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On the Efficiency of Manufacturing Sectors: Evidence from a DEA Additive Bootstrap Model for Tunisia

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Abstract

In this study we apply a DEA additive (Range Adjusted Measure (RAM)) bootstrap model to evaluate industrial sectors of a small open economy according to an input-output efficiency measure. The technical efficiency of the Tunisian manufacturing sectors is estimated for the possible time period following the 90's reform initiatives. The sources of inefficiencies in each sector are also quantified. Our estimates reveal that the most efficient sectors are the wood, followed by the chemicals and the electrical and electronics sectors, whereas the least efficient ones are the non-metallic, food and beverages and basic metals and metal products. Our estimates also provide evidence in favor of an eventual pick-up in the overall efficiency of the manufacturing sectors starting in early 2000's after a steady decline in overall efficiency during the late 90's.

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1. Introduction

Most of the developing economies have been trying to rely on the manufacturing sector as an engine to boost production and enhance growth for their economy. Offering generous financial and fiscal incentives to foreign investors were among the policies adopted by many developing economies in order to develop their manufacturing sector. More precisely, such policies resulted in injecting productive capital into the economy through the inflow of Foreign Direct Investment (FDI). Hence, these policies have been generally considered as being effective in reducing the unemployment rate and in creating growth. However, the literature has not paid much attention to investigating the efficiency of the resulting manufacturing sector's structure. Thus determining appropriate estimates for the efficiency of the manufacturing sectors of any economy not only provides policymakers with a convenient tool to evaluate quantitatively the relative performance of each sector but also provides them with an adequate measure of the competitiveness level attained by each sector.

Tunisia is a perfect example of a small open economy that focused on developing a manufacturing base following its independence. Prior to 1982, the manufacturing sector accounted on average for about 11% of its GDP. After 1982 the manufacturing sector's share of GDP almost doubled to represent on average about one-fifth of GDP. This increase was due to the strong willingness of policymakers to develop the manufacturing sector. In fact, between early 70's and early 80's Tunisia relied on a public sector-led growth development model supported by the creation of an export-oriented manufacturing sector driven by the inflow of FDI.

In order to further develop its manufacturing sector, a structural adjustment program prompted by privatization and trade liberalization was introduced by late 80's and an investment invitation code was implemented in 1992. The initial structural change of the manufacturing sector resulted in a rapid development of the textile and apparel sector. The second structural change witnessed the rapid increase in the manufacturing sectors of machinery, electrical and parts of motor vehicles by the late 1990s.

This study aims to apply a mathematical programming tool, known as Data Envelopment Analysis (DEA) to measure the performance of a small open emerging economy based on sectorial efficiency estimates. Unlike the parametric modeling techniques, DEA modeling does not assume a priori any functional form between the variables under study, in particular between inputs and outputs. In addition to that, DEA technique allows us to include in the model more than one output variable. Last but not least, the deterministic framework of DEA modeling is overcome by employing the bootstrap technique to statistically validate the estimations.

The relative technical efficiency of all Tunisian manufacturing sectors over time are estimated based on a DEA additive bootstrap (RAM-bootstrap) model for the sample input, output data available from the United Nations Industrial Database, INDSTAT2 2014 ISIC Rev.3. For the data set considered by our study the RAM produced the most efficient estimates when compared to the input-oriented and to the output-oriented DEA models. More precisely, the RAM-based estimates showed smaller biases, smaller standard errors and smaller ranges of confidence intervals. In addition to that, the RAM provides estimates of technical efficiency by minimizing inputs and maximizing outputs simultaneously, just in accordance with the main objective of policymakers of any economy. Moreover, the RAM allows us to calculate the excess of each input and the shortfall in each output for each sector relative to the most efficient one. Hence, the RAM-bootstrap model is not only statistically more accurate for our problem setting but also fits well with the objective of policymakers for such a developing economy. In particular, the Tunisian economy's development process of its manufacturing sector is evaluated based on simultaneously minimizing inputs and maximizing outputs. So, not only can we classify manufacturing sectors according to an efficiency measure, but we can also track that efficiency over time allowing us to evaluate the impact of policy actions undertaken to enhance production and boost exports. Moreover, we are able to identify technical inefficiencies for all sectors over time according to input excesses and output shortfalls.

