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# Directional distance function DEA estimators for evaluating efficiency gains from possible mergers and acquisitions

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## Abstract

A modified generalized directional distance function data envelopment analysis model is introduced into the smoothed bootstrap context. The new model handles asymmetrically desirable and undesirable outputs and deals with positive and negative values, while the bias-corrected estimators are independent of the length of the direction vector. The reason for the development of this new efficiency assessment model is the estimation of the degree of operating efficiency gains from possible mergers and acquisitions (M&A) between banks. Our estimations are regarded as more realistic compared to those found in the extant literature, as they take into account not only desirable but also undesirable variables (e.g., non-performing loans) and data irregularities (e.g., negative values) that are crucial to the evaluation of the performance of firms. The new model is applicable not only to the banking sector, as it can be used in any industry. We use two samples, one consisting of 86 conventional and a second one with 21 Islamic banks. Among the findings of this study is the convergence of the conventional and Islamic banks' efficiencies from 2014–2016. Moreover, M&A are useful only for conventional banks to retain or improve their efficiency levels.

**Keywords:** Banking; Bank mergers; Efficiency; Data envelopment analysis; Bootstrap

## 1. Introduction

A great deal of the extant banking literature has elaborated on mergers and acquisitions (M&A) (Berger et al., 1999; Amel et al., 2004; DeYoung et al., 2009). M&A have played a crucial role in the concentration of the banking markets worldwide. According to Fraisse et al. (2018), the reasons behind M&A in the banking industry are: (a) efficiency gains, (b) market power increase, and (c) lending technology improvement. This study extends existing methodologies in order to provide a more realistic evaluation of efficiency gains from hypothetical M&A between banks. The modifications to current methodologies (i.e., Simar et al., 2012; Halkos & Tzeremes, 2013) facilitate the incorporation in this assessment exercise of undesirable variables such as non-performing loans. Moreover, our methodology, which draws on the smoothed bootstrap data envelopment analysis (DEA) framework (Kneip et al., 2011), can address both positive and negative values that are commonly met in financial variables. This methodological extension sheds light on a strand of the M&A literature that has not been analyzed so far, as studies in this area have not taken into account externalities and other data irregularities (Bernad et al., 2010; Peyrache, 2013; Tarsalewska, 2015; Degl'Innocenti et al., 2017; Ahmad & Lambert, 2019; Siganos, 2019; Arocena et al., 2020).

The literature on M&A and banking efficiency has grown considerably in recent years, as consolidations have become more frequent (Avinadav et al., 2017; Fraisse et al., 2018). The main justification for bank consolidations is cost reduction and operating efficiency improvement (Larkin & Lyandres, 2019). Despite the increasing trend of M&A in the banking sector, the outcomes of these transactions are mixed (Berger & Udell, 2002; Amel et al., 2004; Halkos & Tzeremes, 2013).

In this study, we investigate efficiency gains from M&A between banks in the Middle East and North Africa (MENA) region and Turkey. We apply our methodology to the two banking systems (i.e., the conventional and the Islamic) operating in this region separately, as any consolidation between banks across these two systems is not possible. The financial institutions, especially in the MENA region, are largely state-owned and heavily regulated (Sahut & Milli, 2011). The main reason behind M&A is market concentration and the creation of megabanks. Other drivers of M&A in the region, particularly between conventional banks, is the increasing competition from the Islamic banks, whose share in the banking market has grown rapidly. The Islamic banks are less cost-efficient than conventional banks, but are better capitalized and have lower credit risk than the latter financial entities (Beck et al., 2013; Mobarek & Kalonov, 2014; Kabir et al., 2015). Moreover, the liberalization of the banking market in some countries in the MENA region and the privatization of state-owned institutions have created opportunities for cross-border M&A (Sahut & Milli, 2011).

To the best of our knowledge, there is only one publication elaborating on M&A in the MENA banking market (i.e., Gattoufi et al., 2009), which used a conventional DEA program to evaluate efficiency gains from M&A and concluded that a positive effect for consolidated banks is present compared to non-consolidated ones. This study was based on a particularly small data set consisting of only ten banks. In addition, it evaluated M&A efficiency effects without considering externalities or other data irregularities. Reviewing the literature, a small number of papers deal with efficiency measurement for conventional and Islamic banks operating in countries with substantial Muslim populations (Beck et al., 2013; Johnes et al., 2014). The efficiency measurement techniques used in these studies are either DEA or stochastic frontier analysis (SFA). A thorough review of these works and techniques is found in Johnes et al. (2014).

