A Three Stage DEA Approach for Evaluating the Performance of Supply Chains: Case Study of Public Pharmaceutical Products Supply chains in Morocco

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Abstract

Supply chain performance evaluation is a critical and difficult task in supply chain management. This paper presents a performance evaluation framework to evaluate and compare the performance of different supply chains. The framework is based on Data Envelopment Analysis (DEA) as a data oriented tool for evaluating the performance of several supply chains that convert multiple inputs to multiple outputs. The objectives of this study are: (a) to construct a set of aggregated indicators that best characterize the performance of supply chains (b) to estimate the relative technical, pure technical and scale efficiencies of supply chains and interpret the results, and finally (c) to estimate the magnitudes of input adjustments that would have been required to make each supply chain efficient. The proposed approach is then applied to evaluate real-life public pharmaceutical products supply chains in Morocco.

Keywords
Data Envelopment Analysis (DEA), performance evaluation framework, supply chain performance.

1. Introduction

Supply chain performance evaluation is a very complex task the managers should undertake to take appropriate actions for continuous improvement. According to Mentzer et al. (2001), supply chain management is defined as the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purpose of improving the long-term performance of the individual companies and the supply chain as a whole. Thus an effective and efficient supply chain management is an essential foundation for companies to achieve sustainable competitive advantage. In fact, competitive advantage was defined by Porter (1985) as the extent to which an organization is able to create a defensible position over its competitors.

Nelly et al. (1995) consider time, cost, quality and flexibility as the main measures of the performance in manufacturing. Beamon (1999) proposes a supply chains performance measurement framework considering three essential components to supply chain success which are: resources measures (e.g. manufacturing costs, inventory costs etc…), outputs measures (e.g. Sales, profit etc…) and flexibility measures (the system reaction to uncertainty). Indeed, there exist several discrepancies in performance measurement literature, this means that there exists great ambiguity among practitioners and decision makers regarding the use of performance measures to assess systems' performance.

To address this issue, this work aims to stress on the supply chain performance measurement problem. Traditionally, supply chains were driven by manufacturers who managed and controlled the pace at which products were developed, manufactured and distributed (Stewart, 1997). A well-known method for efficiency measurement was the ratio of single output to single input (Zhu, 2014). These measures ignores the interactions among the different supply chain activities and characteristics and are not sufficient to assess overall supply chain efficiency.

Another well-known management tools some researchers used to address supply chain performance are the Balanced Scorecard (BSC), the supply chain operations reference (SCOR model) and the Activity Based Costing (ABC) methods. However, these tools are inconvenient to use if the objective is to benchmark several supply chains with multiple inputs and multiple outputs. Therefore, an approach for measuring the efficiency of supply chains with multiple criterions is extremely required.

This paper takes an opposite position and presents a framework for evaluating and assessing the performance of different supply chains based on Data Envelopment Analysis. Section 2 provides the relevant literature review and lays foundation for section 3, in which a performance evaluation framework for assessing the performance of different supply chains is proposed. In section 4 an application of the proposed approach to an illustrative example of several public pharmaceutical products supply chains in Morocco is provided. Finally, section 5 summarizes some concluding remarks and discusses some potential extensions of the research.

2. Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a "data-oriented" approach for evaluating the relative efficiency of a set of peer entities called Decision-Making Units (DMUs), a DMU is any entity that is to be evaluated in term of its ability to convert multiple inputs into multiple outputs (Cooper et al., 2011). A DMU is to be rated as fully efficient if and only if the performances of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs (Cooper et al., 2011). DEA relies on linear programming to construct a best practice frontier to which each inefficient DMUs is compared. The first model of DEA named after its developers Charnes, Cooper & Rhodes was proposed in 1978. This model had an input orientation and assumed constant-return-to-scale. This, of course, is rather restrictive as constant return to scale doesn't always hold globally in many realistic cases. As a result, Banker, Charnes & Cooper (1984) generalized the original DEA model for firm's exhibiting variable return to scale (constant, increasing or decreasing return to scale). This extension of DEA named BCC model estimates the pure technical efficiency of DMUs which is the component of the overall technical efficiency that can be contributed to the management performance (Cooper et al., 2011).