The paper is organized as follows: Section 2 reviews the literature and section 3 introduces the data and methodology used. Section 4 presents the results and discussion and section 5 concludes.

2. Literature review

The Data Envelopment Analysis (DEA) was initially introduced and developed by Charnes *et al* (1978, 1981) as a novel non-parametric approach destinated to measure efficiency following the seminal works of Koopmans (1951), Debreu (1951) and Farrell (1957). The DEA method employs mathematical programming to estimate a piece-wise-linear frontier over the data and relative to which efficiency is calculated. Economically, efficiency refers to producing certain level of outputs with the minimum inputs or producing maximum outputs out of the certain levels of inputs. Similarly, achieving the highest possible levels of outputs with the minimum levels of inputs is also considered as efficiency.

Most of the literature that dealt with estimating efficiency employed either the input-oriented or the output-oriented method. For instance, Restrepo *et al* (2015) conducted a comparative analysis of industrial sector exports for Colombia by building an input-oriented efficiency index. However, any economy's goal is to produce the maximum out of the minimum resources. To the best of our knowledge, this study is among the first that applies a non-deterministic DEA model with an input-output oriented objective to assess the relative technical efficiencies of manufacturing sectors. It is more plausible that policymakers treat each manufacturing sector as a decision making unit seeking to increase production and boost exports by employing as minimum resources as possible.

3. Data and methodology

Data is taken from the UNIDO Industrial statistics database. The data for the Tunisian manufacturing sectors are obtained at the 2-digit level according to the International Standard Industrial Classification (ISIC Rev. 3). The possible recent data set covers the period 1993 to 2002 and 2006 for which the number of employees is completed by that of 2007.

The variables used as inputs are the number of employees and the Gross Fixed Capital Formation. The number of employees refers to the total number of persons who work in or for the establishment during the reference year and the Gross fixed Capital Formation refers to the value of purchases of fixed assets that are intended for the use of the establishment during the reference year less the value of corresponding sales. Fixed assets include land, buildings, transport equipment, machinery and other equipment.

The variables used as outputs are domestic output and exports, where domestic output is defined as output minus exports. Output refers to the value of goods or services that are produced within an establishment that become available for use outside that establishment, plus any goods and services produced for own final use. The export series for each manufacturing sector are taken from the United Nations Comtrade database.

The model employed in this study utilizes the goal vector approach of Thrall (1996). Hence, an additive model known in the literature as the Range Adjusted Measure (RAM) is applied over time series for a panel of the Tunisian manufacturing sectors. The advantage of this model is that it avoids the problem of choosing between input and output orientation and simultaneously maximizes outputs and minimizes inputs. Hence, we take efficiency as achieving the highest outputs with the lowest possible inputs. Slacks in the objective function are accorded weights as in Cooper *et al* (1999). The reason behind this is to ensure that the mathematical programming solutions are free of the units in which the inputs and the outputs are stated.

For each sector k, $(k = 1, \ldots, n)$ in period τ, $(\tau = 1, \ldots, T)$ the following problem must be solved:

$$\max_{\lambda_{jt}, s_{ik\tau}^{-}, s_{rk\tau}^{+}} Z_{k\tau} = \sum_{i=1}^{m} g_i^{-} s_{ik\tau}^{-} + \sum_{r=1}^{s} g_r^{+} s_{rk\tau}^{+}$$

