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Technical efficiency analysis of MENA Islamic banks during and after the global financial crisis

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Abstract

Despite that the most impressive growth rates realized by Islamic banks was recorded in the Middle East and North Africa (MENA) region, few empirical studies have analyzed their performance especially in the global financial crisis period. Given this, in our paper we measure and analyze the technical efficiency of a sample of 33 MENA Islamic banks during and after the global financial crisis period (2006-2012). To do this, we apply the bootstrap Data Envelopment Analysis (DEA) approach, which is a robust method that allowed us to correct the estimation bias and to construct confidence intervals for the estimated efficiency scores at desired levels of significance. Our results show that over the period of study the technical inefficiency of MENA Islamic banks was mainly explained by pure technical inefficiency rather than scale inefficiency. In addition, we find that all MENA Islamic banks' efficiency levels have increased during the global financial crisis period (2007-2008) and in the early post-crisis period (2009-2010) before decreasing in the last two years of the study period (2011-2012). According to our findings, we suggest that the managers of MENA Islamic banks should focus more on improving their managerial performance rather than on increasing the scale of operations. We also recommend that supervisory authorities in MENA countries undertake many regulatory and financial measures in order to support the development of Islamic banking in the MENA region.

Keywords: Technical efficiency, Islamic banks, MENA, global financial crisis, Bootstrap, Data Envelopment Analysis

1. Introduction

In the last years, Islamic banking has evolved tremendously in many regions of the world becoming a distinctive and fast-growing segment of the international banking and capital markets (Hassan and Lewis, 2007). Furthermore, the performance and relative stability of Islamic banks during the global financial crisis of 2007-2008 compared to conventional banks allowed them to gain popularity among Muslim as well as non-Muslim depositors and investors who are seeking for more secure and confident banking transactions. (Hasan & Dridi, 2010; Cihak & Hesse, 2010; Farooq & Zaheer, 2015, etc.).

Given this, many academic researchers around the world were particularly interested in studying the performance of Islamic banks. Several researchers have conducted cross-country studies using frontier methods such as the Data Envelopment Analysis (DEA) method, in order to evaluate and to analyze the technical efficiency of Islamic banks (Yudistira, 2004; Sufian & Noor, 2009; Ben Hassine & Limani, 2014, etc.). However, few empirical studies have analyzed the technical efficiency of MENA Islamic banks during the global financial crisis (2007-2008) despite that the most important growth rates of Islamic banking assets have been recorded in the MENA region during the last years.

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The current literature showed mixed results regarding the impact of the global financial crisis on the performance of Islamic banks. While some studies confirm that this crisis has a positive impact (Smolo & Mirakhor, 2010; Beck et al., 2013; Alqahtani et al., 2016, etc.), other studies have not found any significant impact (Ftiti et al., 2013; Samad, 2013; Mobarek & Kalonov, 2014, etc.)

In order to contribute to this literature, this paper attempts to provide an understanding of how MENA Islamic banks performed during and after the global financial crisis period in terms of technical efficiency. To do this, we apply Simar and Wilson's (1998) bootstrap DEA approach in order to robustly measure and analyze the technical efficiency of a sample of 33 Islamic banks operating in 11 MENA countries during and after the global financial crisis (2006-2012). The reminder of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes the methodology followed. Section 4 presents the data and the variables used. Section 5 reports and discusses the results found. Conclusions are presented in Section 6.

Literature review

In this review of literature, we focus mainly on the studies that used cross-country-bank level data. Most of these studies have applied different non-parametric methods in order to construct efficiency frontiers and then to measure and analyze bank efficiency. These methods allowed researchers to assess the overall technical inefficiency (*measures inefficiency due to the input/output configuration as well as the size of operations*) and to decompose it into pure technical inefficiency (*measures inefficiency due to managerial underperformance*) and scale inefficiency (*measures inefficiency due to the size of operations*). Yudistira (2004) performed a cross-country analysis of technical efficiency in the case of 18 Islamic banks from GCC, East Asian, African and Middle Eastern countries during the period 1997-2000. By applying the DEA method, he found that across all countries the overall technical inefficiency score of Islamic banks is small at just over 10%, on average. This result is mainly explained by pure technical inefficiency rather than scale inefficiency.