DEA allows each DMU to choose its inputs and outputs weights that most benefits its evaluation. Dyson et al. (2001) suggest that the sample size of DMUs should be at least twice the product of the number of inputs and the number of outputs in order to keep the discriminatory power of DEA. To overcome this limitation only inputs and outputs that provides the bulk of the production process should be used. In order to keep the maximum information required in a minimum number of output and inputs, we suggest to use DEA to aggregate a set of indicators into one composite indicator. Section 2.4 provides more details about the proposed methodology.

2.1 Basic DEA model : CCR model

The CCR model is one of the most basic DEA models, it's the most widely known and used to evaluate the relative efficiency of decision making units. The basic CCR model have an input orientation and assume constant returns to scale. A DMU is operating under constant returns to scale if an increase in the inputs results in a proportionate increase in the output levels. This model calculates the relative efficiency of DMUs and it has been proven that it produces good results in terms of evaluating the global efficiency of decision making units (Charnes et al., 1978).

We are interested in determining the overall technical efficiency θ^*_{CCR} of a selected decision making unit k (DMU_k) according to its ability to convert multiple inputs into multiple outputs. Overall technical efficiency is defined as the ratio of total weighted outputs to the total weighted inputs.

Suppose that we have n DMUs $\{DMU_j, j=1, 2,...,n\}$, which produce s outputs y_{rj} : $r=1,2,....s$, $j = 1, 2,...,n$ by consuming m inputs x_{ij} : $i = 1,2,....m$, $j = 1, 2,...,n$. . Let v_i and u_r be respectively the weights to be determined for input i and output r and v_i* and u_r* the optimal solutions for v_i and u_r. To define the overall technical efficiency θ_k of a selected decision making unit k (DMU_k) the following mathematical model was formulated (Cooper et al., 2011):

$$\left.\begin{aligned} &\max \theta_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \\ &\text{Subject to} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad (1 \leq j \leq n) \qquad (1) \\ &u_r \geq 0 ;\ v_i \geq 0, \quad (1 \leq i \leq m)\ (1 \leq r \leq s) \qquad (2) \end{aligned}\right\} \qquad (2.1)$$

The mathematical programming problem (2.1) is equivalent to the following linear programming problem with the unique free decision variable θ:

$$\left.\begin{aligned} &\min \theta \\ &\text{Subject to} \quad \sum_{j=1}^{n} \lambda_j x_{ij} - \theta x_{ik} \leq 0, \quad (1 \leq i \leq m) \qquad (3) \\ &\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk}, \quad (1 \leq r \leq s) \qquad (4) \\ &\lambda_j \geq 0, \quad (1 \leq j \leq n) \qquad (5) \end{aligned}\right\} \qquad (2.2)$$

θ^*_{CCR} is the optimal solution for the problem (2.2) and λ_{j^*} is the weight to be determined for DMU_j. A DMU is globally inefficient if the efficiency score given by the optimal value for the linear programming problems is less than one (θ^*_{CCR} < 1). All the points with (θ^*_{CCR} = 1) lie on the frontier. An inefficient DMU can be made more efficient by projection into the frontier.
Consider that the optimal solution to (2.2) yields values of λ_j^*, the following conditions identify the situation for return to scale (RTS) for the CCR model (Cooper et al., 2011):

(i) Constant Return to Scale (CRS) prevail at a DMU_k if and only if $\sum_{j=1}^{n} \lambda_j^* = 1$
(ii) Decreasing Return to Scale (DRS) prevail at a DMU_k if and only if $\sum_{j=1}^{n} \lambda_j^* > 1$
(iii) Increasing Return to Scale (IRS) prevail at a DMU_k if and only if $\sum_{j=1}^{n} \lambda_j^* < 1$

