International
Journal
Of Advanced Research in Engineering & Management (IJAREM)
ISSN: 2456-2033 || PP. 31-48

Measuring banking efficiency of the MENA region between 2017 and 2021: Data Envelopment Analysis approach

Ait Soudane Jalila, PhD
Professor at Mohammed V University-Rabat-Morocco
Faculty of Legal, Economic and Social Sciences-Agdal

Benbachir Soufiane (Corresponding Author)
PhD Researcher
Mohammed V University-Rabat-Morocco
Faculty of Legal, Economic and Social Sciences-Agdal

Abstract: In this paper, we applied the Data Envelopment Analysis model under the assumption of variable returns to scale and according to the output orientation to measure the efficiency of banks belonging to 12 countries of the MENA region over the period 2017-2021. We have divided the banks into two categories, conventional banks comprising 59 banks belonging to 11 countries and Islamic banks comprising 22 banks belonging to 7 countries. Regarding the 59 conventional banks, the results showed that the percentage of CCR-efficient conventional banks is low and does not exceed 16% and the average score of CCR-efficiency reached 90% over the study period. We also found that Qatar is the only country whose conventional banks are BCC-efficient during the 5 years and that their CCR-efficiency scores are the highest while the conventional banks of Morocco and Jordan have the lowest mean CCR-efficiency scores. Concerning the 22 Islamic banks, the results showed that the percentage of CCR-efficient Islamic banks is low and does not exceed 14% and that their average CCR-efficiency score reached an average of 64%. We also found that Qatar is the only country whose Islamic banks are on average CCR-efficient during the 5 years and that Islamic banks in Morocco have the lowest average CCR-efficiency score reaching 36%.

Keywords: Technical efficiency, Pure technical efficiency, Scale efficiency, Data Envelopment Analysis, Returns to scale, Input and output orientations
JEL Classification: C61, G21

1. Introduction

The Middle East and North Africa (MENA) region is strategically located between Europe and Asia. It has high a growth potential and benefits from a privileged geographical location giving access to large markets. The region includes the oil-rich countries of the Gulf Cooperation Council (GCC) as well as the Arab countries of the Near East and North Africa.

The main objective of this study is to measure the relative efficiency of 81 banks belonging to 12 countries in the MENA region, namely Saudi Arabia, the United Arab Emirates, Bahrain, Kuwait, Qatar, Oman, Jordan, Lebanon, Egypt, Tunisia, Algeria and Morocco. The sample was divided into two categories, the conventional banks which includes 59 banks, and the Islamic banks which comprises 22 banks. We apply the non-parametric Data Envelopment Analysis (DEA) method which is based on linear optimization to separately measure the technical efficiency of the 59 conventional banks and that of the 22 Islamic banks.

The rest of the article is organized as follows. In section 2, we will present the concepts and theoretical foundations of efficiency measurement. In section 3, we briefly review the literature on the measurement of technical efficiency in the banking sector. In section 4, we will expose the data used and we will present in detail the DEA model. Section 5 will be devoted to the results and their interpretation. We will conclude by section 6.

2. Theoretical foundations of efficiency measurement

Performance or efficiency is a concept that is widely studied in the literature and has been widely used in recent years by professionals in various sectors. Performance measurement becomes more complicated when you want to benchmark between several entities whose data is multiple and complex, such as in the banking or insurance sector.

Usually, the efficiency of a bank is evaluated by a multitude of partial productivity ratios. However, these traditional measures do not allow for rigorous comparisons between banks and complicate the decision-making process.

Farrell (1957) was the first to propose a method to empirically assess the degree of efficiency of decision units. Since then, several researches have been carried out. These researches can be split into two approaches: parametric and non-parametric. The approach is called parametric when a functional form is used for the production boundary; otherwise, the approach is said to be non-parametric.

In their literature review of studies that focus on measuring efficiency in the banking sector, Berger and Humphrey (1997) identify mainly five different techniques grouped into the following two approaches:

- ✓ The non-parametric approach: this is the data envelopment method known as Data Envelopment Analysis (DEA) and the method known as Free Disposal Hull (FDH).
- ✓ The parametric approach: this is the stochastic frontier approach known as Stochastic Frontier Analysis (SFA), the approach known as Free Distribution Analysis (DFA) and the Thick Frontier Approach (TFA).

2.1. Concept of performance

The term performance comes from the old French performance which means completion. In the literature, several definitions are jointly or indiscriminately used in order to establish precisely the concept of performance.

For the project management glossary, performance means the accomplishment of a job, activity or work and the way in which any entity (individual, organization) accomplishes this work.

The OECD explains performance by the ability of an organization or administration to acquire resources on economic terms and to use them efficiently (inputs of products) and effectively (outputs-results) and to achieve set performance targets.

UNDP defines the performance of an organization by the extent to which it has achieved its mission or set objectives. It has several dimensions relating to processes (transformation of inputs into products), results (transformation of products into results), relevance (adaptation to the needs of beneficiaries and situations) and success (fulfilment). The interest in the different components varies according to the end users.

For some authors, performance is equated with efficiency, competitiveness or even capacity, and for others they consider it similar to efficiency, output, productivity. In this paper we will use the terminology Efficiency as in the Anglo-Saxon literature

2.2. Notion of productivity

Originally, the concept of productivity is basically a physical concept that compares the units produced to an implemented factor of production. This is commonly referred to as partial productivity (related to a single factor).

The production function is generally defined according to the relationship between the outputs and the inputs used to obtain them, given the technology of production. Productivity is measured for a given level of production by the ratio between the produced production y and the intermediate consumption used x. This is the indicator generally used to measure productivity.

It should be noted that these are partial productivity indicators which allow the study of the relationship between a particular product and a particular factor of production.

$$Partial\ productivity\ (PP) = \frac{Output}{input} = \frac{y}{x} \tag{1}$$

However, in reality institutions use multiple inputs to produce a multitude of outputs over the same period. To overcome this shortcoming, economists have introduced the notion of “overall productivity” which is based on a weighting system by prices or by factors (De La Villarmois (2001)). Nevertheless, an attempt to move from a partial productivity measure to a global productivity measure comes up against difficulties such as the choice of the functional form of production, the choice of inputs and outputs to be considered and the weights to be used, to get a ratio of single-output and single-input that reduces to a form that looks like formula (1).

The productivity ratio proposed by Charnes et al (1978) in the method known as DEA-CCR is a generalization of the productivity ratio associated with the production function which links inputs and outputs. The aggregation problem is solved by a weighting system that makes no reference to any price system and any functional form of production.

3. Literature review

The Data Envelopment Analysis method has been applied over the past twenty years in several fields and several books have been devoted to it. It is composed of two basic models which are the DEA model of Charnes-Cooper-Rhodes (CCR) (1978) with the assumption of constant returns to scale and the DEA model of Banker-Charnes-Cooper (BCC) (1984) with the assumption of variable returns to scale.

Despite an abundant literature on the measurement of banking efficiency around the world, few studies have been carried out in the context of the MENA region, in particular those that address the efficiency of Islamic and conventional banks.

Mariani et al (2010) found that the efficiency of Islamic banks was higher than that of conventional banks over the period 1996-2002 by applying the DEA method to 111 banks from 10 countries.

Eisazadeh and Shaeri (2012) studied the effects of institutional factors on the efficiency of 266 banks from 19 MENA countries over the past 14 years from 1995 to 2008. They used the Stochastic Frontier method and the Tobit regression to study the impact of institutional and financial variables as well as specific variables on efficiency. Their analysis shows that the factors that affect production efficiency are macroeconomic stability, financial development, degree of market competition, legal rights and contract laws, better governance, and political stability.

Johnes et al. (2012) examined the efficiency of Islamic and conventional banks in GCC countries during the period 2004-2007 using the DEA method. The results suggest that the average efficiency was significantly lower in Islamic banks.

Apergis and Polemis (2016) empirically assessed the relationship between competition and efficiency in the banking sector of 10 MENA countries covering the period 1997-2011. The empirical results provide evidence for the presence of one-way (negative) Granger causality, running from efficiency to competition.

Bahrini (2017) used the bootstrap Data Envelopment Analysis (DEA) approach to estimate technical efficiency, pure technical efficiency and scale efficiency. The main results show that pure technical inefficiency was the main source of technical inefficiency. The results show that GCC Islamic banks had stable efficiency scores during the global financial crisis of 2007-2008 and the early post-crisis period of 2009-2010. However, a decline in the technical efficiency of all Islamic banks in the MENA region was recorded during the last two years of the 2011-2012 study period.

Bekakria and Azzouz (2020) compared the technical efficiency of 10 Islamic banks and 8 conventional banks operating in the MENA zone using the DEA method during the period 2016-2018. Their results show the absence of a significant difference between the efficiency of Islamic banks and conventional banks. For the three years, the two types of banks recorded degrees of efficiency very close to each other.

Tahi et al. (2020) measured the technical efficiency of 66 banks (47 conventional banks and 19 Islamic banks) from 6 selected countries in the MENA region over the period 2010-2014 using the DEA model. Their results suggest that conventional banks are technically more efficient than Islamic banks under the assumption of constant returns to scale.