Hassan (2006) employed both parametric and non parametric frontier methods (SFA and DEA) to assess the cost, profit, allocative, technical, pure technical and scale efficiency of 43 Islamic banks in 21 countries from Middle East, Asia, Africa and Europe over the period 1995-2001. He found that Islamic banks are more cost inefficient than profit inefficient, which means that they are better in generating profits than controlling costs. The analysis of these findings shows that during the study period, the major source of overall technical inefficiency of Islamic banks is scale inefficiency and not pure technical inefficiency like was found by Yudistira (2004). Another empirical analysis have been applied by Sufian and Nour (2009), who have used the non-parametric DEA method to estimate in one hand annual frontiers for a panel of MENA Islamic banks and in the other hand annual frontiers for a panel of Asian Islamic banks in order to compare their technical efficiency over the period 2001-2006. The main results show that MENA Islamic banks have higher technical efficiency scores compared to their Asian counterparts and that all sampled banks suffered from pure technical inefficiency more than scale inefficiency.

Taking into account the importance to understand how Islamic banks performed during the global financial crisis a few cross-country studies have been conducted. Noor and Ahmad (2012) investigated the efficiency of 78 Islamic banks operating in 25 countries during the period 1992–2009. By using the DEA method, they showed that the technical efficiency levels of many Islamic banks in the world have increased during and after the global financial crisis period. They argued this finding by the fact that financial crisis has decreased trust in the conventional banking system in favor of the Islamic banking model. In addition, they found that over the period of study the pure technical efficiency scores of sampled Islamic banks exceed their scale efficiency scores. This result is in contradiction with the results found by Sufian and Nour (2009) and Yudistira (2004).

By focusing on 25 Islamic banks in GCC countries during the period 2003-2009 and using the DEA method, Srairi and Kouki (2012) found that GCC Islamic banks have performed well during and after the global financial crisis period in terms of overall technical efficiency. Results show also that the overall technical inefficiency of GCC Islamic banks is attributed to pure technical inefficiency (29.3%) rather than to scale inefficiency (17%). Similarly, Ftiti et al. (2013) have applied the DEA method on a sample of 30 GCC Islamic banks during the period 2005-2009. They found that the technical efficiency levels of GCC Islamic banks have not been affected by the subprime crisis.

This finding was confirmed by Samad (2013) who has used time varying decay model of stochastic frontier function in order to estimate the efficiency scores of 28 Islamic banks across 16 different countries during the pre-global financial crisis and the global financial crisis periods. Rahman and Rosman (2013) and Rosman et al. (2014) have applied the DEA method to compare the technical efficiency levels of Middle Eastern Islamic banks with those of their Asian counterparts over periods that include the global financial crisis, which are 2006-2009 and 2007-2010, respectively. Their results show that on average Islamic banks from Middle East were less technically efficient compared to Islamic banks from Asia.

Results indicate also that technical efficiency scores of all Islamic banks in the sample have increased during the global financial crisis period (2007-2008). However, the results confirm that in the post-crisis period (2009-2010), technical efficiency of Middle Eastern Islamic banks has declined, while it has increased for their Asian counterparts. In accordance with Noor and Ahmad (2012), scale inefficiency was found to be the major source of technical inefficiency of all sampled Islamic banks.

This result was also confirmed by Mobarek and Kalonov (2014) who have applied both the DEA and the Stochastic Frontier (SFA) approaches on Islamic and conventional banks from 18 OIC (Organization of Islamic Conference) countries during the pre-crisis period (2004-2006) and the crisis period (2007-2009). In addition, they have not found any visible impact of the global financial crisis on the efficiency of sampled Islamic banks. Focusing on a sample of 22 MENA Islamic banks over the period 2005-2009, Ben Hassine and Limani (2014) showed that, contrary to previous findings, pure technical inefficiency is the main source of Islamic banks' technical inefficiency.

In total, this literature review shows that there is a lack of consensus between researchers concerning the impact of the global financial crisis on the technical efficiency of Islamic banks. In addition, previous results were mixed regarding the sources of Islamic banks' technical inefficiency during and after the period of global financial crisis.