Subject to

$$\sum_{t=1}^{T} \sum_{j=1}^{n} x_{ijt}\, \lambda_{jt} + s_{ik\tau}^{-} = x_{ik\tau}\,, \quad i = 1 \ldots m$$

$$\sum_{t=1}^{T} \sum_{j=1}^{n} y_{rjt}\, \lambda_{jt} - s_{rk\tau}^{+} = y_{rk\tau}, \quad r = 1 \ldots s$$

$$\sum_{\mathrm{t}=1}^{\mathrm{T}} \sum_{j=1}^{n} \lambda_{jt} = 1,$$

$$\lambda_{jt} \geq 0\,, \quad j = 1 \ldots n\,, \mathrm{t} = 1, \ldots, \mathrm{T}$$
$$s_{ik\tau}^{-} \geq 0, \quad i = 1 \ldots m\,, \mathrm{t} = 1, \ldots, \mathrm{T}$$
$$s_{rk\tau}^{+} \geq 0\,, \quad r = 1 \ldots s$$

where,

x_{ijt} : quantity of input i, $(i = 1, \ldots, m)$ used by sector j, $(j = 1, \ldots, n)$ in period t, $(t = 1, \ldots, T)$.

y_{rjt}: quantity of output r, $(r = 1, \ldots, s)$ produced by sector j, $(j = 1, \ldots, n)$ in period t, $(t = 1, \ldots, T)$.

$s_{ik\tau}^{-}$: over utilization of input i, by sector k, in period τ.

$s_{rk\tau}^{+}$: under production of output r, by sector k, in period τ.

g_i^{-} and g_r^{+}: weight of the slack variable to input i, and that to output r, respectively. $g_i^{-} = \frac{1}{R_i^{-}}$, where $R_i^{-} = \max_{tj} x_{ijt} - \min_{tj} x_{ijt}$ is the range of input i and

$g_r^{+} = \frac{1}{R_r^{+}}$, where $R_r^{+} = \max_{tj} y_{rjt} - \min_{tj} y_{rjt}$, is the range of output r.

Accordingly, sector k at time τ is efficient if and only if all slacks are null. In particular, the range adjusted measure of technical efficiency is given by, $\Gamma_{k\tau} = 1 - \frac{1}{(m+s)} Z_{k\tau}$. $\Gamma_{k\tau}$ takes values between 0 and 1 with higher values indicating increasing efficiency. More details on the properties of this efficiency measure are provided in Cooper *et al* (1999).

In order to overcome the deterministic framework of the DEA, a bootstrap technique is performed on the estimated efficiency scores. In analogy to the bootstrap algorithm developed by Simar and Wilson (1998) for the radial DEA model, we developed a bootstrap algorithm for the non-radial DEA-RAM model. For the resampling process of input and output data, Simar and Wilson (1998) applied a Data Generating Process (DGP) on the efficiency score, however, in our case the DGP is applied on the slack variables (s^-, s^+). The adjusted bootstrap algorithm is used to test the robustness of the efficiency estimates. In this general multi-input-multi-output model, the bootstrap offers inferences on the calculated efficiency scores by estimating the bias, the variance and construct the confidence intervals. Since, in our case the distribution is unknown and the sample size is small, the bootstrap technique is well justified to test the robustness of our RAM model estimates.

4. Results and discussion

First, the input variables considered are employment and the value of fixed capital formation used by each manufacturing sector, while the output variables are simply the value of domestic outputs and the value of exports generated by each sector. The sectors considered by the analysis are presented in Table I: We retained the sectors that produced a period average of more than 4% of total manufacturing output.

Table I: Average period shares in total manufacturing in percentage

Manufacturing Sector	Labor	Capital	Output	Export
Textile, Apparel & Leather	47.2	21.4	27.5	55.6
Food & Beverages	11.9	22.3	23.2	8.9
Chemicals	4.2	7.9	12.1	8.1
Metals & Metal Products	6.3	6.6	7.0	4.8
Non-metallic	7.5	14.4	6.7	1.7
Electrical & Electronics	6.5	5.5	5.8	11.8
Wood	1.8	3.0	4.6	0.3
Total	85.4	81.2	86.9	91.3

For the considered sample period, these seven sectors on average produced around 87% of total manufacturing output, exported more than 90% of total manufacturing exports, employed more than 80% of total capital utilized by the manufacturing industries and used more than 85% of total employees in the manufacturing sector. So, over the sample period, textile, apparel and leather products utilized on average around one-half of total labor employed by manufacturing and one-fifth of total capital injected in manufacturing to produce more than one-quarter of manufacturing output and exports more than one-half of total manufacturing exports. The food and beverages comes as the second most important manufacturing sector since it produced more than one-fifth of total manufacturing output and exported around one-tenth of total manufacturing exports by utilizing a little bit more than one-tenth of total labor employed in manufacturing and using more than one-fifth of total capital injected in manufacturing. But, how efficient were those performances?