Rizk (2022) studied efficiency in the MENA region throughout the period 1999-2017.The study reveals the existence of shortcomings in the allocation of resources to the banking sectors.

Alber and Attia (2022) explored the causal relationship between efficiency, competition and bank concentration in the banking systems of 15 MENA countries, over the period 2008-2018. They measured banking efficiency using the DEA method. The results indicate the presence of a significant effect of bank efficiency on bank competition and bank concentration.

4. Data and methodology

4.1 Data

The main objective of this study is to measure overall technical efficiency, and its two components, pure technical efficiency and scale efficiency, of 81 banks belonging to 12 countries in the MENA region, namely Saudi Arabia. Arabia, United Arab Emirates, Bahrain, Kuwait, Qatar, Oman, Jordan, Lebanon, Egypt, Tunisia,

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Algeria and Morocco. The sample of 81 banks was divided into two categories, the conventional banks which includes 59 banks and the Islamic banks which comprises 22 banks.

One of the major problems in studying the efficiency of banks is the specification of inputs and outputsof banks. There has been long-standing disagreement among researchers about what banks produce. Generally, there are two ways to measure banks' outputs; the production approach and the intermediation approach. Under the production approach, banks produce accounts of different sizes by processing deposits and loans, and incur capital and labor costs.

Under the intermediation approach, banks are treated as financial intermediaries that combine deposits, labor and capital to produce loans and investments.

This study uses the intermediation approach to specify the input variables and the output variables of banks.

The choice of the number of inputs and outputs is determined considering the condition recommended in the DEA literature (Cooper et al (2002)):

$$N \geq Max\big(I \times J, 3(I+I)\big)$$

where:
N= number of $DMUs$; I =number of inputs; J =number of outputs.

In this study we have specified three inputs (Total liabilities, Operating expenses including employees' expenses, Depreciation and amortization of tangible fixed assets) and two outputs (Operating income, Total assets except tangible fixed assets), which are depicted in the table below:

Input 1	**Input 2**	**Input 3**	**Output 1**	**Output 2**
Total liabilities	Operating expenses	Depreciation and amortization	Total assets except tangible fixed assets	Operating income

All the inputs and outputs variables were taken from the balance sheets and statements of income of the 81 banks. We only included in the database those countries and banks for which data was available. Table 1 shows the 59 conventional banks and able 2 shows the 22 Islamic banks.

Table 1: 59 conventional banks of 11 MENA region countries

Country	N°	Bank	Country	N°	Bank
Bahrain	1	Ahli United Bank	Lebanon	30	Bank Audi
	2	Alubaf Arab International Bank		31	Bank of Beirout
	3	Arab Banking Corporation		32	Crédit Libanais
Algeria	4	BNP Paribas Al-djazair		33	Saradar Bank
	5	Fransabank El Djazaïr SPA	Morocco	34	Al Barid Bank
	6	Société générale Algérie		35	Attijariwafa Bank
United Arab Emirates	7	Abu Dhabi Commercial Bank		36	Bank of Africa
	8	Bank of Sharjah		37	Banque Centrale Populaire
	9	Commercial Bank of Dubai		38	Banque marocaine pour le commerce et l'industrie
	10	Emirates NBD		39	Crédit Agricole du Maroc
	11	First Abu Dhabi Bank		40	Crédit Immobilier et Hôtelier
	12	National Bank of Fujairah		41	Crédit du Maroc
	13	National Bank of Ras Al Khaimah		42	Société générale Maroc
	14	National Bank of Umm Al Qaiwain		43	CaixaBank Casablanca
	15	United Arab Bank		44	CDG Capital
Egypt	16	Bank of Alexandria		45	CFG Bank
	17	Banque du Caire		46	CITIBANK Maghreb
	18	Commercial International Bank	Oman	47	Bank Dhofar
	19	HSBC Bank Egypt S.A.E.		48	Bank Muscat
Jordan	20	Arab Jordan Investment Bank		49	Oman Arab Bank
	21	Bank of Jordan	Qatar	50	Ahli Bank
	22	Capital Bank of Jordan		51	Commercial Bank of Qatar
	23	Jordan Ahli Bank		52	Doha bank
	24	Jordan Commercial Bank	Tunisia	53	Bank ABC tunisia
Kuwait	25	Al Ahli Bank of Kuwait		54	Amen Bank
	26	Burgan Bank		55	Banque de Tunisie
	27	Commercial Bank of Kuwait		56	Banque internationale arabe de Tunisie
	28	Gulf Bank		57	Banque Tunisie arabe
	29	National Bank of Kuwait		58	Société Tunisienne de Banque

				59	TunisianSaudi Bank

Table 2: 22 Islamic banks of 7 countries MENA region

Country	N°	Bank	Country	N°	Bank
Bahrain	1	Al Salam Bank	United Arab Emirates	12	Ajman Bank
	2	BahrainIslamic Bank		13	Al Hilal Bank
Saudi Arabia	3	Bank Aljazira		14	DubaiIslamic Bank
	4	Al Rajhibank	Morocco	15	Al Akhdar Bank
	5	Alimna Bank		16	Bank Assafa
	6	Arab National Bank		17	Uminabank
	7	Bank Al Bilad	Oman	18	AlizzIslamic Bank
	8	Banque Britannique Saoudienne	Qatar	19	Masraf Al Rayan bank
	9	Banque SaudiFransi		20	Qatar Islamic Bank
	10	National Commercial Bank ou Saudi National Bank	Tunisia	21	Banque Al-Baraka Tunisie
	11	Ryad Bank		22	Banque Zitouna

4.2 Methodology

The history of the DEA (Data Envelopment Analysis) method began with Edwardo Rhodes' doctoral thesis in 1978 at the School of Urban and Public Affairs, now the H. J. Heinz III School of Public Policy and Management from Carnegie Melon University. Edwardo Rhodes evaluated the program of education (Program Follow Through, PFT) for disadvantaged students (mainly black or Hispanic students), undertaken in American public schools with the support of the federal government. The analysis involved comparing the efficiency of a matched group of school districts that participated and did not participate in the PFT.

We present below the DEA method through a conceptual and methodological introduction describing the different DEA models, namely the CCR model (Charnes et al (1978)) under the assumption of constant returns to scale and the BCC model (Banker et al (1984)) under the assumption of variable returns to scale.

- **Presentation of the Data Envelopment Analysis (DEA)**

The Data Envelopment Analysis is a nonparametric deterministic method for estimating production frontiers.

The measurement of technical efficiency by the DEA method can be done according to two orientations. The first, called output orientation, which is oriented towards the maximization of outputs and is applied when one seeks to increase the quantities of outputs without changing the quantities of inputs used. The second, called input orientation, which is oriented towards the minimization of inputs and is applied when one seeks to proportionally reduce the quantities of inputs without modifying the quantities of outputs.

The DEA method is based on linear programming techniques to estimate a production frontier of a sample of observations. This production frontier is located at the top of the observations and corresponds to the best efficient units in the sample. It envelops the set of observations in such a way that the efficient units are located on the boundary and the less efficient units are located below the envelope.

Each unit is considered as a decision-making unit (DMU) which transforms inputs into outputs. Each DMU thus consumes a certain number of inputs to produce a certain number of outputs.

Definition of relative efficiency:

Suppose we have N decision units DMU_n, for $1 \leq n \leq N$.. Each decision unitDMU_n, consumes the set of I inputs $X_n = \{x_{in}/1 \leq i \leq I\}$and produces a set of J outputs $Y_n = \{y_{jn}/1 \leq j \leq J\}$.

Consider a decision unit DMU_m (for $1 \leq m \leq N$). The efficiency indicator (or score) of the DMU_m is defined by the ratio:

$$E_m = \frac{Weightedsumoftheoutputsofthe DMU_m}{Weightedsumoftheinputsofthe DMU_m} \Leftrightarrow$$

$$E_m = \frac{\sum_{j=1}^{J} v_{jm} \times y_{jm}}{\sum_{i=1}^{I} u_{im} \times x_{im}} \quad (2)$$

where:

y_{jm} : j^{th} output of DMU_m; x_{im} : i^{th} input ofDMU_m

u_{im} : weighting factor of i^{th} input ; v_{jm} : weighting factor of j^{th} output

The efficiency frontier (envelope) is made up of decision units displaying scores equal to 1. The technical inefficiency of any DMU in the sample thus corresponds to the distance that separates it from the envelope. It is a relative inefficiency insofar as it depends on the best efficient DMUs in the sample.

For each inefficient DMU, the DEA analysis identifies the sources and the level of inefficiency for each of the inputs and outputs. The level of inefficiency is determined by comparison to a single reference DMU or a convex combination of other reference DMUs, located on the efficiency frontier, which use the same level of inputs and produce the same or a higher level output; this is obtained by imposing to the solutions to satisfy inequality constraints that can increase certain outputs (or decrease certain inputs) without having a negative effect on the other inputs or outputs.