2.2 BCC model

The pure technical efficiency of a specific DMU_k under variable return to scale can be calculated by the following BCC model with the unique free decision variable θ (Cooper et al., 2011):

$$\left.\begin{aligned} &\min \theta \\ &\text{Subject to} \quad \sum_{j=1}^{n} \lambda_j x_{ij} - \theta x_{ik} \leq 0, \quad (1 \leq i \leq m) \qquad (6) \\ &\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk}, \quad (1 \leq r \leq s) \qquad (7) \\ &\sum_{j=1}^{n} \lambda_j = 1, \quad (1 \leq j \leq n) \qquad (8) \end{aligned}\right\} \qquad (2.3)$$

The objective function aims to maximize the pure technical efficiency θ^*_{BCC} of the decision making unit under evaluation (DMU_k).The additional constraint provides that the reference set is formed as a convex combination of DMUs. It also ensures that the composite unit is of similar scale size as the unit being measured (Martic et al., 2009)

2.3 A two stage CCR-BBC models for examinating technical, pure and scale efficiencies

The ratio of the overall technical efficiency (CCR model) to the pure technical efficiency (BCC model) is called the scale efficiency SE.

$$SE = \theta^*_{CCR} / \theta^*_{BCC} \qquad (9)$$

Overall technical efficiency obtained from the CCR model measures inefficiencies due to the input/output configuration as well as the size of operations, where pure technical efficiency or managerial efficiency obtained from the BCC model is the component of the overall technical efficiency that measures inefficiencies due to only managerial underperformance (short term), and scale efficiency is the component of overall technical efficiency that can be attributed to the size of operations (long term) (Cooper et al., 2011; Kumar and Gulati, 2008).

A unit is said to be scale efficient when its size of operations is optimal so that any modifications on its size will render the unit less efficient (Cooper et al., 2011)

Illustrative Example:

Suppose that we have five supply chains (DMUs) (A, B, C, D, E) consuming a single input x to produce a single output y. The values of inputs and outputs of these DMUs are shown in Fig.1.: A = (1,1) ; B = (1.5 , 2) ; C = (3,4) ; D = (4,5) ; E = (4, 4.5) .An inefficient DMU can be made more efficient by projection onto the frontier. Projection onto the BCC frontier will remove the managerial underperformance while projection onto the CCR frontier will remove inefficiencies due to the size of operation as well as managerial performance. Ray OBC is the constant returns to scale (CCR) frontier. Segments AB, BC, and CD constitute the BCC frontier, and exhibit respectively increasing, constant, and decreasing returns to scale. We can solve the problem (2.3) for DMU_A to prove that IRS prevails at DMU_A. The application of (2.3) to DMU_A yields the values θ^*_{CCR} =3/4 ; λ_C^* = 1/4 and λ_j^* =0 (for j≠C) which means that DMU_A is CCR inefficient, $\lambda_A^* + \lambda_B^* + \lambda_C^* + \lambda_D^* + \lambda_E^* < 1$ thus IRS prevails at DMU_A. By applying (2.3) to DMU_E, we have a frontier point E'' = (3.375, 4.5) on the ray OBC where CRS prevails. However, if we apply (2.4) to DMU_E, the projection yields E'= (3.5, 4.5) where DRS prevails. This means that the $DMU_{E'}$ is BCC efficient (after removing managerial inefficiencies) while $DMU_{E''}$ is globally efficient or CCR efficient (after removing managerial and scale inefficiencies).