Methodology

In this section we firstly introduce the DEA method. Secondly, we present the bootstrap DEA approach used to measure and analyze the technical efficiency of MENA Islamic banks during and after the global financial crisis.

The DEA method

The DEA method is a nonparametric method initially developed by Charnes et al. (1978) that uses the linear programming techniques in order to construct the *best practice* frontier from the observed inputs and outputs of all the sampled Decision Making Units (DMUs). This method aims to measure how efficiently a DMU uses his available inputs to produce a set of outputs. By comparing DMUs outside the frontier (inefficient DMUs) with those that lie on the frontier (efficient DMUs), this method can provide efficiency measures for each DMU (Coelli et al., 2005). Following Seiford and Zhu (1999), we present the CCR DEA model proposed by Charnes, Cooper and Rhodes (1978). Suppose that we have *n* DMUs to be evaluated. Each DMU_j, $j = 1, \ldots, n$ uses *m* different inputs, noted x_{ij} $(i = 1, \ldots, m)$, to produce *s* different outputs, noted y_{rj} $(r = 1, \ldots, s)$. The technical efficiency score θ^* for a particular DMU, called DMU_o, is determined by solving the following linear programming problem:

$$\begin{aligned} &\theta^* = \text{Min}\,\theta \\ \text{s.t.}\ &\textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} && i = 1, \ldots\ldots, m; \\ &\textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} && r = 1, \ldots\ldots, s; \\ &\lambda_j \geq 0 && j = 1, \ldots\ldots, n; \end{aligned} \tag{1}$$

$\theta^* < 1$ Means that the evaluated DMU is technically inefficient. $\theta^* = 1$ Indicates a point on the frontier and hence a technically efficient DMU. In order to estimate the efficiency scores of all the DMUs in the sample, the above problem must be solved n times, once for each DMUj, *j =1, …., n* (Coelli et al., 2005).

By considering that DMUs are not always operating under a Constant return to Scale (CRS) (at an optimal scale) like was assumed in the CCR model, Banker, Charnes and Cooper (1984) have proposed a new DEA model called the BCC model. This model considers that DMUs are operating under a Variable Return to Scale (VRS) (increasing, constant or decreasing returns to scale). According to this model, the technical efficiency score b^* for the particular DMU$_o$ is determined by solving the following linear programming problem (Seiford & Zhu, 1999):

$$
\begin{aligned}
& b^* = \text{Min } b \\
\text{s.t. } & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} && i = 1, \dots\dots, m; \\
& \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} && r = 1, \dots\dots, s; \qquad (2) \\
& \textstyle\sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j \geq 0 && j = 1, \dots\dots, n;
\end{aligned}
$$

Where $\sum_{j=1}^{n} \lambda_j = 1$ is the convexity constraint added to transform the CCR model to a BCC model?

The application of both the CCR and the BCC DEA models allow us to decompose the overall technical efficiency into pure technical efficiency and scale efficiency. The following figure illustrates this by providing a simple example of a DMU that uses one input (x) to produce one output (y):