Obviously, the most important issue at this stage is the evaluation weights u_{im} and v_{jm}. This is a tricky problem because there is no single set ofweight. This issue of weight assignment is addressed in the DEA method by assigning a unique set of weights for each DMU.

The weights for DMU_m are determined, using mathematical programming, to be the weights that maximize the efficiency of DMU_m provided that the efficiencies of the other DMUs (computed using the same set of weight) are limited to values between 0 and 1. This is formulated in the following program.

Fractional DEA Program:

The mathematical program that allows the evaluation of the efficiency of the DMU_m is:

$$\underset{u_{im},v_{jm}}{\text{Max}} \; z_m = \frac{\sum_{j=1}^{J} v_{jm} \times \boldsymbol{y_{jm}}}{\sum_{i=1}^{I} u_{im} \times \boldsymbol{x_{im}}}$$

$$\begin{cases} 0 \le \dfrac{\sum_{j=1}^{J} v_{jm} \times \boldsymbol{y_{jn}}}{\sum_{i=1}^{I} u_{im} \times \boldsymbol{x_{in}}} \le 1, \quad 1 \le n \le N \\ u_{im} \ge 0, v_{jm} \ge 0, \quad 1 \le i \le I, 1 \le j \le J \end{cases} \tag{3}$$

The objective is to find the weights u_{im} and v_{jm} which maximize the ratio z_m of the DMU_m. Under the constraints, the optimal value z_m^* is between 0 and 1.

This rational formulation of the mathematical program poses the problem of the existence of an infinity of solutions $u_m = (u_{1m}, u_{2m}, \cdots, u_{Im})$ and $v_m = (v_{1m}, v_{2m}, \cdots, v_{Jm})$.Indeed, it is clear that if u_m^* and v_m^* are solutions of the mathematical program then $\alpha . u_m^*$ and $\alpha . v_m^*$ also constitute solutions. This problem will be overcome further by reducing the rational mathematical problem to a linear program.

Two models exist in the DEA family: the CCR model initiated byCharnes et al (1978) and the BCC model proposed by Banker et al (1984). The CCR model is used to measure the overall efficiency of each DMU assuming that the returns to scale are constant, while the BCC model, an extension of the CCR model, decomposes the overall efficiency into two components, pure technical efficiency and efficiency of scale by taking into account the variable returns to scale.

Efficiency scores can be measured following two types of orientation, input orientation where it is possible to produce as much by reducing inputs and output orientation where it is possible to produce more with the same inputs.

To overcome the problem of fractional programs it is necessary to normalize the numerator or the denominator of the objective function.

- **DEA-CCR models:**

The DEA-CCR model of Output-Maximization Multipliers:

By normalizing the denominator of the objective function to 1, we obtain:

$$\underset{u_{im},v_{jm}}{\text{Max}} \; z_m = \sum_{j=1}^{J} v_{jm} \times y_{jm}$$

$$\begin{cases} \sum_{i=1}^{I} u_{im} \times x_{im} = 1 \\ \sum_{j=1}^{J} v_{jm} \times y_{jn} - \sum_{i=1}^{I} u_{im} \times x_{in} \le 0 \,, 1 \le n \le N \\ u_{im} \ge 0 \text{ et } v_{jm} \ge 0, 1 \le i \le I \text{ et } 1 \le j \le J \end{cases} \tag{4}$$

Where u_{im} and v_{jm} are multipliers-inputs and multipliers-outputs.

Matrix form of the DEA-CCR model of Output Maximization:
By setting:

$$U_m = \begin{pmatrix} u_{1m} \\ u_{2m} \\ \vdots \\ u_{Im} \end{pmatrix},\ V_m = \begin{pmatrix} v_{1m} \\ v_{2m} \\ \vdots \\ v_{Jm} \end{pmatrix}, X_m = \begin{pmatrix} x_{1m} \\ x_{2m} \\ \vdots \\ x_{Im} \end{pmatrix}, X_n = \begin{pmatrix} x_{1n} \\ x_{2n} \\ \vdots \\ x_{In} \end{pmatrix},\ Y_m = \begin{pmatrix} y_{1m} \\ y_{2m} \\ \vdots \\ y_{Jm} \end{pmatrix}, Y_n = \begin{pmatrix} y_{1n} \\ y_{2n} \\ \vdots \\ y_{Jn} \end{pmatrix} \text{ for } 1 \leq n \leq N$$

$$X_n^t = matrixtransposeof X_n = (x_{1m} x_{2m} \cdots x_{Im})$$

$$X = (X_1 X_2 \quad \cdots \quad X_N) = (x_{in})_{\substack{1 \leq i \leq I \\ 1 \leq n \leq N}} \text{ and } Y = (Y_1 Y_2 \quad \cdots \quad Y_N) = (y_{jn})_{\substack{1 \leq j \leq J \\ 1 \leq n \leq N}}$$

we obtain the matrix form of the DEA-CCR model of Output-Maximization:

$$\max_{U_m, V_m} z_m = V_m^t \cdot Y_m$$

$$\begin{cases} U_m^t \cdot X_m = 1 \\ V_m^t \cdot Y - U_m^t \cdot X \leq 0 \\ U_m \geq 0, V_m \geq 0 \end{cases} \tag{5}$$

U_m:*Multiplier-input vectors*; V_m : *multiplier-output vectors*.

The optimal solutions of this model are denoted (z_m^*, U_m^*, V_m^*).

Definition: CCR-efficiency
We say that the DMU_m is CCR-efficient if it satisfies the following two conditions:
1) $z_m^* = 1$
2) There exists at least one solution (U_m^*, V_m^*) such that $U_m^* > 0$ and $V_m^* > 0$

Matrix form of the DEA-CCR model of Input-Minimization Multipliers:

If we keep the same notations as before and we set:

$$Q_m = \begin{pmatrix} q_{1m} \\ q_{2m} \\ \vdots \\ q_{Im} \end{pmatrix} \text{ and } R_m = \begin{pmatrix} r_{1m} \\ r_{2m} \\ \vdots \\ r_{Jm} \end{pmatrix}$$

We obtain the DEA-CCR model of Input-Minimization Multipliers:

$$\min_{U_m, V_m} w_m = Q_m^t \cdot X_m$$

$$\begin{cases} R_m^t \cdot Y_m = 1 \\ R_m^t \cdot Y - Q_m^t \cdot X \leq 0 \\ Q_m \geq 0, R_m \geq 0 \end{cases} \tag{6}$$

Q_m : *multiplier-input vectors*; R_m : *multiplier-output vectors*

These two DEA-CCR models of multipliers are those that Charnes et al. (1978) initially introduced in 1978. Immediately afterwards in 1979, Charnes et al. (1979) made a minor modification. In a conventional linear program, the decision variables are non-negative, i.e., they are assumed to be positive or zero. However, Charnes et al. (1979) changed this assumption by requiring the decision variables to be strictly positive. So, they changed the non-negativity constraints:

$$u_{im} \geq 0 \text{ et } v_{jm} \geq 0\ ;\ (1 \leq i \leq I \text{ et } 1 \leq j \leq J) \Leftrightarrow U_m \geq 0, V_m \geq 0$$

by the constraints of strict positivity:

$$u_{im} > 0 \text{ et } v_{jm} > 0\ ;\ (1 \leq i \leq I \text{ et } 1 \leq j \leq J) \Leftrightarrow U_m > 0, V_m > 0$$

or by:

$$u_{im} > \varepsilon \text{ et } v_{jm} > \varepsilon\ ;\ (1 \leq i \leq I \text{ et } 1 \leq j \leq J) \Leftrightarrow U_m > \varepsilon . E_I^t, V_m > \varepsilon . E_J^t$$

Where $E_I = \left(\underbrace{1\ 1\ \cdots 1 \cdots 1}_{I-times}\right)$,$E_J = \left(\underbrace{1\ 1\ \cdots 1 \cdots 1}_{J-times}\right)$ and ε is an infinitesimal or non-archimedean constant , usually on the order of 10^{-5} or 10^{-6}. The infinitesimal constant ε was introduced by

Charnes et al. (1979) to distinguish DMUs that have an efficiency score equal to 1 and whose input-slacks or output-slacks are not zero. With these new constraints, the two multiplier models change form.

The DEA-CCR model of Output-Maximization Multipliers (with constant ε)

$$\max_{U_m, V_m} z_m = V_m^t \cdot Y_m$$
$$\text{SC} \begin{cases} U_m^t \cdot X_m = 1 \\ V_m^t \cdot Y - U_m^t \cdot X \leq 0 \\ U_m \geq \varepsilon, V_m \geq \varepsilon \end{cases} \tag{7}$$

The DEA-CCR model of Input-Minimization Multipliers (with constant ε)

$$\min_{Q_m, R_m} w_m = Q_m^t \cdot X_m$$
$$\text{SC} \begin{cases} R_m^t \cdot Y_m = 1 \\ R_m^t \cdot Y - Q_m^t \cdot X \leq 0 \\ Q_m \geq \varepsilon. E_I^t, R_m \geq \varepsilon. E_J^t \end{cases} \tag{8}$$

In what follows we describe the DEA-CCR Envelopment models which are the dual programs of the preceding DEA-CCR Multipliers models.