This study draws on a smoothed bootstrap expression of the generalized directional distance function (GDDF) DEA. Chung et al. (1997) and Chambers et al. (1998) used directional distance function (DDF) to interpret efficiency measures. The DDF DEA is regarded as an appropriate approach for handling desirable and undesirable outputs, and it is the most widely used in the literature for dealing with such variables (Lozano & Gutierez, 2011; Podinovski & Kuosmanen, 2011). The GDDF DEA model (Cheng & Zervopoulos, 2014) used in this study introduces a new definition of efficiency that yields scores independent of the length of the direction vector, while respecting all properties of the conventional DDF DEA approach. A modification of the GDDF DEA is incorporated in the smoothed bootstrap algorithm put forth by Simar et al. (2012) in order to obtain bias-corrected efficiencies in the presence of desirable and undesirable variables and positive and negative values. Smoothed bootstrap is the most commonly used approach for correcting bias of DEA efficiency estimators (Kneip et al., 2008).

This study has both methodological and empirical contributions. In particular, emphasizing the methodology, it extends the work of Simar et al. (2012) on the estimation of DEA efficiencies using directional distance functions (DDF). A generalized directional distance function (GDDF) is used instead of a conventional DDF, as found in Simar et al. (2012)'s paper, which is incorporated in the smoothed bootstrap context. A discussion of the advantages of the GDDF model compared to DDF is provided in Cheng and Zervopoulos (2014) and Kounetas and Zervopoulos (2019). Based on the GDDF model, Simar et al. (2012)'s algorithm is modified to deal with undesirable variables (e.g., non-performing loans) and both positive and negative values in a data set. These modifications have direct implications for the estimation of the degree of operating efficiency gains from potential M&A originally put forth by Halkos and Tzeremes (2013). The methodological extensions facilitate a more realistic assessment of potential M&A in any industry. Emphasizing banks (i.e., conventional and Islamic) based in the MENA region, country- and firm-level analyses of the operating efficiency gains from possible M&A are provided to shed light to opportunities and threats for both acquirers and targets.

The remainder of this paper is organized as follows. Section 2 presents the GDDF DEA and its modification for addressing positive and negative values in the data set. Moreover, it describes the new smoothed bootstrap algorithm, which incorporates the modified GDDF DEA model and discusses steps for estimating the degree of operating efficiency gains from possible M&A. Section 3 presents the sample firms and the data set. Section 4 discusses the results obtained from the empirical analysis. Section 5 concludes the paper.

## 2. Methodology

### 2.1 Efficiency measurement

In this study, inputs $x = (x_1, \dots, x_m) \in \mathbb{R}^m_+$ are utilized to produce desirable outputs $y = (y_1, \dots, y_s) \in \mathbb{R}^s$ and undesirable outputs $b = (b_1, \dots, b_p) \in \mathbb{R}^l_+$. The production possibility set is defined as follows:

$$T = \{(x, y, b) \in \mathbb{R}^{m+s+l}; x \text{ can produce } (y, b)\} \qquad (1)$$

The assumptions met by the technology ($T$) are: ($T.1$) closedness, ($T.2$) free disposability of inputs and desirable outputs: $\forall (x, y) \in T, \text{if } x' \geq x \text{ and } y' \leq y \text{ then } (x', y') \in T$, ($T.3$) weak disposability of undesirable outputs: $\forall (x, b) \in T \Rightarrow (x, \kappa b) \in T \quad \forall \, \kappa \geq 1$, ($T.4$) no free lunch: if $(x, y, b) \in T$ and $x = 0$, then $y = 0 \; and \; b = 0$, and ($T.5$) convexity (Färe et al., 1994).

For a given technology $T$, the directional distance function (DDF) is:

$$\vec{D}_T(x, y, b; g_x, g_y, g_b) = \sup \{\beta : (x + \beta g_x, y - \beta g_y, b - \beta g_b) \in T(x, y, b)\} \qquad (2)$$

where $\beta$ expresses inefficiency and the non-zero direction vector $\vec{g} = (g_x = |x_o|, g_y = |y_o|, g_b = -|b_o|)$ of the inputs ($x$), desirable outputs ($y$) and undesirable outputs ($b$), respectively, and $x_o, y_o$ and $b_o$ are the inputs, desirable and undesirable output, respectively, of the reference units ($j = 0$ where $j = 1, \dots, n$).

Analogous to conventional efficiency measurement using DDF, where efficiency is obtained by introducing the optimal efficiency computed by function (2) into a measure, such as: $\min \frac{1-\beta}{1+\beta}$ (Chen et al., 2011), the GDDF yields efficiency ex-post by using the measure: $\min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\beta g_i/x_{io}}{1+\frac{1}{s+l}(\sum_{r=1}^{s}\beta g_r/y_{ro}+\sum_{\eta=1}^{l}\beta g_\eta/b_{\eta o})}$ (Cheng & Zervopoulos, 2014). In this study, we use a modified expression of the GDDF, which combines Kerstens and Van de Woestyne (2011)'s and Cheng et al. (2013)'s approaches to dealing with negative data with Cheng and Zervopoulos (2014)'s GDDF model that handles asymmetrically desirable and undesirable outputs. The modified GDDF respects the assumptions $(T.1)-(T.5)$. The modified GDDF used in this work for measuring bank efficiency ($\theta$) reads as follows:

$$\vec{D}_T(x,y,b;g_x,g_y,g_b) = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\beta|x_{io}|/x_{io}}{1+\frac{1}{s+l}\left(\sum_{r=1}^{s}\beta|y_{ro}|/y_{ro}+\sum_{\eta=1}^{l}\beta|b_{\eta o}|/b_{\eta o}\right)}$$

$$\begin{aligned} s.t.\ & \textstyle\sum_{j=1}^{n}\lambda_j x_{ij} + \beta|x_{io}| \le x_{io} \quad i=1,\dots,m \\ & \textstyle\sum_{j=1}^{n}\lambda_j y_{rj} - \beta|y_{ro}| \ge y_{ro} \quad r=1,\dots,s \\ & \textstyle\sum_{j=1}^{n}\lambda_j b_{\eta j} - \beta|b_{\eta o}| = b_{\eta o} \quad \eta=1,\dots,l \\ & \textstyle\sum_{j=1}^{n}\lambda_j = 1 \end{aligned} \tag{3}$$

## 2.2 Efficiency estimators

The upward bias of DEA efficiency estimators for finite samples has been proven by Banker (1993) and Banker and Natarajan (2011). Asymptotically, this bias reduces to zero. The convergence of DEA efficiency estimators to the population efficiencies depends not only on the sample size, but also on the dimension of the input-output space (Simar, 2007). Kneip et al. (2008) highlighted the virtues of smoothed bootstrap put forth by Simar and Wilson (1998, 1999) for bias correction of DEA efficiency estimators, stating that it is the most commonly used method. Zervopoulos et al. (2019) provided a thorough discussion of the strengths and weaknesses of the smoothed bootstrap.

In this study, we extended the concept of Halkos and Tzeremes (2013) on the estimation of efficiency gains from potential bank mergers and acquisitions by using the modified GDDF (model (3)) in conjunction with the directional distance function transformation procedure put forth by Simar et al. (2012) and the smoothed bootstrap algorithm developed by Kneip et al. (2011). By applying Simar et al. (2012)'s approach, we transform the coordinate system to express the frontier and its estimator using scalar-valued functions. This transformation is described below.

Let $w_o = (x_o, y_o, b_o)$ be the point of interest and $w$ express the vector $(x, y, b) \in T$. Then, $\mu = m + s + l$ is the length of vector $w$. We want to estimate the distance from $w_o$ to the frontier of $T$ in the direction of $\vec{g}$. A linear transformation from $\mathbb{R}^{m+s+l}$ to $\mathbb{R}^{m+s+l-1}$ is given by:

$$h_{w_o}: w \mapsto (z, u) = \Psi(w - w_o) \qquad (4)$$

where $\Psi' = \left(V \frac{\vec{g}}{\|\vec{g}\|}\right)$, $V$ is a $\mu \times (\mu - 1)$ matrix whose column $\left\{v_\rho \middle| \rho = 1, \dots, \mu - 1\right\}$ is the orthogonal basis for $\vec{g}$, $z = V'(w - w_o) \in \mathbb{R}^{m+s+l-1}$, $u = \frac{\vec{g}(w - w_o)}{\|\vec{g}\|} \in \mathbb{R}$, $\|\vec{g}\|$ is the Euclidean norm of $\vec{g}$. This transformation of $h_{w_o}$ can be inverted as follows: $w = w_o + \Psi'(z, u)$, where $h_{w_o}(w_o) = 0$.

Based on the linear transformation presented above, the production possibility set $T$ is represented by:

$$\Gamma(w_o) = \left\{(z, u) \middle| (z, u) = h_{w_o}(w), w \in T\right\} \qquad (5)$$

The boundary of $T$ is expressed by a scalar-valued function:

$$\varphi(z|w_o) = \sup\{u|(z, u) \in \Gamma(w_o)\} \qquad (6)$$

Let $W = (X', Y', B')$; then $W$ is a $\mu \times n$ matrix containing the sample observations. Then, $\forall\ (z, u) \in Z_n$, the frontier function can be estimated by the following variable returns to scale program:

$$\begin{aligned}
&\hat{\varphi}(z|Z_n, w_o) = \max u \\
&s.t.\ V'W\Lambda + V'\left(s_x, -s_y, 0\right) = z + V'w_o \\
&\qquad \vec{g}'W\Lambda/\|\vec{g}\| + \vec{g}'\left(s_x, -s_y, 0\right)/\|\vec{g}\| = u + \vec{g}'w_o/\|\vec{g}\| \\
&\qquad I'\Lambda = 1 \\
&\qquad \Lambda \in \mathbb{R}^n_+,\ s_x, s_y > 0 \qquad (7)
\end{aligned}$$

where $\left(s_x, -s_y, 0\right)$ is the vector of input, desirable output and undesirable output slacks. The term 0 ensures the weak disposability of the undesirable output $b$. $I'$ is a $n \times 1$ all-ones vector.