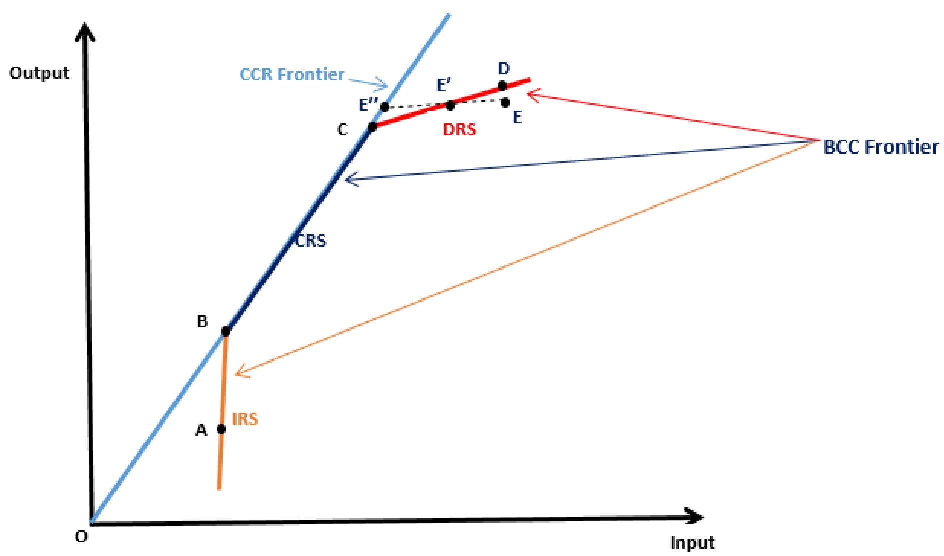

Figure 1. CCR and BCC Frontiers

2.4 Aggregation of indicators using DEA

Many methods have been used to construct aggregate indicators (Nardo et al., 2005; Olsthoorn et al. 2001). The existing aggregation tools for constructing aggregate indicators can be divided into two categories: the indirect approach which frequently involves the normalization of the underlying sub-indicators and the weighting and aggregation of the normalized sub-indicators by using Multi Criteria Decision Analysis (MCDA), and the direct approach, in which an aggregate indicator is directly obtained from the underlying sub-indicators using DEA. The advantage of the direct approach is that it doesn't require the determination of weights for the original sub-indicators. In recent years, many researches for constructing aggregate indicators have been undertaken using DEA (Mahlberg and Obersteiner, 2001; Cherchye, 2001; Despotis, 2005; Zhou et al., 2007). This chapter describes a methodology based on DEA for indicators aggregation. This method is widely inspired from the seminal work of Zhou et al.(2007). We consider the case where there are *m* supply chains under evaluation. Suppose we have classified all the indicators into several categories and our aim is to aggregate each category into one indicator called aggregated indicator or composite indicator to evaluate the performance of supply chain *i* with respect to a given category.

The problem is to aggregate a set of indicators I_{ij} (j=1,2,... n) into a composite indicator I_i that can be used to evaluate the performance of supply chain *i* with respect to all the underlying sub-indicators of a given category of indicators. DEA is used to suggest the "best" and the "worst" set of weights for each supply chain which are used to aggregate the sub-indicators into a performance score.

The following method which combines two DEA models (2.4) and (2.5) can be used.
To determine the "best" vector of weights w_{ij}^{g} for each supply chain *i*, the following model can be formulated:

$$\left.\begin{array}{ll} \max\ gI_i = \sum_{j=1}^{n} w_{ij}^{g}\, I_{ij} & \\ \text{Subject to } \sum_{j=1}^{n} w_{ij}^{g}\, I_{kj} \leq 1\ ,\ (1 \leq k \leq m) & (10) \\ w_{ij}^{g} \geq 0\ ,\ (1 \leq j \leq n) & (11) \end{array}\right\} \quad (2.4)$$

The mathematical model (2.4) is an input oriented DEA model with multiple outputs and constant inputs, which measures how far the evaluated supply chain is from the best practice category under the best possible weights. It provides an aggregated performance score for supply chain i in terms of all the underlying sub-indicators of a given category. By solving (2.4) repeatedly for each supply chain, we will obtain the optimal index gI_i^* for each supply chain i. Let $[gI_1^*, gI_2^*, ..., gI_m^*]$ be the optimal indices vector for these supply chains.
Model (2.5) determines the "worst" vector of weights w_{ij}^{b} for each supply chain *i*, it is very similar to an output oriented DEA model with multiple inputs and constant outputs:

$$\left.\begin{array}{ll} \min\ bI_i = \sum_{j=1}^{n} w_{ij}^{b}\, I_{ij} & \\ \text{Subject to } \sum_{j=1}^{n} w_{ij}^{b}\, I_{kj} \geq 1,\ (1 \leq k \leq m) & (12) \\ w_{ij}^{b} \geq 0\ ,\ (1 \leq j \leq n) & (13) \end{array}\right\} \quad (2.5)$$

bI_i^* is the optimal solution for the problem (2.5).
The two indexes provided by (2.4) and (2.5) are based on the weights that are most favorable and least favorable for each supply chain. We can combine them into an overall index by the following way:

$$I_i(\alpha) = \alpha.\frac{gI_i^* - gI^-}{gI^+ - gI^-} + (1-\alpha).\frac{bI_i^* - bI^-}{bI^+ - bI^-} \qquad (14)$$

Where:

- $gI^+ = \max\ \{gI_i^*, i=1, 2 \ldots m\}$
- $gI^- = \min\ \{gI_i^*, i=1, 2 \ldots m\}$
- $bI^+ = \max\ \{bI_i^*, i=1, 2 \ldots m\}$
- $bI^- = \min\ \{bI_i^*, i=1, 2 \ldots m\}$

$0 \leq \alpha \leq 1$ is an adjusting parameter which reflects the decision maker's preferences. If α = 1, I_i will become a normalized version of gI_i^*. If α = 0, I_i will become a normalized version of bI_i^*. For other cases, $I_i(\alpha)$ makes a compromise between the two indexes. If the decision maker is neutral α = 0.5 is generally used.

3. A three stage DEA approach for evaluating the performance of a supply chain

This chapter explains the motivations behind the use of DEA for supply chain performance evaluation and introduces a three stage DEA approach for evaluating the performance of a supply chain.

3.1 DEA for supply chain performance evaluation

Performance measurement enables supply chains to continuously manage and control achieving objectives. It provides the necessary assistance for performance improvement in pursuit of supply chain excellence. There are many reasons which justify the adoption of DEA to evaluate the supply chain performance: First DEA is a very powerful tool for supporting the process of decision making. It has the ability to handle multiple inputs and outputs**,** and allows the analysis of quantitative as well as qualitative measures (Cooper et al., 2011). In addition, it doesn't require to define any relationship between the chosen inputs and outputs and gives information about the efficient DMUs as well as the inefficient DMUs (Cooper et al., 2011). Finally, DEA is easily compatible with other analytical methods such as statistical analysis, sensitivity analysis and other multi criteria decision analysis techniques**.**

3.2 Proposed performance evaluation framework for supply chains

In order to assess the performance of supply chains, we introduce the following performance evaluation framework (Fig.2).

