvantages, too compared to other econometric methods: Among these drawbacks, we can highlight that these models could not generate the same technical efficiency scores due to the use of a different concept of returns to scale; They are not capable of creating any information about the causes to help look for a different efficiency. Finally these models could not determine accurately the efficiency scores of performance in the distance function of Shepard.

For this reason and in order to correct this problem, Efron (1979) proposed a Bootstrap method to improve the accuracy efficiency score through a statistical inference. Later, some economists like Simar and Wilson (2000) developed this technique and introduced the Bootstrap-DEA model as a method to vary the true efficiency score of DMU or the bias corrected efficiency scores. This estimation allows us to construct the confidence intervals at the same time. The fundamental function of the bias corrected efficiency score of DEA-Bootstrap can be given as follows:

$$\text{bi\hat{a}s} = \bar{\hat{\theta}}_A^b - \hat{\theta}_A \tag{3}$$

where $\hat{\theta}_A$ is the true efficiency score; θ_A is not biased DEA and $\hat{\theta}_A^b$ is the median of the bootstrap of efficiency scores of the DMU. The success of this method lies in the assumption that the distribution of the DEA-bootstrap bias is similar to the DEA-traditional model which:

$$\left\{(\hat{\theta}_A^b - \hat{\theta}_A) \approx (\hat{\theta}_A - \theta_A)\right\} \tag{4}$$

According to Hao and Siping (2015), the confidence interval of the level of α can be presented in these successive steps:

$$\begin{cases} \Pr(-\hat{b}_r \le \hat{\theta}_{kb}^* - \hat{\theta}_k \le -\hat{a}_\alpha) = 1 - \alpha \\ \Pr(-\hat{b}_\alpha \le \hat{\theta}_k^* - \hat{\theta}_k \le -\hat{a}_\alpha) = 1 - \alpha \\ \hat{\theta}_k + \hat{a}_\alpha \le \hat{\theta}_k \le \hat{\theta}_k + \hat{b}_\alpha \end{cases} \tag{5}$$

However, some recent studies argue the case of the double-bias-corrected efficiency score proposed by Simar and Wilson (1998) and was considered in our research in equation (4). Tziogkidis (2012), however, showed that this equation might create some kinds of theoretical problems between the bootstrap bias and the DEA bias. He also says that using Simar and Wilson’s (2000) measurement of the confidence intervals of the DEA-Bootstrap can lead to inconsistent results and cause these probabilities to be invalid.

Thereupon, the bootstrap estimator might fail to calculate the accurate efficiency score. In such situations situations, we may wonder if it has become difficult to define whether the yearly improvements of outputs efficiency are the result of a technical efficiency evolution or a technological one.

Results

The results analysis shows that during these recent years especially after the revolution, the Tunisian economy has known radical changes that catastrophically affected the industrial evolution and therefore the growth of the economy.

Obviously, the Tunisian economy future seems to be rather gloomy because almost of the indicators are so low and sometimes negative. In this regard, we conclude that the revolution has not yet achieved its goal. Thus, for the new Tunisia, the post-revolution period require very careful studies based on rigorous data which would allow suggesting new opportunities and to apply immediate solutions on the short-run in order to solve certain socio-economic and political problems of the country otherwise we risk having more and more disastrous results.

The results also indicate an eventual capacity shortfall, since the most important productive resource does not seem to cope with the growing demand in the future.

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