The variable returns to scale directional distance function estimator at any point $w = (x, y, b) \in T$ is:

$$\hat{\beta}(x, y, b|\vec{g}, \mathcal{X}_n) = (\hat{\varphi}(z|Z_n, w_o) - u)/\|\vec{g}\| \tag{8}$$

For the point of interest $w_o$, expression (8) becomes:

$$\hat{\beta}(x, y, b|\vec{g}, \mathcal{X}_n) = \hat{\varphi}(0|Z_n, w_o)/\|\vec{g}\| \tag{9}$$

To obtain bias-corrected estimators, we applied Kneip et al. (2011)'s algorithm. This method requires two smoothing parameters, $h_1$ and $h_2$, which are defined using the rule-of-thumb suggested by Kneip et al. (2011). The bias-correction algorithm reads as follows:

[1] Using the linear transformation presented in (4), form the set $Z_n$ and calculate $\hat{\beta}_j$ and $\hat{\beta}_o$ for each $(z_j, u_j) \in Z_n$ and $w_o$, respectively, by applying (7), (8) and (9).

[2] Set $h_1 = 4\hat{\beta}_{median} n^{-2/(3(m+s+l+1))}$, where $\hat{\beta}_{median}$ expresses the median of $\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_n$ measured in step [1].

[3] Compute the smoothed frontier points $\left(z_j, \hat{\varphi}'_{z_j}\right) = \left(z_j, \hat{\varphi}(0|Z_n, w_o) + h_2^2\left(\hat{\varphi}\left(\frac{z_j}{h_2}\middle| Z_n, w_o\right) - \hat{\varphi}(0|Z_n, w_o)\right)\right), j = 1, \ldots, n.$

[4] Construct a bootstrap sample $Z_n^* = \left\{(z_j^*, u_j^*)\right\}_{j=1}^{n}$, where $z_j^* = z_j^{(naive)}$ and $u_j^* = \begin{cases} \hat{\varphi}'_{z_j^{(naive)}} - \hat{\beta}_{z_j^{(naive)}}, \text{if } \hat{\beta}_{z_j^{(naive)}} > h_1 \\ \hat{\varphi}'_{z_j^{(naive)}} - \hat{\xi}_{z_j^{(naive)}}, \text{otherwise} \end{cases}$; $\hat{\xi}_{z_j^{(naive)}}$ is a random, independent draw from a uniform distribution on $[0, h_1]$; $z_n^{(naive)} = \left\{(z_j^{(naive)}, u_j^{(naive)})\right\}_{j=1}^{n}$ is a naive bootstrap sample.

[5] Obtain $\hat{\beta}_j^* \; \forall \; (z_j^*, u_j^*) \in z_n^*$ and $\hat{\beta}_o^*$ for $w_o$ from expressions (7), (8) and (9) by using the bootstrap sample in place of the original observations.

[6] Calculate the smoothed frontier points corresponding to $z_n^*$ in the same way as in step [3]; generate bootstrap sample $\left\{z_{n,q}^{**}\right\}_{q=1}^{Q}$ of size $Q$ (i.e., $Q = 2000$) for $z_n^*$ and calculate $\hat{\beta}_{o,q}^{**}$ for $w_o$ by solving (7) and (9) taking into account the reference set $z_{n,q}^{**}$, $q = 1, \ldots, Q$.

[7] Use the estimate $\hat{\beta}_o^*$ and the set $\{\hat{\beta}_{o,q}^{**}\}_{q=1}^{Q}$ to construct a $(1-\alpha)\times 100\%$ confidence interval for $\hat{\beta}_o$ .

[8] Loop over steps [4]−[7] $Q$ (i.e., $Q = 2000$) times to construct a bootstrap sample $\{z_{n,q}^*\}_{q=1}^{Q}$, generate estimates $\{\beta_{j,q}^*\}_{q=1}^{Q}$ for $j = 1,\dots,n$ and count the number of times $\tau$ the confidence interval for $\hat{\beta}_o$ was estimated in step [7].

[9] Use $\hat{\beta}_j$ and the set $\{\beta_{j,q}^*\}_{q=1}^{Q}$ (i.e., $Q = 2000$) to estimate a $(1-\alpha)\times 100\%$ confidence interval for $\beta_j$ , which has an estimated size $\hat{\alpha}(h_2) = 1 - \tau/Q$.

The bias-corrected estimates of the DDF are:

$$\tilde{\beta} = \hat{\beta} - (\omega/n)^{2/(m+s+l+1)} \frac{1}{Q}\sum_{q=1}^{Q}(\hat{\beta}_q^{**} - \hat{\beta}) \tag{10}$$

where $n$ stands for the sample size and $\omega$ ($\omega < n$) is the subsample size. The selection of the size of $\omega$ is based on Politis et al. (2001).