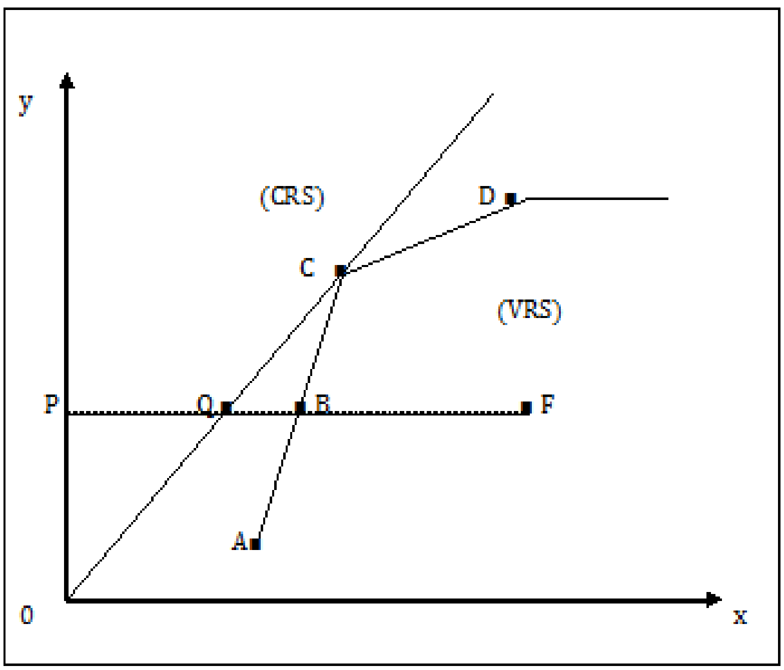

Figure 1: CRS and VRS efficiency frontiers (Coelli et al, 2005).

The line through the points Q and C represents the CRS efficiency frontier and the curve (ABCD) represents the VRS efficiency frontier. Each DMU that is on the frontier is technically efficient. For this reason, the particular DMU "F" is technically inefficient. When we refer to the CRS frontier, the distance FQ measures the technical inefficiency of the DMU "F". However, when we consider the VRS frontier, the technical inefficiency of the DMU "F" is only the distance FB. The difference between the CRS and the VRS frontiers is the distance QB which is a measure of scale inefficiency.

In total we can determine for the particular DMU "F":

- The overall technical efficiency score (under the CRS frontier): $\mathrm{TE_{CRS}} = \mathrm{PQ/PF}$
- The pure technical efficiency score (under VRS frontier): $\mathrm{TE_{VRS}} = \mathrm{PB/PF}$
- The scale efficiency score : $\mathrm{SE} = \mathrm{PQ/PB}$

From this, we can deduce that $\mathrm{TE_{CRS}} = \mathrm{TE_{VRS}} \times \mathrm{SE}$ which means that we can decompose the overall technical efficiency of a particular DMU into a measure of pure technical efficiency and a measure of scale efficiency.

The Bootstrap DEA approach

Despite the wide use of non-parametric efficiency methods in measuring the efficiency of DMUs, these methods are deterministic which means that they not allow for random errors and therefore underestimate the distance to the frontier leading to biased efficiency scores. (Simar & Wilson, 1998).

Aiming to improve the non-parametric efficiency methods, Simar and Wilson (1998) proposed to use the bootstrap DEA approach. Introduced by Efron (1979), the bootstrap is a computer-based approach considered as a resampling procedure that makes inferences about a sampling distribution by resampling the sample itself with replacement (Efron & Tibshirani, 1993; Horowitz, 2001; Chernik & LaBudde, 2011).

With reference to Simar and Wilson (1998), bootstrapping the DEA efficiency scores can be summarized in the following steps:

1. Compute the efficiency scores $\hat{\theta}_j$ for each $\mathrm{DMU_j}$, $j = 1, \ldots, n$, by solving the linear programming models presented in the previous paragraph.
2. Generate a random sample of size n $\{\theta^*_{1b}, \ldots, \theta^*_{nb}\}$ by drawing with replacement from $\{\hat{\theta}_1, \ldots, \hat{\theta}_n\}$. We apply here the "*smoothed bootstrap*" (see Simar & Wilson, 1998 for a detailed explanation).
3. Compute a pseudo data set $\{(x^*_{jb}, y_j);\ j = 1 \ldots\ldots, n\}$ to form the reference bootstrap technology, where $x^*_{jb} = \frac{\hat{\theta}_j}{\theta^*_{jb}}\, x_j$.
4. Compute the bootstrap estimate $\hat{\theta}^*_{jb}$ of the efficiency scores $\hat{\theta}_j$ for each $\mathrm{DMU_j}$, $j = 1, 2, \ldots, n$, by solving the bootstrap counterparts of the linear programming models previously presented.
5. Repeat steps 2 – 4 a number of times B, in order to provide for $j = 1, \ldots, n$, a set of bootstrap estimates $\{\hat{\theta}^*_{jb};\ b = 1 \ldots\ldots, B\}$. In order to give a reasonable approximation of confidence intervals, Simar and Wilson (2000) recommend a value of B = 2000.