DEA-CCR Envelopment Models

Linear programming theory states that any problem in linear programming (usually called a primal problem) is closely related to another program called a dual problem.

DEA-CCR Envelopment and Orientation-Input model (with constant ε):

$$\min_{\theta_m \Lambda, S^+, S^-} \phi_m = \theta_m - \varepsilon\left(E_J.S^+ + E_I.S^-\right)$$
$$\begin{cases} Y.\Lambda - S^+ = Y_m \\ \theta_m.X_m - X.\Lambda - S^- = 0 \\ \Lambda \geq 0, S^+ \geq 0, S^- \geq 0, \theta_m \in \mathbb{R} \end{cases} \tag{9}$$

Where

$$S^+ = \begin{pmatrix} s_1^+ \\ s_2^+ \\ \vdots \\ s_j^+ \\ \vdots \\ s_J^+ \end{pmatrix}, S^- = \begin{pmatrix} s_1^- \\ s_2^- \\ \vdots \\ s_i^- \\ \vdots \\ s_I^- \end{pmatrix}, \quad \Lambda = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \vdots \\ \lambda_N \end{pmatrix}, E_I = \left(\underbrace{1\ 1\ \cdots 1 \cdots 1}_{I-times}\right), E_J = \left(\underbrace{1\ 1\ \cdots 1 \cdots 1}_{J-times}\right)$$

$$X_n = \begin{pmatrix} x_{1n} \\ x_{2n} \\ \vdots \\ x_{In} \end{pmatrix}, \ Y_n = \begin{pmatrix} y_{1n} \\ y_{2n} \\ \vdots \\ y_{Jn} \end{pmatrix} \text{ for } 1 \leq n \leq N$$

$$X = (X_1 \quad \cdots \quad X_N) = (x_{in})_{\substack{1 \leq i \leq I \\ 1 \leq n \leq N}} \text{ and } Y = (Y_1 \quad \cdots \quad Y_N) = \left(y_{jn}\right)_{\substack{1 \leq j \leq J \\ 1 \leq n \leq N}}$$

We have previously reported that the infinitesimal constant ε was introduced by Charnes et al. (1979) to distinguish weakly efficient DMUs from highly efficient DMUs. However, the numerical values of ε should be chosen in calculations much smaller than the numerical values of the inputs and outputs so that they do not affect the optimization. A two-phase optimization procedure was suggested by Ali and Seiford (1993) and Joro et al. (1998) to overcome this technical problem.

Two-phase resolution:

Phase 1: We solve the DEA-CCR program with Envelopment and Orientation-Output without the infinitesimal constant ε.

$$\min_{\theta_m, \Lambda} \phi_m = \theta_m \tag{10}$$

$$\begin{cases} Y.\Lambda \geq Y_m \\ \theta_m.X_m \leq X.\Lambda \\ \Lambda \geq 0, \theta_m \in \mathbb{R} \end{cases}$$

We note θ_m^* the optimal solution of this program.

Phase 2: We use the optimal solution θ_m^* from phase 1 to solve the following maximization program (of slacks)

$$\min_{\Lambda,S^+,S^-} E_J.S^+ + E_I.S^-$$
$$\begin{cases} Y.\Lambda - S^+ = Y_m \\ \theta_m^*.X_m - X.\Lambda - S^- = 0 \\ \Lambda \geq 0, S^+ \geq 0, S^- \geq 0 \end{cases} \quad (11)$$

The optimal solution of this program will be denoted $(\Lambda^*, S^{+*}, S^{-*})$.

Definition: *Vector of inputs in Excess (Inputs-Slacks) and vector of outputs in Deficits (Outputs-Slacks)*
The vectors S^+ and S^- solutions of phase 2 are defined by:

$$\begin{cases} S^+ = Y.\Lambda^* - Y_m \\ S^- = \theta_m^*.X_m - X.\Lambda^* \end{cases} \quad (12)$$

are respectively called Vector of Excess Inputs and Vector of Deficit Outputs.

Definition: *Max-Slack solution, Zero-Slack solution*
The optimal solution $(\Lambda^*, S^{+*}, S^{-*})$ of the PL of the phase 2 is called the Max-Slack solution. If the Max-Slack solution satisfies $S^+ = 0$ and $S^- = 0$ then it is called Zero-Slack solution.

Definition: *CCR-Efficiency, Radial Efficiency, Technical Efficiency, Mix-Inefficiency*
If an optimal solution $(\theta_m^*, \Lambda^*, S^{+*}, S^{-*})$ of the PL of the two phases verifies $\theta_m^* = 1$ and is Zero-Slack ($S^+ = 0, S^- = 0$) then the DMU_m is said to be *CCR-efficient*. Otherwise, it is said to be *CCR-inefficient*. If only the first condition is satisfied, then the DMU_m is said to be *radially efficient*. If the second condition is not satisfied, then we speak of *Mix-inefficiency*.

Definition: *Reference set of an inefficient DMU*
Let $(\Lambda^*, S^{+*}, S^{-*})$ be the Max-Slack solution of the PL DMU_m of the phase 2. If the DMU_m is CCR-inefficient then we define the reference set of the DMU_m, noted E_m:

$$E_m = \{n/\lambda_n^* > 0, 1 \leq n \leq N\} \quad (13)$$

The optimal solution $(\Lambda^*, S^{+*}, S^{-*})$ then verifies:

$$Y_m = Y.\Lambda^* - S^{+*} = (Y_1 Y_2 \cdots Y_n \cdots Y_N).\begin{pmatrix} \lambda_1^* \\ \lambda_2^* \\ \vdots \\ \lambda_n^* \\ \vdots \\ \lambda_N^* \end{pmatrix} - S^{+*} = \sum_{n \in E_m} \lambda_n^*.Y_n - S^{+*}$$

$$\theta_m^*.X_m = X.\Lambda^* + S^{-*} = (X_1 X_2 \cdots X_n \cdots X_N).\begin{pmatrix} \lambda_1^* \\ \lambda_2^* \\ \vdots \\ \lambda_n^* \\ \vdots \\ \lambda_N^* \end{pmatrix} + S^{-*} = \sum_{n \in E_m} \lambda_n^*.X_n + S^{-*}$$

It is clear that:

$$\begin{cases} X_m \geq \theta_m^*.X_m - S^{-*} = \sum_{n \in E_m} \lambda_n^*.X_n \\ Y_m \leq Y_m + S^{+*} = \sum_{n \in E_m} \lambda_n^*.Y_n \end{cases} \quad (14)$$

These inequalities suggest that the efficiency of the DMU_m can be improved by radially reducing the vector of inputs X_m by the ratio θ_m^* and by subtracting the vector of excess inputs S^{-*}. Similarly, the efficiency of the DMU_m can be improved by increasing the vector of outputs Y_m by the vector of outputs in deficits S^{+*}.

The formulas permitting theimprovement of efficiency are given by:

$$\begin{cases} \hat{X}_m = X_m - \Delta X_m = \theta_m^*.X_m - S^{-*} \leq X_m : \text{Vecteur Input} - \text{cible de la } DMU_m \\ \hat{Y}_m = Y_m + \Delta Y_m = Y_m + S^{+*} \geq Y_m : \text{Vecteur Output} - \text{cible de la } DMU_m \end{cases} \quad (15)$$

These are projection formulas on the efficiency frontier.

Advantage of using a CCR Envelopment model:

Note that in practice the number N of DMUs is considerably larger than the number $I + J$ of inputs and outputs ($N \geq 3(i + J)$). Note also that the number of constraints of a DEA-CCR Multiplier model is equal to N while the number of constraints of a DEA-CCR Envelopment model is equal to $I + J$. The second advantage is the fact that a DEA-CCR model with Envelopment guarantees the obtaining of the Input Vectors in Excess and the Output Vectors in Deficits $(\Lambda^*, S^{+*}, S^{-*})$which allow the improvement of the efficiency of inefficient DMUs.

In what follows we present the Envelopment and Orientation-Input DEA-CCR model.

$$\max_{\eta_m, \Gamma, T_I^-, T_J^+} \psi_m = \eta_m + \varepsilon\left(E_J.T^+ + E_I.T^-\right)$$
$$\begin{cases} X_m = X.\Gamma + T_I^- \\ \eta_m.Y_m = Y.\Gamma - T_J^+ \\ \Gamma \geq 0, T_I^- \geq 0, T_J^+ \geq 0, \eta_m \in \mathbb{R} \end{cases} \quad (16)$$

Where

$$T^+ = \begin{pmatrix} t_1^+ \\ t_2^+ \\ \vdots \\ t_j^+ \\ \vdots \\ t_J^+ \end{pmatrix}, T^- = \begin{pmatrix} t_1^- \\ t_2^- \\ \vdots \\ t_i^- \\ \vdots \\ t_I^- \end{pmatrix}, \quad \Lambda = \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_n \\ \vdots \\ \gamma_N \end{pmatrix}$$

DEA-BCC models:

Recall that DEA-CCR models assume that decision units operate in an environment with constant returns to scale. This constraining assumption limited the use for a long time of these models. Banker et al. (1984) were the first to propose models that improve DEA-CCR models by taking into account variable returns to scale. Their idea was simple and consisted in introducing a convexity condition among the constraints of the DEA-CCR Envelopment models. The convexity constraint is given by $\sum_{n=1}^{N} \lambda_n = 1$ for the Envelopment and Orientation-Input model and by $\sum_{n=1}^{N} \gamma_n = 1$ for the Envelopment and Orientation-Output model. In the DEA literature, DEA-BCC models are also called DEA-VRS (variable returns to scale) and DEA-CCR models are also called DEA-CRS (constant returns to scale).