Given that $\beta$ expresses inefficiency in DDF DEA models, we estimate bias-corrected efficiencies ($\tilde{\theta}$) by introducing $\tilde{\beta}$ (expression (10)) in the objective function of program (3), which is rewritten as follows:

$$\tilde{\theta} = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\tilde{\beta}|x_{io}|/x_{io}}{1+\frac{1}{s+l}(\sum_{r=1}^{s}\tilde{\beta}|y_{ro}|/y_{ro}+\sum_{\eta=1}^{l}\tilde{\beta}|b_{\eta o}|/b_{\eta o})} \tag{11}$$

### 2.3 M&A performance measurement

In this section we estimate the degree of operating efficiency gains (DOEG) from potential bank M&A. This estimation is based on a modified expression of the algorithm developed by Halkos and Tzeremes (2013), which reads as follows:

[1] Using program (3) we measure the efficiency of conventional and Islamic banks separately.

[2] Drawing on the results obtained from step [1], we identify the efficient conventional and Islamic banks. All possible M&A are developed by combining efficient conventional banks with their inefficient counterparts by

adding their corresponding inputs and outputs. The same principle applies to the group of Islamic banks between efficient and inefficient firms. Each group of banks now consists of the original and virtually consolidated firms.

[3] Introducing the new data sets into the algorithm presented in Section 2.2, we estimate bias-corrected efficiencies for original and virtual conventional banks and original and virtual Islamic banks.

[4] Using the bias-corrected efficiencies obtained from program (11), the DOEG of a potential bank M&A (e.g., between banks B1 and B2) is estimated as follows:

$$\mathrm{DOEG}_{(\mathrm{B1,B2})} = 1 - \frac{\tilde{\theta}_{(\mathrm{B1})} + \tilde{\theta}_{(\mathrm{B2})} - \tilde{\theta}_{(\mathrm{B1,B2})}}{\tilde{\theta}_{(\mathrm{B1,B2})}} \tag{12}$$

where $\tilde{\theta}_{(B1,B2)}$ expresses the bias-corrected efficiency estimator assigned to the potential M&A between banks B1 and B2.

If $\mathrm{DOEG}_{(\mathrm{B1,B2})} > 0$ then the potential M&A is likely to be successful because of the potential operating efficiency gains. If $\mathrm{DOEG}_{(\mathrm{B1,B2})} < 0$ the M&A between firms is regarded as unfavorable while a $\mathrm{DOEG}_{(\mathrm{B1,B2})} = 0$ implies that the M&A between B1 and B2 is indifferent.

## 3. Variables and data

This study focuses on performance measurement of potential M&A in the banking sector in the Middle East and North Africa (MENA) region, including Turkey. The sample under review consists of two sub-samples of conventional and Islamic banks. There are 86 conventional and 21 Islamic banks in the original sample. The review period is 2014–2016, where there are no missing values for all banks and variables included in the analysis. For the years after 2016, the sample size is significantly reduced as there is a considerable increase in missing values. This significant decrease in the number of banks given the number of variables in the analysis would lead to a rise of bias in efficiency and M&A performance estimators due to the dimensionality of the production set (Simar & Wilson, 2000; Kneip et al., 2008, 2011).

Considering the development of virtual banks from the consolidation of their inputs and outputs (discussion of the consolidation process is provided in step [2] of the algorithm in Section 2.3), the sample size increases and varies from year to year. In particular, the size of the sample of conventional banks, which includes both the actual and virtual banks, is 581 in 2014 (# of virtual banks: 495), 680 in 2015 (# of virtual banks: 594) and 630 in 2016 (# of virtual banks: 544). The sample size of Islamic banks is 42 in 2014 (# of virtual banks: 21), 45 in 2015 (# of virtual banks: 24) and 48 in 2016 (# of virtual banks: 27).

The data for the variables used in this study are available in the BankFocus database provided by Moody's Analytics and Bureau van Dijk. For measuring the efficiency of banks and the DOEG from potential bank M&A, we used three inputs (i.e., $x_1$: deposits & short-term funding; $x_2$: fixed assets; $x_3$: personnel expenses), two desirable outputs (i.e., $y_1$: gross loans; $y_2$: other earning assets) and one undesirable output (i.e., $b_1$: non-performing loans). The selection of the variables drew on studies on bank efficiency measurement (Casu & Molyneux, 2003; Casu & Girardone, 2004, 2006; Zha et al., 2016).

Descriptive statistics of the input and output variables of conventional and Islamic banks are presented in Tables 1 and 2, respectively. Comparing the results shown in the two tables, the sample conventional banks report higher deposits and short-term funding, staff expenses, gross loans, other earning assets, and non-performing loans than those of the sample Islamic banks during the review period (2014–2016). On the contrary, Islamic banks have higher fixed assets than conventional banks. The non-performing loans both of the conventional and Islamic banks reduce over the years 2014–2016 reporting a CAGR of -2.92% and -2.47%, respectively. The burden of non-performing loans is considerably higher for the sample conventional than the Islamic banks, as the exposure of the former banks to loans in default is at least 51.1% higher than that of the latter banks.