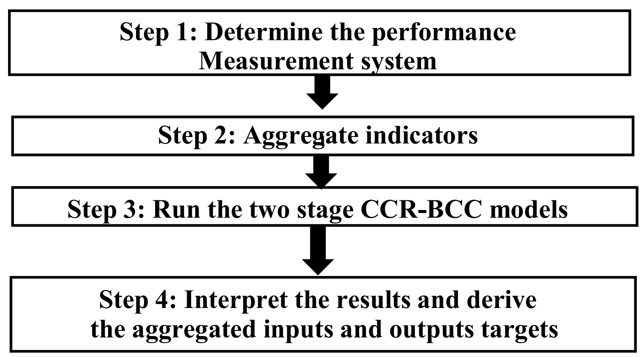

Figure 2. Proposed performance evaluation framework for supply chains

Step 1: Determine the performance measurement system represented by a set of indicators that best characterize the supply chain's activities.
Step 2: in this step, we propose to classify indicators into several categories and then to aggregate each category into an aggregated indicator or composite indicator.
We propose to use the aforementioned method for indicators aggregation.
Step 3: In this stage we run the aforementioned two stage CCR-BCC models to determine the overall technical, pure technical and scale efficiencies of each supply chain with regard to other supply chains.
Step 4: While interpreting the results we can propose a short term performance actions to overcome the managerial underperformance and long term performance actions to achieve optimal scale size. An optimal scale size is identified when the CCR and BCC scores are both equal to one, we say that we are in the most productive scale size (MPSS) (Cooper et al., 2011). We can also deduce the aggregated inputs and outputs targets according to the CCR model in order to take into account inefficiencies due to the input/output configuration as well as the size of operations. In fact the input (output) target for an inefficient unit is the amount of input (output) which shall be used by the inefficient DMU to produce the same level of output (input) so as to make the DMU efficient one(Cooper et al., 2011). We can run the CCR-BCC model to the aggregated inputs (outputs) targets to ensure that the resulted model is at MPSS region.

4. Illustrative application to public pharmaceutical products supply chains in Morocco

Health care supply chains face more challenges for delivering health care products and services effectively and efficiently. Hence it's mandatory to improve their performances. Improvements in health care are very important as they help promote healthy communities and improve people's well-being. Historically, the search for high performance in health care has been a difficult problem. Many studies to improve the health care performance were undertaken by many practitioners using the DEA technique. The first application of DEA in health care goes back to Nunamaker and

Lewin (1983), their work aims to measure the routine nursing service efficiency. Since, DEA has been widely used in health care studies all over the world (Ozcan, 2008). As a numerical illustration, we apply the proposed framework for evaluating several Health-care scenarios for the public pharmaceutical products supply chain in Morocco.

4.1 Determine the performance measurement system

We have used an integrated performance management system (Chorfi et al., 2018) to determine all the performance indicators that best describe the Moroccan public pharmaceutical products supply chain. The proposed performance measurement indicators are defined as follows: total supply chain management cost (TSCMC), budgetary gap (BG), cost per unit (CPU), expenses to net revenue (ENR), inventory turnover (IT), rate of loss due to obsolescence (RLO), order fulfillment cycle time (OFCT), social benefit (SB) -number of patient served-, Health satisfaction index (HSI) -patient satisfaction-, perfect order fulfillment (POF), short term availability of health products (STA), consumption exactitude (CE), compliance of health products with standards (CS), total density of health premises per 100000 population (TD).
The number of facilities (NF), the total storage capacity (TSC) and the distance travelled per year (DT).

4.2 Aggregate indicators

We propose to categorize the indicators according to the following performance attributes to characterize the inputs and the outputs of DEA: The supply chain cost based indicators, the supply chain responsiveness indicators, the supply chain effectiveness indicators and the design based indicators. The Cost based indicators are: TSCMC, BG, CPU, ENR, IT, and RLO. The responsiveness indicator is the OFCT. The effectiveness indicators are: SB, HIS, POF, STA, CE, CS, TD, and finally, the design based indicators including the facilities and the transportation indicators which are NF and TSC and DT.
By using the aforementioned DEA method for indicators aggregation, we can aggregate the cost based indicators into the aggregated cost based indicator, the effectiveness indicators could also be aggregated into the aggregated effectiveness indicator, and finally, the design based indicators could be aggregated into the aggregated design indicator. The results of aggregation are set out in table 2, table 3 and table 4. It must be noted that the head of the Supply chain Department of the Ministry of Health in Morocco is neutral, so we put $\alpha = 0.5$.

4.3 Run the two stages CCR-BCC models

To evaluate the performance of supply chains, we can consider that each supply chain being evaluated corresponds to a DMU. By this, let's say that DMU (i) = supply chain (i). We use the CCR-BCC DEA models to evaluate the overall technical efficiency, pure technical efficiency and scale efficiency of the DMUs.

4.3.1 Data for running DEA

In order to illustrate the applicability of the proposed approach, we have used data that represent the potential public pharmaceutical products supply chains in Morocco. Table 2, Table 3 and Table 4 summarize the proposed values of inputs and outputs for analyzing the performance of these supply chains, and the results of the aggregation process. The aggregated indicators will be used as inputs and outputs of DEA for evaluating the performance of supply chains:
Aggregated inputs indicators: The aggregated cost based indicator, the responsiveness indicator (order fulfillment cycle time), and the aggregated design indicator.
Aggregated output indicators: The aggregated effectiveness indicator.