We give below the Envelopment DEA-BCC models with infinitesimal constant.

Envelopment DEA-BCC models with constant ε:

Envelopment and Orientation-Input Model DEA-BCC with constant ε :

$$\min_{\theta_m,\Lambda,S^+,S^-} \phi_m = \theta_m - \varepsilon\left(E_J.S^+ + E_I.S^-\right)$$
$$\begin{cases} Y_m = Y.\Lambda - S^+ \\ \theta_m.X_m = X.\Lambda + S^- \\ E.\Lambda = 1 \\ \Lambda \geq 0, S^+ \geq 0, S^- \geq 0, \theta_m \in \mathbb{R} \end{cases} \quad (17)$$

Envelopment and Orientation-Output Model DEA-BCC with constant ε :

$$\max_{\eta_m,\Gamma,T^+,T^-} \psi_m = \eta_m + \varepsilon\left(E_J.T^+ + E_I.T^-\right)$$
$$\begin{cases} X_m = X.\Gamma + T^- \\ \eta_m.Y_m = Y.\Gamma - T^+ \\ E.\Gamma = 1 \\ \Gamma \geq 0, T^+ \geq 0, T^- \geq 0, \eta_m \in \mathbb{R} \end{cases} \quad (18)$$

with :

$$S^+ = \begin{pmatrix} s_1^+ \\ s_2^+ \\ \vdots \\ s_j^+ \\ \vdots \\ s_J^+ \end{pmatrix}, S^- = \begin{pmatrix} s_1^- \\ s_2^- \\ \vdots \\ s_i^- \\ \vdots \\ s_I^- \end{pmatrix}, \quad \Lambda = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \vdots \\ \lambda_N \end{pmatrix}, \quad T^+ = \begin{pmatrix} t_1^+ \\ t_2^+ \\ \vdots \\ t_j^+ \\ \vdots \\ t_J^+ \end{pmatrix}, T^- = \begin{pmatrix} t_1^- \\ t_2^- \\ \vdots \\ t_i^- \\ \vdots \\ t_I^- \end{pmatrix}, \quad \Gamma = \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_n \\ \vdots \\ \gamma_N \end{pmatrix}$$

$$E_I = \left(\underbrace{1\ 1\ \cdots 1 \cdots 1}_{I-times}\right), E_J = \left(\underbrace{1\ 1\ \cdots 1 \cdots 1}_{J-times}\right), \ E = \left(\underbrace{1\ 1\ \cdots 1 \cdots 1}_{N-times}\right) \quad ; \quad X_n = \begin{pmatrix} x_{1n} \\ x_{2n} \\ \vdots \\ x_{In} \end{pmatrix} \text{ et } Y_n = \begin{pmatrix} y_{1n} \\ y_{2n} \\ \vdots \\ y_{Jn} \end{pmatrix}$$

$$X = (X_1 \quad \cdots \quad X_N) = (x_{in})_{\substack{1 \leq i \leq I \\ 1 \leq n \leq N}} \text{ and } Y = (Y_1 \quad \cdots \quad Y_N) = \left(y_{jn}\right)_{\substack{1 \leq j \leq J \\ 1 \leq n \leq N}}$$

- Returns to scale and DEA-CCR Envelopment models:

Consider the optimal solution $(\theta_m^*, \Lambda^*, S^{*+}, S^{*-})$of the DEA-CCR model with Envelopment and Orientation-Input associated with the DMU_m where

$$S^{*+} = \begin{pmatrix} s_1^{*+} \\ s_2^{*+} \\ \vdots \\ s_j^{*+} \\ \vdots \\ s_J^{*+} \end{pmatrix}, S^- = \begin{pmatrix} s_1^{*-} \\ s_2^{*-} \\ \vdots \\ s_i^{*-} \\ \vdots \\ s_I^{*-} \end{pmatrix}, \quad \Lambda^* = \begin{pmatrix} \lambda_1^* \\ \lambda_2^* \\ \vdots \\ \lambda_n^* \\ \vdots \\ \lambda_N^* \end{pmatrix}$$

The result below gives the relationship between the type of returns to scale exhibited by the DMU_m and the values taken by the variablesλ_n^*.

Result:

1) $\sum_{n=1}^{N} \lambda_n^* < 1$: the DMU_m operates under increasing returns to scale
2) $\sum_{n=1}^{N} \lambda_n^* > 1$: the DMU_m operates under decreasing returns to scale
3) $\sum_{n=1}^{N} \lambda_n^* = 1$: the DMU_m operates under constant returns to scale

Technical efficiency, pure technical efficiency and scale efficiency:

We can distinguish two types of efficiency of a DMU according to the nature of the model CCR (constant returns to scale) or BCC (variable returns to scale). The DEA-CCR model estimates overall technical efficiency which breaks down into pure technical efficiency and scale efficiency. Technical efficiency describes efficiency in converting inputs into outputs, while scale efficiency recognizes that economies of scale cannot be achieved at all scales of production and that there is a Most Productive Scale Size where scale efficiency is at its maximum 100 percent. The DEA-BCC model considers the variation in efficiency relative to the scale of the operation, so it measures pure technical efficiency. CCR efficiency breaks down as follows:

$$CCR - Efficiency = (Scale\ Efficiency) \times (BCC - Efficiency)$$

The following inequality always holds:

$$CCR - Efficiency \leq BCC - Efficiency$$

Equality occurs when the scale efficiency is equal to one, i.e. the DMU is operating at its Most Productive Scale Size.

5. Results and interpretation

5.1 Evaluation of technical efficiency of the 59 conventional banks of the 11 countries of the MENA region between 2017 and 2021 by the DEA method

We applied the DEA model using the output-oriented approach under the VRS hypothesis to the 59 conventional banks of the 11 countries of the MENA region over the period 2017-2021. Table 3 displays some scores of technical efficiency, pure technical efficiency and efficiency of scale as well as the type of returns to scale of the 59 conventional banks.

Table 3: Some technical efficiency, pure technical efficiency and scale efficiency scores of 59 conventional banks in 11 MENA countries over the period 2017-2021

	2017				2018				2019				2020				2021			
	cte	vte	ste		cte	vte	ste		cte	vte	ste		cte	vte	ste		cte	vte	ste	
1	0,98	1,00	0,98	D	0,94	1,00	0,94	D	0,91	0,99	0,91	D	0,93	0,98	0,95	D	0,94	1,00	0,94	D
2	1,00	1,00	1,00	-	0,95	0,97	0,98	I	0,93	1,00	0,93	I	0,94	0,99	0,95	I	1,00	1,00	1,00	-
3	0,83	0,97	0,85	D	0,81	0,98	0,83	D	0,78	0,97	0,80	D	0,76	0,95	0,80	D	0,75	0,93	0,81	D
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
57	0,77	0,77	0,99	D	0,76	0,76	1,00	-	0,72	0,72	1,00	-	0,74	0,74	1,00	-	0,78	0,78	1,00	D
58	0,75	0,77	0,97	D	0,77	0,79	0,98	D	0,81	0,82	0,99	D	0,84	0,84	1,00	I	0,86	0,86	1,00	D
59	0,83	0,86	0,97	D	0,93	0,93	1,00	D	0,84	0,88	0,95	I	0,81	0,86	0,95	I	0,79	0,79	1,00	-

cte: constant return scale technical efficiency
vte: variable return scale technical efficiency
ste: scale efficiency; C : constant return scale ; D : Decreasing return scale ; I : Increasing return scale

Table 4 shows the evolution of the minimum, maximum and average scores of the 59 conventional banks over the period 2017-2021.

Table 4: Minimum, maximum and average scores of the 59 conventional banks over 2017 and 2021

	2017			2018			2019			2020			2021		
Min	0,670	0,697	0,770	0,679	0,682	0,751	0,645	0,657	0,710	0,667	0,694	0,728	0,657	0,697	0,690
Max	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Average	0,868	0,919	0,945	0,852	0,922	0,927	0,824	0,910	0,909	0,850	0,910	0,935	0,860	0,917	0,939

We note that the average score of the CCR-efficiency of the 59 banks reaches on average 90% during the five years from 2017 to 2021. This means that on average the conventional banks are CCR-inefficient in the five years.

Table 5 shows the evolution of the percentages of efficient conventional banks of type CCR, BCC and scale during the five years from 2017 to 2021.