**Table 1.** Descriptive statistics of variables for conventional banks (in thousand USD)

| Variables | Measures | 2014 | 2015 | 2016 | CAGR |
|---|---|---|---|---|---|
| Inputs | | | | | |
| Deposits & Short-term funding | Mean | 18,727,566.43 | 20,369,659.03 | 20,726,820.55 | 0.0344 |
| | St. Dev. | 22,742,172.35 | 24,795,632.63 | 25,281,514.07 | |
| | Min | 103,662.58 | 101,239.51 | 103,580.61 | |
| | Max | 95,822,433.53 | 109,353,301.22 | 120,231,963.29 | |
| Fixed assets | Mean | 183,522.87 | 215,906.47 | 222,554.78 | 0.0664 |
| | St. Dev. | 205,473.50 | 290,026.11 | 286,288.37 | |
| | Min | 2,556.63 | 1,515.69 | 829.84 | |
| | Max | 945,086.13 | 2,042,829.41 | 1,703,554.36 | |
| Staff expenses | Mean | 197,128.98 | 208,878.97 | 210,180.48 | 0.0216 |
| | St. Dev. | 222,935.85 | 233,871.43 | 230,792.44 | |
| | Min | 5,892.96 | 6,639.44 | 7,063.38 | |
| | Max | 943,813.78 | 993,141.15 | 946,908.85 | |
| Desirable outputs | | | | | |
| Gross loans | Mean | 14,330,930.30 | 15,626,353.56 | 16,315,712.30 | 0.0442 |
| | St. Dev. | 18,293,237.55 | 19,911,507.61 | 21,108,155.65 | |
| | Min | 14,106.16 | 20,399.83 | 18,958.05 | |
| | Max | 87,121,878.71 | 94,795,728.81 | 108,622,386.08 | |
| Other earning assets | Mean | 6,331,476.88 | 6,755,147.55 | 6,648,532.26 | 0.0164 |
| | St. Dev. | 8,019,955.00 | 8,804,155.35 | 8,283,601.75 | |
| | Min | 80,746.34 | 115,871.52 | 62,353.79 | |
| | Max | 37,315,014.75 | 46,896,657.38 | 41,846,041.38 | |
| Undesirable output | | | | | |
| Non-performing loans | Mean | 566,377.97 | 514,852.51 | 518,273.41 | -0.0292 |
| | St. Dev. | 1,131,407.67 | 750,755.55 | 758,637.41 | |
| | Min | 909.56 | 310.98 | 350.25 | |
| | Max | 9,844,731.26 | 5,650,627.02 | 5,684,994.62 | |

**Table 2.** Descriptive statistics of variables for Islamic banks (in thousand USD)

| Variables | Measures | 2014 | 2015 | 2016 | CAGR |
|---|---|---|---|---|---|
| Inputs | | | | | |
| Deposits & Short-term funding | Mean | 13,545,702.07 | 15,481,345.96 | 16,197,805.84 | 0.0614 |
| | St. Dev. | 16,698,730.17 | 18,316,981.81 | 17,676,616.01 | |
| | Min | 348,357.00 | 304,539.00 | 331,502.00 | |
| | Max | 62,727,689.14 | 68,856,612.66 | 69,542,935.09 | |
| Fixed assets | Mean | 433,883.79 | 462,975.02 | 273,568.84 | -0.1425 |
| | St. Dev. | 851,232.11 | 884,239.45 | 370,685.54 | |
| | Min | 1,510.64 | 14,501.00 | 10,398.94 | |
| | Max | 2,881,048.51 | 2,996,454.97 | 1,487,715.01 | |
| Staff expenses | Mean | 168,572.74 | 183,531.06 | 187,141.37 | 0.0354 |
| | St. Dev. | 193,827.98 | 203,054.89 | 201,649.74 | |

| | | | | | |
|---|---|---|---|---|---|
| | Min | 15,330.00 | 12,771.00 | 14,112.00 | |
| | Max | 613,684.03 | 670,427.50 | 709,611.50 | |
| Desirable outputs | | | | | |
| Gross loans | Mean | 11,082,764.41 | 12,628,513.27 | 13,407,772.92 | 0.0655 |
| | St. Dev. | 12,615,162.51 | 13,602,458.92 | 13,886,624.93 | |
| | Min | 56,224.00 | 15,579.00 | 77,338.00 | |
| | Max | 50,839,751.98 | 56,178,435.73 | 57,504,677.67 | |
| Other earning assets | Mean | 3,313,647.83 | 3,764,900.22 | 4,127,729.21 | 0.0760 |
| | St. Dev. | 3,704,816.30 | 4,208,214.19 | 4,669,796.42 | |
| | Min | 31,878.87 | -34,484.51 | -57,921.13 | |
| | Max | 13,529,987.37 | 14,366,929.82 | 16,271,015.52 | |
| Undesirable output | | | | | |
| Non-performing loans | Mean | 364,732.96 | 340,734.09 | 338,391.61 | -0.0247 |
| | St. Dev. | 459,702.37 | 373,226.83 | 330,420.25 | |
| | Min | 2,974.00 | 9,000.00 | 9,269.00 | |
| | Max | 1,452,587.82 | 1,202,069.69 | 969,379.33 | |