Applying the above bootstrapping procedure allows us to construct confidence intervals at a desired level of significance for the efficiency scores. Simar and Wilson (2000) show that the estimated (1 - α)-percent confidence interval of each $\mathrm{DMU_j}$, $j = 1, \ldots, n$, is :

$$\hat{\theta}_j + \hat{a}_\alpha \leq \theta_j \leq \hat{\theta}_j + \hat{b}_\alpha \qquad (3)$$

Where $\hat{a}_\alpha$ and $\hat{b}_\alpha$ are parameters calculated by sorting the values $(\hat{\theta}^*_{jb} - \hat{\theta}_j)$ for $b = 1 \ldots\ldots, B$ in increasing order and then deleting $(\alpha/2 \times 100)$-percent of the elements at either end of the sorted list, with $\hat{a}_\alpha \leq \hat{b}_\alpha$.

Furthermore, the bias of the estimated efficiency scores $\hat{\theta}_j$, $j = 1, \ldots, n$, is determined as follows :

$$\widehat{\mathrm{Bias}}_j\left(\hat{\theta}_j\right) = \mathrm{B}^{-1}\sum_{\mathrm{b}=1}^{\mathrm{B}} \hat{\theta}^{*}_{jb} - \hat{\theta}_j \qquad (4)$$

From the equation (4), the bias-corrected estimation of each efficiency score θ_j, $j = 1, \ldots, n$, is :

$$\hat{\hat{\theta}}_{\mathrm{j}} = \hat{\theta}_j - \widehat{\mathrm{Bias}}_j\left(\hat{\theta}_j\right) \qquad (5)$$

Data and variables

Data

We use cross-country level data, which consists of inputs and outputs sourced from the BankScope database and the financial statements of 33 Islamic banks[3] operating in 11 MENA countries during the period 2006-2012. This allows us to have 231 bank-year observations. Furthermore, all the values used are converted to U.S. dollar using the appropriate average exchange rates for each year and deflated by the Customer Price Index (CPI) of each country where the bank originates from in order to ensure the comparability of data across countries.

Inputs and outputs of Islamic banks

According to Sealey and Lindley (1977), the intermediation approach was one of the approaches most used in the literature to define banks' inputs and outputs. This is also true in the case of Islamic banks. Indeed, most empirical studies dealing with Islamic bank efficiency have adopted the intermediation approach considering these banks as financial intermediaries providing funds to investors and collecting deposits from depositors (see, Yudistira, 2004; Sufian & Nour, 2009; Mobarek & Kalonov, 2014; etc.).

Given this, we consider that MENA Islamic banks produce two outputs namely, *Total loans* (Y1), which includes Murabaha and deferred sales, leasing and hire purchase, Mudarabah and Musharakah and *Investment portfolio* (Y2), which includes investment in companies, funds and shares, investment in bonds, bills and securities and investment in properties and real estate, by using three inputs namely, *Labor* (X1), valued as the amount of staff costs, *Fixed assets* (X2), valued as the book value of property, plant and equipment and *Total deposits* (X3), valued as the amount of customer's funds and due to banks and other financial institutions.

Table 1 below presents the summary statistics of inputs and outputs used in the estimations. This table shows that the mean values of all the inputs and the outputs have increased steadily during the financial crisis period (2007-2008) and in the post-crisis period (2009-2012). This could eventually indicate that MENA Islamic banks' activities have not been negatively affected by the global financial crisis.

Table 1: Summary statistics of outputs and inputs (mean values)

		2006	2007	2008	2009	2010	2011	2012
Outputs	Total loans (Y1)	3155	2587	2851	3121	3484	3762	4141
	Investment portfolio (Y2)	747	824	1025	1034	787	960	987
Inputs	Labor (X1)	46	41	45	46	47	51	54
	Fixed Assets (X2)	155	107	131	137	149	167	156
	Total Deposits (X3)	3481	3086	3622	3861	4209	4362	4673

Note: all values are in US$ million

1 The sample used in this study consists of 5 banks from Bahrain, 4 banks from United Arab Emirates, 3 banks from Kuwait, 2 banks from Qatar, 3 banks from Saudi Arabia, 2 banks from Jordan, 1 bank from Yemen, 2 banks from Iran, 2 banks from Egypt, 1 bank from Tunisia and 8 banks from Sudan.