Table 5: Percentages of CCR, BCC and scale efficient conventional banks between 2017 and 2021

	2017			2018			2019			2020			2021		
	cte	vte	ste	cte	vte	ste	cte	vte	ste	cte	vte	ste	cte	vte	ste
% of efficient conventional banks	15,25	32,20	18,64	13,56	30,51	18,64	11,86	25,42	15,25	15,25	25,42	20,34	20,34	32,20	27,12

We find that the percentage of CCR-efficient conventional banks is low, 15% in 2017, 14% in 2018, 12% in 2019, 15% in 2020 and 20% in 2021.

The following figures represent the evolution of the average scores of overall technical efficiency (CCR), pure technical efficiency (BCC) and scale efficiency of the 59 banks of the 11 MENA countries between 2017 and 2021.

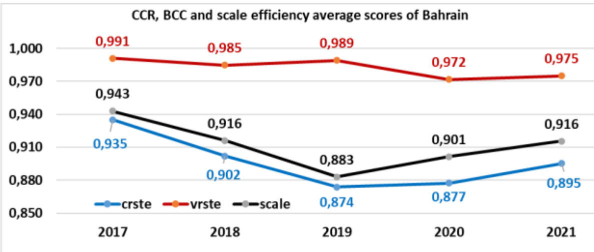

Figure 1 : Bahrain

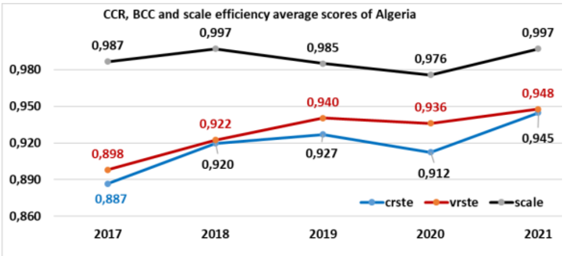

Figure 2 : Algeria

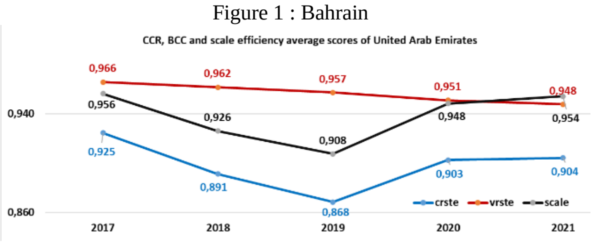

Figure 3 : United Arab Emirates

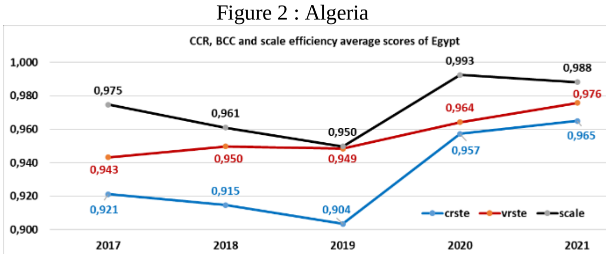

Figure 4 : Egypt

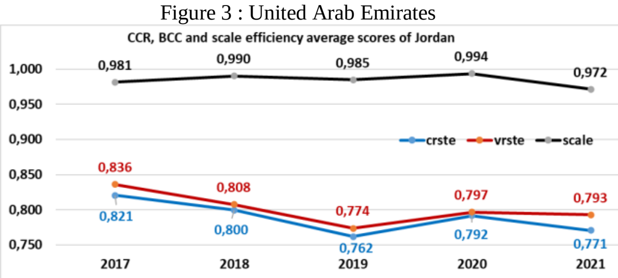

Figure 5 : Jordan

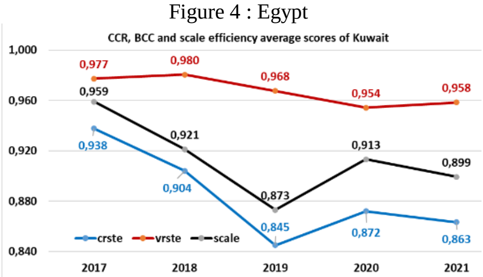

Figure 6 : Kuwait

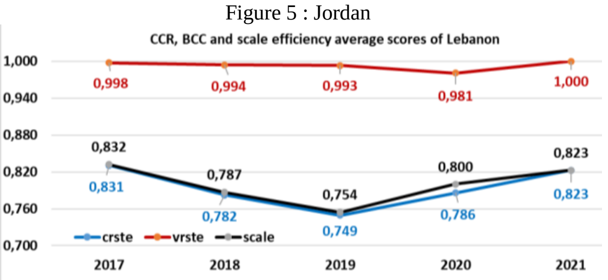

Figure 7 : Lebanon

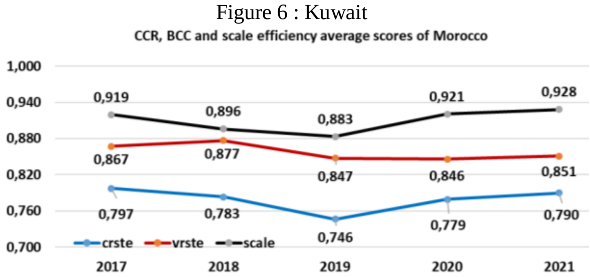

Figure 8 : Morocco

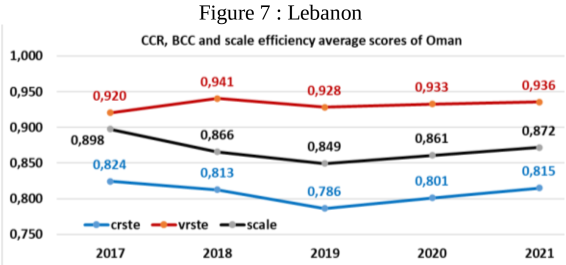

Figure 9 : Oman

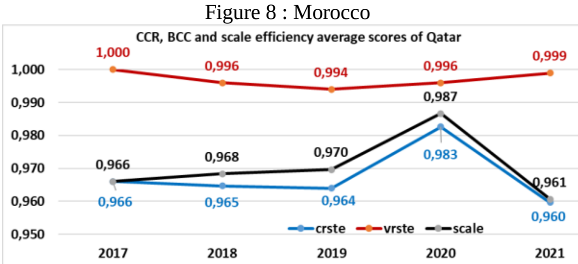

Figure 10 : Qatar

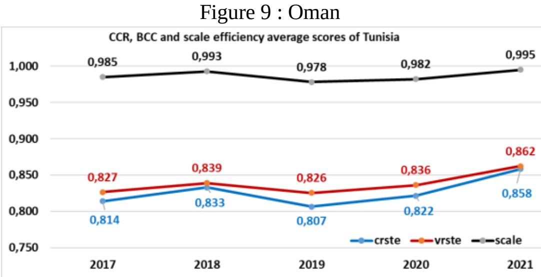

Figure 11 : Tunisia

Table 6 compares the average CCR, BCC and Scale efficiency scores of the 59 conventional banks of the 11 MENA countries during the period 2017-2021.

Table 6: Average CCR, BCC and Scale efficiency scores of conventional banks in the 11 countries

	Bahrain	Algeria	UAE	Egypt	Jordan	Kuwait	Lebanon	Morocco	Oman	Qatar	Tunisia
N°	1	2	3	4	5	6	7	8	9	10	11
cte	0,897	0,918	0,898	0,932	0,789	0,884	0,794	0,779	0,808	0,967	0,827
vte	0,982	0,929	0,957	0,956	0,801	0,968	0,993	0,858	0,932	0,997	0,838
ste	0,912	0,988	0,939	0,973	0,984	0,913	0,799	0,910	0,869	0,970	0,987

Figure 12 shows the evolution of the average CCR, BCC and Scale efficiency scores of the 59 conventional banks of the 11 MENA countries during the period 2017-2021.

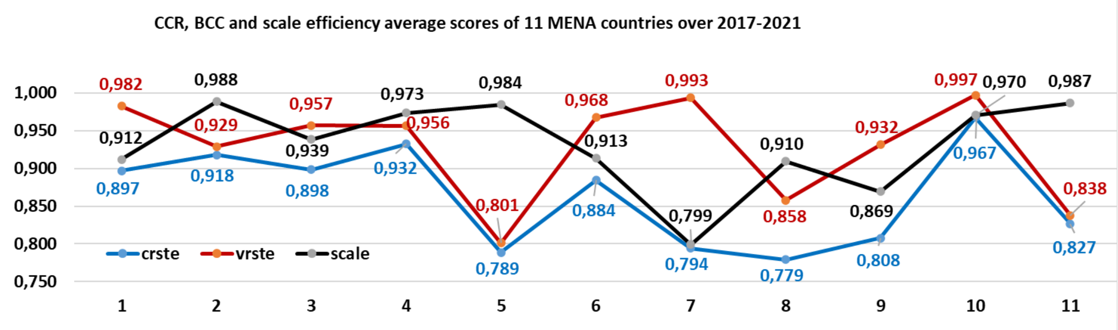

Figure 12: Average CCR, BCC and Scale efficiency scores of conventional banks in the 11 countries

We find that conventional banks in Qatar have the highest average CCR-efficiency score during 2017-2021. Ahli bank in Qatar is CCR and BCC efficient during 2017-2021 and operates in a situation of constant returns to scale. The Commercial bank of Qatar is BCC-efficient during 2017-202. The Commercial bank of Qatar and the Doha bank operate in a situation of decreasing returns to scale. This situation occurs when the average consumption of resources increases with an increase in the outputs produced. These two banks in such a situation have already exceeded their optimal sizes. To improve their scale efficiency scores, they must reduce their output. In a situation of diseconomies of scale, a variation in the production of outputs of 1% implies a variation in the consumption of inputs of more than 1%.