4.3.2 Global results

The global results obtained by applying the input oriented CCR-BCC models are summarized in the table 1.

Table 1. The efficiency summary of the Moroccan public pharmaceutical products supply chains.

Supply chains	CCR efficiency	BCC efficiency	Scale efficiency	Return to scale
DMU1	1,000	1,000	1,000	CRS
DMU2	1,000	1,000	1,000	CRS

DMU3	0,862	1,000	0,862	IRS
DMU4	0,293	0,532	0,552	IRS
DMU5	0,936	1,000	0,936	IRS
DMU6	1,000	1,000	1.000	CRS
Mean	**0,849**	**0,922**	**0.892**	

Table 2. The Data of the Moroccan public pharmaceutical products supply chains operations: Cost based indicators

DMUs	**Cost based indicators**						**Aggregated cost based indicator (input 1) (α =0.5)**
	TSCMC	**BG**	**CPU**	**ENR**	**IT**	**RLO**	
DMU1	19000000	0,05	9,5	16	0,65	0,012	0,500
DMU2	20000000	0	10	15	0,59	0,024	0,500
DMU3	21000000	0,05	10,5	12	0,48	0,025	0,500
DMU4	22000000	0,1	11	13	0,88	0,032	0,937
DMU5	23000000	0,15	11,5	9	0,77	0,014	0,500
DMU6	24000000	0,2	12	10	0,64	0,019	0,696

Table 3. The Data of the Moroccan public pharmaceutical products supply chains operations: Responsiveness and Design indicators

DMUs	**Responsiveness indicator (input 2)**	**Design indicators**			**Aggregated design indicator (input 3) (α =0.5)**
	OFCT	**NF**	**TSC**	**DT**	
DMU1	1	1285	24,8	703005	0,500
DMU2	2	1234	30,4	569000	0,286
DMU3	3	1214	28,4	656000	0,722
DMU4	4	1254	34,2	590000	1,000
DMU5	5	1265	25,4	601000	0,384
DMU6	6	1200	27,5	600000	0,000

Table 4. The Data of the Moroccan public pharmaceutical products supply chains operations: Effectiveness indicators

DMUs	**Effectiveness indicators**							**Aggregated effectiveness indicator (output) (α =0.5)**
	SB	**HSI**	**POF**	**STA**	**CE**	**CS**	**TD**	
DMU1	15896000	4,7	0,75	0,98	0,97	0,77	5,9	0,577
DMU2	14004000	4,2	0,97	0,87	0,89	0,88	6	0,500
DMU3	16000014	5,4	0,96	0,85	0,74	0,85	7	0,500
DMU4	15105477	3,9	0,78	0,90	0,91	0,89	1	0,318
DMU5	10006800	5,6	0,94	0,72	0,90	0,92	9	0,500
DMU6	16010024	4,6	0,84	0,79	0,98	0,9	11	0,528

4.4 Interpretations of results

The average technical efficiency score obtained through CRS model is 0.849, indicating capacity for lots of improvement for the different Pharmaceutical products supply chains through partnership and collaboration both internally and externally with other supply chains. The average efficiency score obtained through the BCC model is higher than that of the CCR model with the average score being 0.922 which means that the management performance of the different Pharmaceutical products supply chains (wise management and employees' engagement) is relatively performant with regards to the size of operations.

The overall sample average BCC technical efficiency (pure technical efficiency) score was 92.2%, meaning that inefficient DMUs could on average reduce by 7.8 % their inputs without changing their current output level. The managers are likely to focus first on removing the pure technical inefficiency of these supply chains in the short term without changing the scale of operations. Besides, the majority of inefficiency is due to the small size of operations, that is, IRS, then these DMUs will need to plan for expansion (Cooper et al., 2011).