Results and discussions:

In this section, we present and discuss the results found by applying the standard and the bootstrap DEA approaches on a sample of 33 Islamic banks operating in 11 MENA countries between 2006 and 2012.

Standard and bias-corrected technical efficiency

Firstly, we employ a standard DEA CCR model in order to measure the overall technical efficiency of sampled MENA Islamic banks during the study period (2006-2012). Secondly, we apply the Simar and Wilson's (1998) bootstrap DEA approach in order to estimate the bias-corrected overall technical efficiency scores and to construct confidence intervals for the estimated efficiency scores. The main results are summarized in Table 2 bellow, which presents the standard overall technical efficiency scores (OTE), the estimation bias (BIAS) and the bias-corrected overall technical efficiency scores (OTE_BC).

Table 2: Standard and bias-corrected overall technical efficiency scores

	OTE	BIAS	OTE_BC
2006	0.795	0.164	0.631*
2007	0.886	0.076	0.810*
2008	0.899	0.071	0.828*
2009	0.881	0.083	0.799*
2010	0.889	0.071	0.819*
2011	0.792	0.124	0.668*
2012	0.790	0.121	0.670*
Mean	0.847	0.101	0.746

Notes: * denotes an efficiency score significant at 5%. Details on confidence intervals for each bank in each year are available upon request

According to Table 2, there is an estimation bias (BIAS) of 0.101, on average. This means that the CCR DEA model yields a biased standard overall technical efficiency scores (OTE) which are overestimated by 10.1 percent on average, compared to the bias-corrected overall technical efficiency scores (OTE_BC) provided by the bootstrap DEA approach. Table 2 shows also that unlike the standard efficiency scores which are not statistically significant, all the bias-corrected efficiency scores are significant at 5%, which means that all their values are between the lower and the upper bound of the 95% confidence intervals. By focusing only on the bias-corrected efficiency scores, Table 2 shows that MENA Islamic banks have an average efficiency score of 0.746 over the period 2006-2012. This means that to be fully technically efficient, MENA Islamic banks still need to reduce their current inputs by 25.4 percent while leaving their outputs unchanged.

Sources of technical inefficiency

We estimate a BCC DEA model in order to decompose the bias-corrected overall technical efficiency scores (OTE_BC) into scores of pure technical efficiency (PTE_BC) and scale efficiency (SE_BC). This decomposition allows us to identify the sources of overall technical inefficiency. Results are presented in Table 3 below. This table shows that MENA Islamic banks are more scale efficient (average score 0.909) than pure technically efficient (average score 0.821) during the period 2006-2012. This means that the dominant source of overall technical inefficiency for these banks during the period of study is pure technical inefficiency rather than scale inefficiency.

Table 3: Bias-corrected overall technical, pure technical and scale efficiency scores

	OTE_BC	PTE_BC	SE_BC
2006	0.631*	0.770*	0.815*
2007	0.810*	0.868*	0.932*
2008	0.828*	0.898*	0.923*
2009	0.799*	0.891*	0.898*
2010	0.819*	0.868*	0.945*
2011	0.668*	0.745*	0.900*
2012	0.670*	0.709*	0.946*
Mean	0.746	0.821	0.909

Note: * denotes an efficiency score significant at 5%

In accordance with the previous studies of Srairi and Kouki (2012) and Ben Hassine and Limani (2014), our findings allow us to state that the management of MENA Islamic banks is not able to avoid wasting inputs. Indeed, by following appropriate and efficient management practices in allocating resources, MENA Islamic banks' mangers can reduce their inputs by 17.9%, on average, while producing the same amount of outputs. Furthermore, a little improvement of overall technical efficiency of MENA Islamic banks can be achieved through increasing scale efficiency. Indeed, by raising their sizes to reach the optimum scale, MENA Islamic banks can reduce their current inputs by 9.1% on average without changing their level of outputs.