Conventional banks in Morocco and Jordan have the lowest average CCR-efficiency scores (77.9% and 78.9% respectively) during 2017-2021. Their inefficiency is essentially due to a non-optimal size (scale inefficiency).

5.2 Evaluation of the technical efficiency of 22 Islamic banks of the 7 countries of the MENA region between 2017 and 2021 by the DEA method

We applied the DEA model using the output-oriented approach under the VRS hypothesis to the 22 Islamic banks of 7 countries in the MENA region between 2017 and 2021. Table 7 displays some scores of technical efficiency, pure technical efficiency and efficiency of scale as well as the type of returns to scale of the 22 Islamic banks.

Table 7: Some scores of technical efficiency, pure technical efficiency and scale efficiency of the 22 Islamic banks of the 7 MENA countries over 2017-2021

	2017				2018				2019				2020				2021			
N°	cte	vte	ste		cte	vte	ste		cte	vte	ste		cte	vte	ste		cte	vte	ste	
1	0,59	0,59	0,99	I	0,56	0,59	0,94	I	0,64	0,69	0,93	I	0,79	0,83	0,95	I	0,84	0,85	0,99	I
2	1,00	1,00	1,00	C	0,95	0,96	0,99	I	0,49	0,51	0,96	I	0,53	0,59	0,90	I	0,52	0,57	0,92	I
3	0,45	0,45	1,00	C	0,46	0,46	1,00	C	0,52	0,52	1,00	C	0,54	0,54	1,00	I	0,50	0,51	0,98	D
⋮	⋮	⋮	⋮		⋮	⋮	⋮		⋮	⋮	⋮		⋮	⋮	⋮		⋮	⋮	⋮	
19	1,00	1,00	1,00	C	1,00	1,00	1,00	C	1,00	1,00	1,00	C	1,00	1,00	1,00	C	1,00	1,00	1,00	C
20	1,00	1,00	1,00	C	1,00	1,00	1,00	C	1,00	1,00	1,00	C	1,00	1,00	1,00	C	1,00	1,00	1,00	C
21	0,31	0,31	0,99	D	0,38	0,55	0,70	I	0,41	0,63	0,65	I	0,36	0,54	0,66	I	0,42	0,68	0,62	I
22	0,36	0,36	1,00	I	0,33	0,33	0,99	I	0,30	0,33	0,90	I	0,38	0,42	0,89	I	0,40	0,43	0,92	I

Table 8 displays the evolution of the minimum, maximum and average scores of the 22 Islamic banks during the period 2017-2021.

Table 8: Minimum, maximum and average scores of the 22 Islamic banks over 2017-2021

	2017			2018			2019			2020			2021		
	cte	vte	ste	cte	vte	ste	cte	vte	ste	cte	vte	ste	cte	vte	ste
Min	0,16	0,32	0,29	0,27	0,27	0,31	0,33	0,30	0,32	0,31	0,45	0,51	0,31	0,28	0,29
Max	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Moyenne	0,66	0,66	0,61	0,65	0,62	0,72	0,75	0,73	0,78	0,73	0,90	0,89	0,85	0,85	0,85

We note that the average CCR-efficiency score of the 22 banks averages has reached 64% during the 2017-2021 period.

Table 9 displays the percentage of CCR, BCC and scale efficient Islamic banks during the period 2017-2021.

Table 9: Percentage of CCR, BCC and scale efficient Islamic banks over 2017-2021

	2017			2018			2019			2020			2021		
	cte	vte	ste	cte	vte	ste	cte	vte	ste	cte	vte	ste	cte	vte	ste
% of Islamic efficient banks	14%	27%	18%	14%	27%	23%	14%	32%	18%	14%	36%	14%	14%	32%	14%

We find that the percentage of CCR-efficient Islamic banks is low, 14% in 2017, 2018, 2019, 2020 and 2021. While the percentage of BCC-efficient Islamic banks has reached averages 31% between 2017 and 2021.

The following figures represent the evolution of the average scores of overall technical efficiency (CCR), pure technical efficiency (BCC) and scale efficiency of the 22 Islamic banks of the 7 MENA countries during the period 2017-2021.

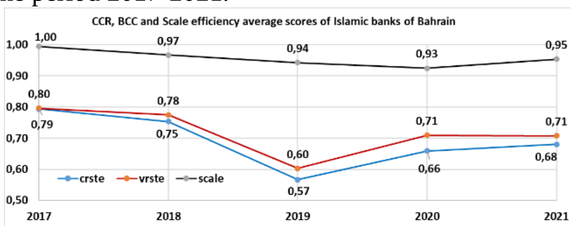

Figure 13

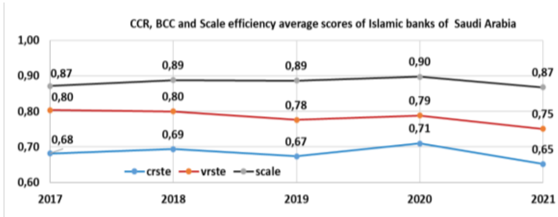

Figure 14

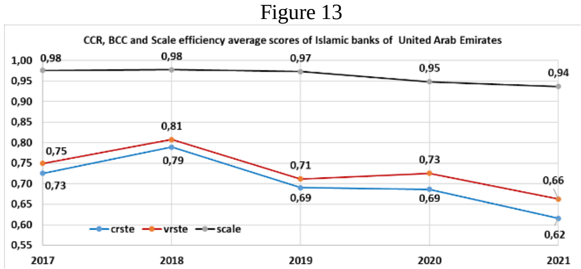

Figure 15

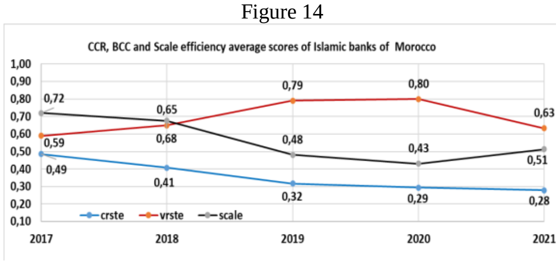

Figure 16

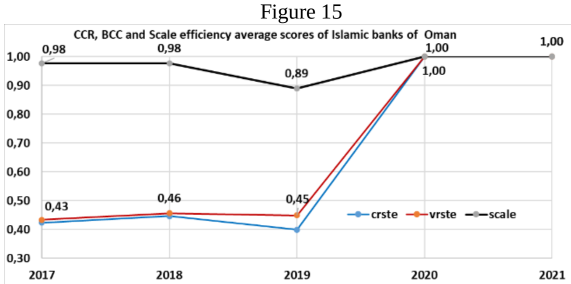

Figure 17

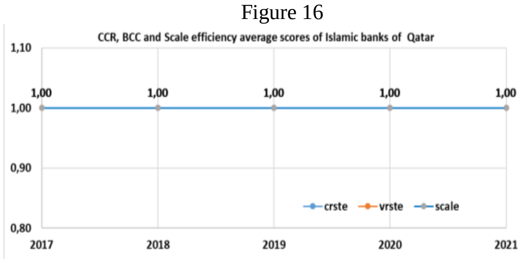

Figure 18

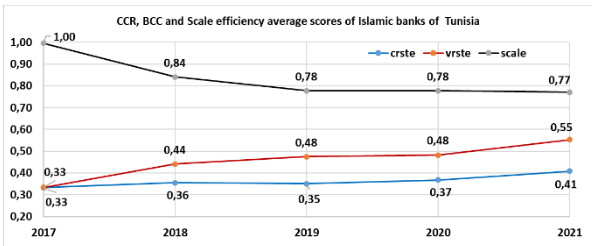

Figure 19

We note from these figures that Qatar is the only country whose Islamic banks are on average CCR-efficient and BCC-efficient in the 5 years. Islamic banks in Oman were also CCR-efficient in 2021 but their average CCR-efficiency score reached 44% from 2017 to 2020.

Morocco is the country in the MENA region whose Islamic banks have the lowest average CCR-efficiency score reaching 36% during the 5 years.

Table 10 compares the average CCR, BCC and Scale efficiency scores of the 22 Islamic banks in the 7 MENA countries during the period 2017-2021.