## 4. Empirical analysis

In this section, we apply step-by-step the algorithm presented in Section 2.3 of the study. In particular, according to step [1], we run program (3) twice, once for the conventional and a second time for the Islamic banks. According to Table 3, on average, a 36% of the conventional banks are efficient over the review period (2014–2016). Among them, the number of efficient GCC-based banks is higher than that of the non-GCC-based banks for the years 2014–2016 (i.e., efficient banks: 18.99% GCC-based; 17.05% non-GCC-based). Most of the efficient conventional banks are in Turkey (≅10% of the total sample conventional banks) followed by the UAE-based (≅6.6%).

According to Table 3, 38.8% out of 64% of the sample inefficient conventional banks are based in non-GCC countries, while the remaining 25.2% of the inefficient banks are GCC-based.

**Table 3.** Efficiency scores of conventional banks for 2014–2016

| # | Bank name | Country of Origin | Region | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|
| 1 | Qatar National Bank | Qatar | GCC | 1.0000 | 1.0000 | 1.0000 |
| 2 | Emirates NBD PJSC | UAE | GCC | 1.0000 | 1.0000 | 1.0000 |
| 3 | National Commercial Bank (The) | Saudi Arabia | GCC | 1.0000 | 1.0000 | 1.0000 |
| 4 | National Bank of Abu Dhabi | UAE | GCC | 1.0000 | 0.9905 | 1.0000 |
| 5 | T.C. Ziraat Bankasi A.S. | Turkey | Other | 1.0000 | 0.9586 | 0.9497 |
| 6 | Turkiye Garanti Bankasi A.S. | Turkey | Other | 1.0000 | 1.0000 | 1.0000 |
| 7 | Akbank T.A.S. | Turkey | Other | 1.0000 | 1.0000 | 1.0000 |
| 8 | National Bank of Kuwait S.A.K. | Kuwait | GCC | 0.8878 | 1.0000 | 1.0000 |
| 9 | Yapi Ve Kredi Bankasi A.S. | Turkey | Other | 0.9622 | 0.9898 | 0.9743 |
| 10 | Abu Dhabi Commercial Bank | UAE | GCC | 1.0000 | 1.0000 | 1.0000 |
| 11 | First Gulf Bank | UAE | GCC | 1.0000 | 1.0000 | 1.0000 |
| 12 | Turkiye Vakiflar Bankasi TAO | Turkey | Other | 0.9148 | 0.9457 | 0.9557 |
| 13 | Samba Financial Group | Saudi Arabia | GCC | 1.0000 | 1.0000 | 1.0000 |
| 14 | Riyad Bank | Saudi Arabia | GCC | 1.0000 | 1.0000 | 1.0000 |
| 15 | Saudi British Bank JSC (The) | Saudi Arabia | GCC | 0.9323 | 0.9803 | 0.9736 |
| 16 | Banque Saudi Fransi JSC | Saudi Arabia | GCC | 1.0000 | 1.0000 | 1.0000 |
| 17 | Arab National Bank Public Joint Stock Company | Saudi Arabia | GCC | 0.9941 | 0.9610 | 0.9498 |
| 18 | Bank Audi SAL | Lebanon | Other | 0.8854 | 0.7701 | 0.7510 |
| 19 | HSBC Bank Middle East Limited | UAE | GCC | 1.0000 | 1.0000 | 1.0000 |
| 20 | Denizbank A.S. | Turkey | Other | 0.9063 | 0.8818 | 0.8837 |
| 21 | Ahli United Bank BSC | Bahrain | GCC | 0.8926 | 0.9267 | 0.9121 |
| 22 | The Commercial Bank (QSC) | Qatar | GCC | 0.9967 | 0.9914 | 0.9982 |
| 23 | Mashreqbank PSC | UAE | GCC | 0.8847 | 0.8622 | 0.8178 |
| 24 | Bank Muscat SAOG | Oman | GCC | 0.9694 | 0.9308 | 0.8250 |
| 25 | Finansbank A.S. | Turkey | Other | 0.9920 | 0.9590 | 0.9450 |
| 26 | Alawwal Bank | Saudi Arabia | GCC | 0.9789 | 0.9843 | 0.9619 |
| 27 | Banque Marocaine du Commerce Extérieur-BMCE Bank | Morocco | Other | 0.9118 | 0.8880 | 0.8595 |
| 28 | Arab Banking Corporation BSC-Bank ABC | Bahrain | GCC | 1.0000 | 1.0000 | 1.0000 |