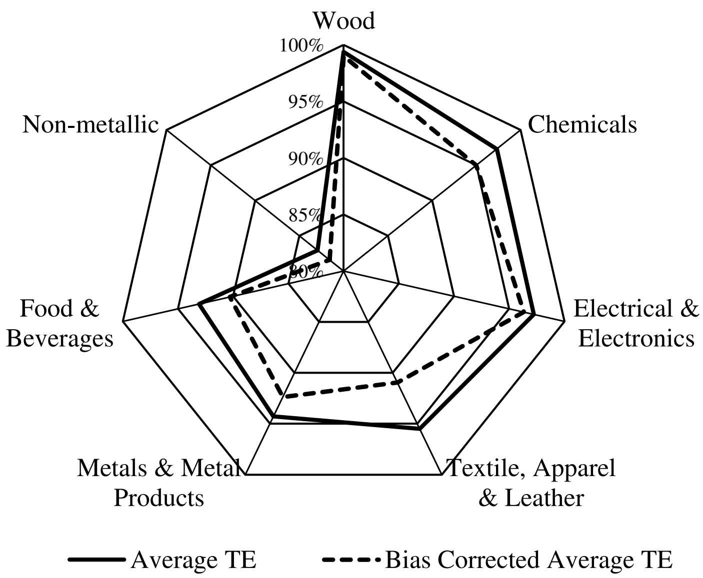
In order to answer such a question, the technical efficiencies of each sector are estimated for each point in time according to the DEA-RAM model. In fact, DEA is best suited to measure technical efficiencies to homogenous Decision Making Units (DMUs) and when the input and the output variables are measured in physical counts rather than in their equivalent currency value. However, most of the labor demanded by the Tunisian manufacturing industry at that time were unskilled, World Bank (2009). Hence, for our problem setting, labor can be considered as interchangeable between sectors. In addition to that, using value-based measures for fixed capital formation and for the output variables is well justified. Besides the fact that data in physical units for such variables is not available and may not be comparable across different manufacturing sectors, policymakers are mainly concerned about how to identify engines of growth in the economy by allocating available resources measured in monetary value to the most efficient sectors, those that employ the least value of inputs to get the highest value of outputs. Moreover, the output prices of the sectors considered in our study are not that much different. In fact, during that period the manufacturing sectors mainly produced low-skilled labor-intensive products such as garments, food products and beverages, fertilizers, parts and electrical components, etc.(World Bank (2009)). Therefore, manufacturing sectors can be treated as homogenous DMUs, just in line with the conventional DEA model.

The period averages of the estimated technical efficiencies (TE) for each sector k, $\bar{\Gamma}_k$ are calculated and presented in Table II. Based on the bootstrap technique, our estimates turned out to be very robust as it can be easily deduced from the values of the estimates corrected for the bias, $\bar{\Gamma}_k^c$ and from the small biases, small standard errors and small ranges of confidence intervals. We also report absence of outliers indicating that the data set used is homogenous.

Table II: Period averages of the estimates of sectorial technical efficiencies in percentage

	Manufacturing Sector	$\bar{\Gamma}_k$	$\bar{\Gamma}_k^c$	**Bias**	**Std. Dev.**	**Lower**	**Upper**
1	Wood	99.4	99.0	0.4	0.8	97.7	101.8
2	Chemicals	97.3	95.0	2.3	1.1	92.2	96.5
3	Electrical & Electronics	97.2	96.3	0.9	4.7	87.4	107.0
4	Textile, Apparel & Leather	95.5	91.0	4.5	3.6	85.2	95.1
5	Metals & Metal Products	94.3	92.4	1.9	0.8	90.5	94.0
6	Food & Beverages	93.1	90.3	2.8	2.6	84.6	92.4
7	Non-metallic	82.9	81.6	1.3	0.4	80.9	82.2