Table 10: Average CCR, BCC and Scale efficiency scores of Islamic banks in the 7 MENA countries

	Bahrain	Saoudi Arabia	United Arab Emirates	Morocco	Oman	Qatar	Tunisia
	1	2	3	4	5	6	7
cte	0,69	0,68	0,70	0,36	0,65	1,00	0,36
vte	0,72	0,78	0,73	0,69	0,67	1,00	0,46
ste	0,96	0,88	0,96	0,56	0,97	1,00	0,83

Figure 20 shows the evolution of the average CCR, BCC and Scale efficiency scores of the Islamic banks of the 7 MENA countries during the period 2017-2021.

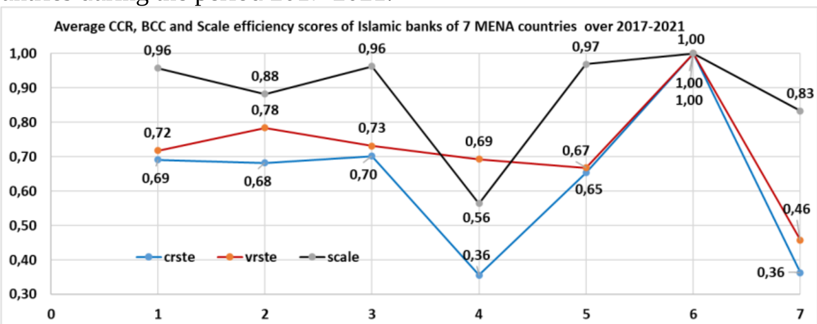

Figure 20: Average CCR, BCC and Scale efficiency scores of Islamic banks in the 7 countries

We find that Islamic banks in Qatar have the highest average CCR-efficiency score during 2017-2021. Indeed, the two Islamic banks analyzed in Qatar, Masraf Al Rayan Bank and Qatar Islamic Bank are CCR-efficient during the 5 years.

Islamic banks in Morocco have the lowest average efficiency-CCR score during 2017-2021, reaching 36%. The inefficiency is due to perfectible management (pure technical inefficiency) on the one hand and to a non-optimal size on the other (scale inefficiency).

6. Conclusion

In this paper, we have applied the Data Envelopment Analysis model to measure the efficiency of banks in the MENA region. Given the unavailability of data, we have limited our study to 81 banks belonging to 12 MENA countries. We divided the 81 banks into two categories, the conventional banks comprising 59 banks which belong to 11 countries and the Islamic banksincluding 22 banks which belongs to 7 countries. For the two categories of banks, we have specified three input variables which Total liabilities, Operating expenses including employees' expenses, Depreciation and amortization of tangible fixed assets and two outputs which are Operating income, Total assets except tangible fixed assets.

The results were obtained by applying the DEAP Version 2.1 software (Coelli (1996)). We have applied the output-orientation DEA method under the assumption of variable returns to scale.

Regarding the 59 conventional banks, the results have showed that the average CCR-efficiency score have reached 90% during the period 2017-2021. We also have found that the percentage of CCR-efficient conventional banks is low, without exceeding 16%. The results also have demonstrated that Qatar is the only country whose conventional banks are BCC-efficient during the 5 years. Qatar's CCR-efficiency scores have exceeded 93% during the 5 years and the inefficiency on average is mainly due to non-optimal size. We also have compared the evolution of the average CCR, BCC and Scale efficiency scores of the 59 conventional banks of the 11 MENA countries. We have found that conventional banks in Qatar have the highest average CCR-efficiency score during the period 2017-2021 reaching 96.7%. Ahli bank in Qatar was CCR-efficient throughout the study period and has evolved in a situation of constant returns to scale. The other two banks in Qatar, the Commercial bank of Qatar and Doha bank were almost both BCC-efficient and have operated in a situation of decreasing returns to scale throughout the period. In other words, the inefficiency of these two banks is mainly due to the exceeding of the optimal size thus,to improve their efficiency, the two banks had to reduce their production. Conventional banks in Morocco and Jordan have exhibited the lowest average CCR-efficiency scores (77.9% and 78.9% respectively) during 2017-2021. Their inefficiency was mainly due to a non-optimal size.

Regarding the 22 Islamic banks, the results have showed that their average CCR-efficiency score have reached on average 64% during 2017-2021. We also have found that the percentage of CCR-efficient Islamic banks is low, 14% during the five years of the period, while the percentage of BCC-efficient Islamic banks has on average reached 31% between 2017 and 2021. We also have found that Qatar is the only country whose Islamic banks were on average CCR-efficient during the 5 years. The average CCR-efficiency score of Islamic banks in Oman also have reached 100% in 2021 but with average scores around 44% from 2017 to 2020.

Islamic banks in Morocco have exhibited the lowest average CCR-efficiency score, with an average of 36% over the 5 years. Their inefficiency is due to perfectible management on the one hand and non-optimal size on the other.

References

[1]. Alber N., Attia H. (2022). Bank Efficiency, Competition and Concentration in MENA Region Countries: A Granger Causality Approach. *European Journal of Business and Management Research, 2022.7.6.1688 Vol 7 | Issue 6 | November 2022*.

[2]. Ali A., Seiford M. (1993). The Mathematical Programming Approach to Efficiency Analysis. *In Fried HO and SS Schmidt (eds.). The Measurement of Productive Efficiency: Techniques and Applications, Oxford U.K.: 120-159.*

[3]. Banker R., Charnes R., Cooper W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science vol. 30, pp. 1078-1092*.

[4]. Apergis N., Polemis M.L. (2016). Competition and efficiency in the MENA banking region: a non-structural DEA approach. *Applied Economics, DOI: 10.1080/00036846.2016.1176112*.

[5]. Bahrini R. (2017). Efficiency Analysis of Islamic Banks in the Middle East and North Africa Region: A Bootstrap DEA Approach. *International journal of financial studies. 2017, 5(1), 7; https://doi.org/10.3390/ijfs5010007.*

[6]. Bekakria I. . Azzouz S. (2020). Etude comparative entre l'efficience des Banques islamiques et des banques conventionnelles : Méthode DEA. *Revue des sciences commerciales et de gestion. Volume 16, Numéro 1, Pages 78-96. 2020-12-31.*

[7]. Berger A.N., Humphrey D.B. (1997). Efficiency of financial institutions. International surveys and directions for future research. *European Journal of Operational Research, vol. 98, pp 175-212.*

[8]. Charnes, A., Cooper, W.W., Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research, 2, 429-444.*

[9]. Charnes A., Cooper W., and Rhodes E. (1978). Measuring the Efficiency of Decision Making Units. European Journal of Operational Research, 2, 429-444.

[10]. Charnes A., Cooper W., Rhodes E. (1979). Short Communication: Measuring the Efficiency of Decision Making Units. EJOR: 339.

[11]. Coelli, T. J. (1996). A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program. *Working Paper 96/08). Brisbane: Centre for Efficiency and Productivity Analysis, University of Queensland..*

[12]. Cooper W., Seiford L., Tone K. (2002). Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software. *Boston: Kluwer Academic Publishers.*

[13]. Cook W. D., Zhu J. (2014). Data Envelopment Analysis. A Handbook on the Modeling of Internal Structures and Networks. Research & Management Science. Springer Science+Business Media New York 2014.

[14]. De La Villarmois O. (2001). Le concept de performance et sa mesure : un état de l'art. *Cahier de la recherche, GREMCO/CLAREE-IAE de Lille. 2001.*

[15]. Eisazadeh S., Shaeri Z. (2012). An analysis of bank efficiency in the MENA. *The International Journal of Banking and Finance, Volume 9 (Number 4) 2012: pages 28-47.*

[16]. Farrell M. J. (1957). The Measurement of Productive Efficiency.*Journal of the Royal Statistical Society. Series A (General), Vol. 120, No. 3 (1957), pp. 253-290.*

[17]. Hwang S. N., Lee H. S., Zhu J. (2016). Handbook of Operations Analytics Using Data Envelopment. *International Series in Operations Research & Management Science. Springer Science+Business Media New York 2016.*

[18]. Johnes J., Izzeldin M., Pappas V. (2012). A comparison of performance of Islamic and conventional banks 2004 to 2009.*Working Papers 12893801, Lancaster University Management School, Economics Department.*

[19]. Joro T., Korhonen P., Wallenius J. (1998). Structural comparison of data envelopment analysis and multiple objective linear programming. *Management Sci. 40, 962-970. Journal of Productivity Analysis 5:171-180.*

[20]. Mariani A., Saal D., Battisti G. (2010). Efficiency in Islamic and conventional banking: an international comparison. *Journal of Productivity Analysis, 2010, vol. 34, issue 1, 25-43.*

[21]. Wen M. (2015). Uncertain Data Envelopment Analysis. *Springer-Verlag Berlin Heidelberg.*

[22]. Rizk S.(2022). Efficiency in the MENA banking industry, the stochastic frontier approach. *Financial Markets, Institutions and Risks, Volume 6, Issue 2, 2022 ISSN– 2521-1242 ISSN- 2521-1250.*

[23]. Tahi A., Djebbouri M., Benzai Y. (2020). Assessing the efficiency of Islamic and conventional banks in the MENA banking system: Data Envelopment Analysis DEA investigation.*International Journal of Innovation and Applied Studies ISSN 2028-9324 Vol. 30 No. 1 Jul. 2020, pp. 414-426.*