Moreover, an average scale efficiency of 89.2 % suggests a great potential to upsize the sector. Expansion can be achieved for example by acquisition and/or mergers within different parts of the supply chains. Three supply chains (DMU_1, DMU_2 and DMU_6) had a scale efficiency of 100% meaning that they were at the optimal size for their particular input/output configuration, meaning that increasing their inputs by a given proportion would result in an increase in their health service outputs by the same proportion. This means that they were operating at their most productive scale sizes (MPSS).The remaining supply chains had scale efficiency scores of less than 100% and were thus deemed scale inefficient. Increasing returns to scale in the three supply chains (DMU_3, DMU_4 and DMU_5), means that increasing their inputs by a given proportion would result in an increase in their health service outputs by a greater proportion. Thus, these DMUs would have needed to increase their size to achieve optimal scale (the region at which there are constant returns to scale in the relationship between inputs and outputs).

The long term aggregated inputs targets for individual supply chains (after removing the scale and managerial inefficiencies) are obtained by the CCR model and are set out in Table 5. Table 6 illustrate the efficiency summary of the proposed efficient DMUs (DMU1',DMU2',DMU3',DMU4',DMU5' and DMU6') with the aggregated inputs targets, where it is apparent that the average efficiency scores obtained through the CCR model are equal to that obtained through the BCC model which means that we are in the Most productive scale size region (MPSS)

Table 5. Aggregated inputs targets for the inefficient DMUs according to the input oriented CCR model (long term)

DMU	**Aggregated input**	**Aggregated input**	
		Actual	**Target**
DMU1	Aggregated cost based indicator	0,5	
	Responsiveness indicator	1	
	Aggregated design indicator	0,5	
DMU2	Aggregated cost based indicator	0,5	
	Responsiveness indicator	2	
	Aggregated design indicator	0,29	
DMU3	Aggregated cost based indicator	0,5	0,431
	Responsiveness indicator	3	0,862
	Aggregated design indicator	0,720	0,431
DMU4	Aggregated cost based indicator	0,936	0,276
	Responsiveness indicator	4	0,552
	Aggregated design indicator	1	0,276
DMU5	Aggregated cost based indicator	0,5	0,468
	Responsiveness indicator	5	1,471
	Aggregated design indicator	0,384	0,356
DMU6	Aggregated cost based indicator	0,7	
	Responsiveness indicator	6	
	Aggregated design indicator	0	

Table 6. The efficiency summary of the resulted efficient dmus with the aggregated inputs and outputs targets

Supply chains	**CCR efficiency**	**BCC efficiency**	**Scale efficiency**	**Return to scale**
DMU1'	1,000	1,000	1,000	CRS
DMU2'	1,000	1,000	1,000	CRS
DMU3'	1,000	1,000	1,000	CRS
DMU4'	0,999	1,000	0,999	IRS
DMU5'	1,000	1,000	1,000	CRS
DMU6'	1,000	1,000	1.000	CRS
Mean	**1,000**	**1,000**	**1,000**	

5. Conclusion

The overarching objectives of this research are to propose a three stage DEA approach to aggregate and evaluate the performance of supply chains. The outcome of this study will assist the supply chains managers in comparing their supply chains against peers and dimensioning their resources to achieve a given level of productions. Data envelopment analysis is first used to aggregate a set of performance indicators into one composite indicator and then to measure the relative technical, pure technical and scale efficiencies of supply chains. Decomposing technical efficiency scores into pure technical efficiency and scale efficiency provides guidance on what can be achieved in the short and long term. The efficiency scores have been calculated under Constant Return to Scale (CRS) and Variable Return to Scale (VRS) with an input orientation which aims to reduce the amount of inputs for a given level of outputs. However, the proposed approach has a serious limitation as it produces the aggregated inputs targets and doesn't allow the derivation of the original inputs targets. Thus, the process of decision making is difficult as managers can't directly act on the aggregated indicators. Hence future researches are needed to overcome this shortcoming.

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