Figure 1: Period averages of sectorial technical efficiencies



As it can be seen from Figure 1, the manufacturing sectors over the study period are ranked according to the period averages of the estimated efficiencies. The least efficient sectors turned out to be the non-metallic, the food & beverages and the metals and metal products, whereas, the most efficient ones are the wood, chemicals and the electrical and electronics sectors. Hence, relative to other sectors wood, chemicals and the electrical and electronics produced the maximum domestic output and the maximum exports out of the minimum employees and capital assets. It is straightforward to notice that the most efficient sectors are not the most important ones in terms of output shares or input utilization. Hence these sectors are far from their optimal sizes and policymakers can devise strategies to develop wood, chemicals and electrical and electronics sectors. In fact, in the late 90's, Tunisia promoted the electrical components sector by attracting foreign direct investment in the automotive components. Nevertheless, based on our results, it were able to include in its manufacturing development program the promotion of the wood and chemicals sectors too.

In order to obtain more insight from the mathematical model developed to estimate these technical efficiencies, the sources of technical inefficiencies are determined for each sector at each point in time and the period averages of the excesses in input utilization and shortfalls in outputs are calculated and given in Table III.

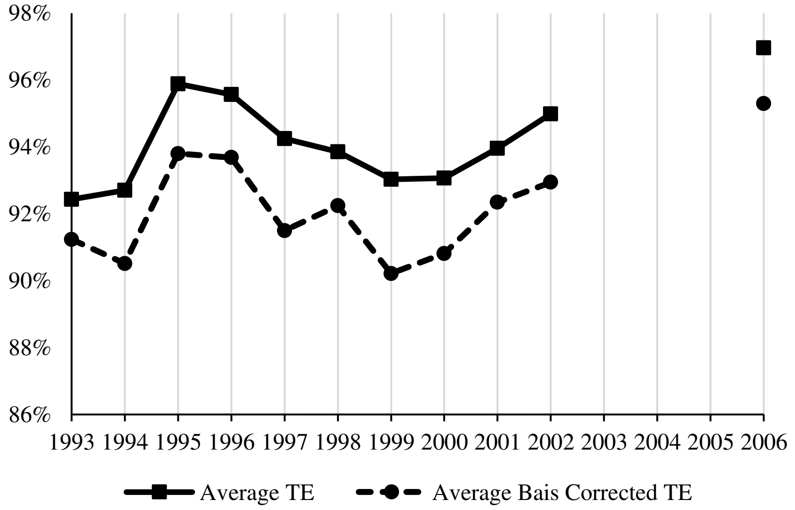
Table III: Period averages of the excesses and shortfalls in percentage

	Manufacturing Sector	**Excess Labor**	**Excess Capital**	**Shortfall Domestic Output**	**Shortfall Export**
1	Wood	20.8	0.8	8.0	103.3
2	Chemicals	0.0	9.6	11.2	40.8
3	Electrical & Electronics	2.0	0.0	212.6	0.0
4	Textile, Apparel & Leather	3.0	16.2	5.5	0.0
5	Metals & Metal Products	22.8	0.0	106.3	121.7
6	Food & Beverages	40.8	15.9	0.0	57.7
7	Non-metallic	34.1	41.3	85.7	779.1

The slack analysis provides an insight into inefficiencies in the least productive units. For example, the non-metallic sector which turned out to be the least efficient one had the capacity to produce about 86% more and export about eight times more than what actually did. Moreover, it could have produced and exported the same amounts with 41% less capital and 34% less labor. The inefficiency of the non-metallic sector could be due to the fact that the privatization process of public cement companies which started in the late 1990s and lead to considerable flows of FDIs to the non-metallic sector, was not accompanied with sectorial price liberalization.