To further analyze the evolution of technical efficiency in the case of MENA Islamic banks during and after the global finance period, we present the following figure:

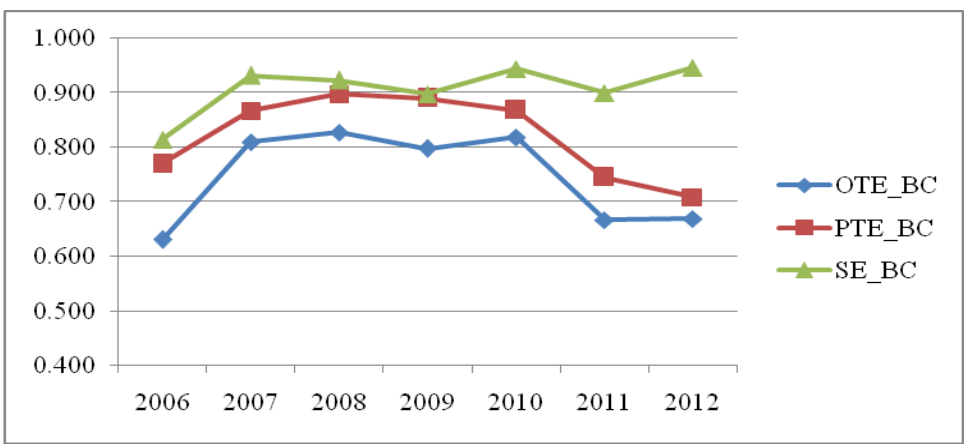

Figure 2: Bias-corrected efficiency scores between 2006 and 2012.

It is clear from Figure 2 that the efficiency scores of MENA Islamic banks were relatively stable during the global financial crisis (2007-2008) and in the early post-crisis period (2009-2010. However, Figure 2 reveals also that MENA Islamic banks' technical efficiency levels have declined in the last two years of the post-crisis period (2011-2012). This decline was due essentially to the decrease of their pure technical efficiency levels. A possible explanation of these results is that MENA Islamic banks have taken advantage of the global financial crisis which gave them the opportunity to increase their market shares in terms of credits and deposits, while it have negatively affected conventional banks that became more vulnerable and therefore less competitive. However, the end of the post-crisis period (2011-2012) was less beneficial for MENA Islamic banks, as they eventually had great difficulty to expand their activities as well as conventional banks which have gradually recovered from the negative effects of the financial crisis.

Conclusions

In this paper, we measured and analyzed the technical efficiency of a sample of 33 MENA Islamic banks during and after the global financial crisis period (2006-2007). To do this, we applied the Simar and Wilson's (1998) bootstrap DEA approach, which is a robust approach that corrects the estimation bias and constructs confidence intervals for the estimated DEA efficiency scores at desired levels of significance. We found that on average MENA Islamic banks were technically inefficient during the period of study and that their inefficiency is attributed to pure technical inefficiency instead of scale inefficiency. By analyzing the efficiency changes, our results indicated that all the estimated efficiency scores were relatively stable during the crisis period (2007-2008) and in the two first years of the post-crisis period (2009-2010). This could indicate that MENA Islamic banks have benefited from the last financial crisis which caused many difficulties to conventional banks. This is consistent with earlier studies that have proved that MENA Islamic banks were the most stable, profitable and efficient during the financial crisis period (Beck et al., 2013; Farooq & Zaheer, 2015, etc.).

However, results indicated that MENA Islamic banks have known a decrease in their efficiency levels in the end of the post-crisis period, which could be explained by managerial underperformance. However, this decline could also be due to the fact that in the last two years of the study period MENA Islamic banks were operating in a business environment more favorable to the development of conventional banks. Indeed, several empirical analyses have demonstrated that conventional banks have performed better than Islamic banks after the global financial crisis period (Mobarek & Kalonov, 2014; Alqahtani et al., 2016, etc.). From these results we can suggest that managers of MENA Islamic banks should improve their performance in allocating resources. In addition, we recommend that policy-makers and financial authorities in the MENA countries develop the legal and the regulatory infrastructure in order to promote the expansion of Islamic banking activities in the MENA region.

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