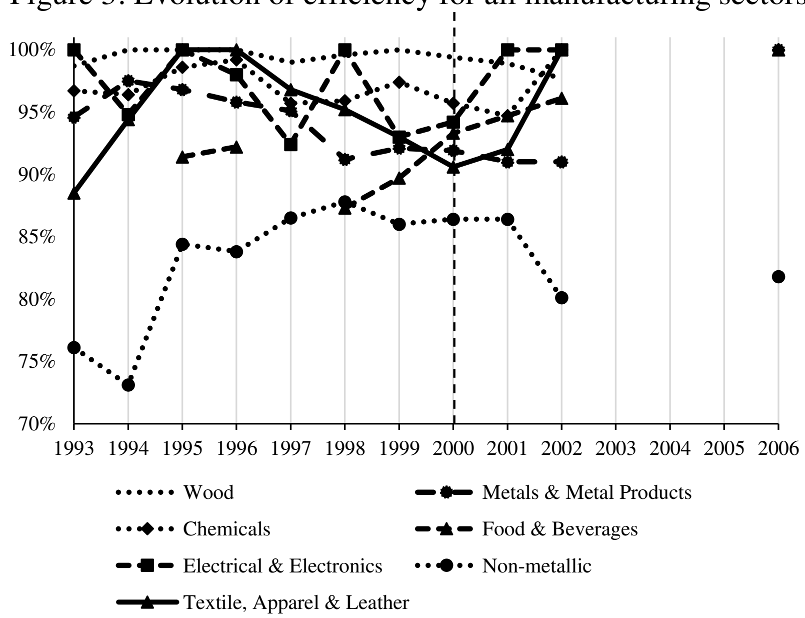
A clear policy implication that can be derived from Table III is that Tunisia could have benefited better from the development program of its manufacturing sector if the excesses and shortfall given in Table 3 were available in early 2000. In particular, a better strategy for the development of its manufacturing sector would have been to slow down the inflow of capital to the textile, apparel and leather and the food and beverages sectors and instead encourage the investment in the manufacture of wood, chemicals, electrical and electronics, and with a lesser extent in the basic metals and fabricated metal products sectors. Our estimated measures produced by the RAM model are also used to sketch the evolution of the average efficiency of the total manufacturing industry over time, hence help in evaluating the ongoing manufacturing development process. As it can be seen from Figure 2, the overall average efficiency was steadily falling during the late 90's and a clear pick up in overall average efficiency is detected during early 2000, witnessing a positive impact of the preset reforms on the efficiency of the manufacturing development process.

Figure 2: Evolution of the overall average efficiency for the manufacturing industry



Based on Figure 3, where the evolution of the sectorial average estimated efficiencies are plotted, we can notice that the pick-up in overall average efficiency after the year 2000 is due to the net improvement in the efficiency for the electrical and electronics, textile, apparel and leather and food and beverages sectors.

Figure 3: Evolution of efficiency for all manufacturing sectors



5. Conclusion

The DEA-RAM model applied over a panel of sectorial time series can be considered as an excellent tool that can be employed to measure the relative performance of manufacturing sectors over time. In particular, estimating adequately the relative efficiencies of all sectors as well as their evolution over time can only be of great help to policymakers of any economy. In fact, assessing whether an economy is producing the maximum out of the minimum resources can provide policymakers with insights to reallocate resources and optimize the capacity utilization of its economy. Despite the lack of observations Tunisia is a perfect example of a small open economy which has been trying developing its manufacturing sector to boost exports and generate growth. Based on the estimations of the technical efficiencies for the considered manufacturing sectors derived from a DAE additive bootstrap model, several findings are reached.

First, the most important sectors which are the textile, apparel and leather and the food and beverages sectors were not the most efficient but performed well since the source of inefficiency was mainly due to the excess capital employed.

Second, some evidence in favor of a pick-up in efficiency is detected in early 2000 suggesting that the manufacturing adjustment programs adopted in the mid 90's were to some extent successful.

Third, the economy of Tunisia could have been improved if policymakers did not exaggerate in encouraging investment in sectors like the textile, apparel, and leather; and food and beverages, and instead investigated the promotion of investment in other sectors such as the manufacture of wood, chemicals, electrical and electronics and/or basic metals and fabricated metal products sectors.

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