| 29 | Union National Bank | UAE | GCC | 0.9878 | 1.0000 | 0.9372 |
| 30 | Turk Ekonomi Bankasi A.S. | Turkey | Other | 0.9044 | 0.9109 | 0.9300 |
| 31 | Saudi Investment Bank (The) | Saudi Arabia | GCC | 1.0000 | 1.0000 | 1.0000 |
| 32 | Gulf International Bank BSC | Bahrain | GCC | 1.0000 | 1.0000 | 1.0000 |
| 33 | Doha Bank | Qatar | GCC | 0.9874 | 0.9748 | 0.9998 |
| 34 | Burgan Bank KPSC | Kuwait | GCC | 0.8600 | 0.8974 | 0.8776 |
| 35 | Byblos Bank S.A.L. | Lebanon | Other | 1.0000 | 0.9994 | 1.0000 |
| 36 | Fransabank sal | Lebanon | Other | 0.8008 | 0.8212 | 0.8747 |
| 37 | ING Bank A.S. | Turkey | Other | 1.0000 | 1.0000 | 1.0000 |
| 38 | Société Générale de Banque au Liban - SGBL | Lebanon | Other | 0.8593 | 0.9046 | 1.0000 |
| 39 | Commercial Bank of Dubai P.S.C. | UAE | GCC | 0.9693 | 0.9419 | 0.8484 |
| 40 | Al Khalij Commercial Bank | Qatar | GCC | 1.0000 | 1.0000 | 1.0000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 41 | Bankmed, sal | Lebanon | Other | 0.8294 | 0.8836 | 0.8264 |
| 42 | Commercial International Bank (Egypt) S.A.E. | Egypt | Other | 0.7216 | 0.7315 | 0.8381 |
| 43 | Al Ahli Bank of Kuwait (KSC) | Kuwait | GCC | 0.9625 | 0.9847 | 0.9337 |
| 44 | Commercial Bank of Kuwait K.P.S.C. (The) | Kuwait | GCC | 0.9234 | 1.0000 | 0.9054 |
| 45 | Housing Bank for Trade & Finance (The) | Jordan | Other | 0.8275 | 0.7752 | 0.8328 |
| 46 | National Bank of Ras Al-Khaimah (P.S.C.) (The)-RAKBANK | UAE | GCC | 0.8552 | 0.8634 | 0.8211 |
| 47 | HSBC Bank A.S. | Turkey | Other | 0.9904 | 0.9684 | 0.9764 |
| 48 | QNB Al Ahli | Egypt | Other | 0.8540 | 0.8839 | 0.9220 |
| 49 | Crédit Libanais S.A.L. | Lebanon | Other | 0.9404 | 0.8364 | 0.8752 |
| 50 | National Bank of Fujairah PJSC | UAE | GCC | 0.9211 | 0.8714 | 0.8283 |
| 51 | BBK B.S.C. | Bahrain | GCC | 0.9029 | 0.8783 | 0.8993 |
| 52 | International Bank of Qatar Q.S.C. | Qatar | GCC | 1.0000 | 0.9821 | 1.0000 |
| 53 | Sekerbank T.A.S. | Turkey | Other | 0.9182 | 0.8578 | 0.7951 |
| 54 | Bank of Sharjah | UAE | GCC | 0.8772 | 0.9055 | 0.8837 |
| 55 | United Arab Bank PJSC | UAE | GCC | 0.9673 | 0.9111 | 0.7874 |
| 56 | HSBC Bank Oman | Oman | GCC | 0.9030 | 0.8516 | 0.7938 |
| 57 | IBL Bank sal | Lebanon | Other | 1.0000 | 1.0000 | 1.0000 |
| 58 | Alternatifbank A.S. | Turkey | Other | 1.0000 | 1.0000 | 1.0000 |
| 59 | Anadolubank A.S. | Turkey | Other | 0.9523 | 0.7916 | 0.7541 |
| 60 | Commercial Bank International P.S.C. | UAE | GCC | 0.8981 | 0.8738 | 0.7270 |
| 61 | Credit Agricole Egypt SAE | Egypt | Other | 0.6796 | 0.6204 | 0.5818 |
| 62 | Invest Bank P.S.C. | UAE | GCC | 0.9893 | 1.0000 | 0.9483 |
| 63 | Jordan Kuwait Bank | Jordan | Other | 0.8234 | 0.8482 | 0.8043 |
| 64 | Burgan Bank AS | Turkey | Other | 1.0000 | 1.0000 | 1.0000 |
| 65 | Fibabanka As | Turkey | Other | 1.0000 | 1.0000 | 0.9726 |
| 66 | National Bank of Umm Al-Qaiwain PSC | UAE | GCC | 0.9495 | 1.0000 | 0.9459 |
| 67 | Cairo Amman Bank | Jordan | Other | 0.8640 | 0.8568 | 0.8133 |
| 68 | Jordan Ahli Bank Plc | Jordan | Other | 0.7480 | 0.7233 | 0.7180 |
| 69 | CreditBank SAL | Lebanon | Other | 0.6917 | 0.7321 | 0.7110 |
| 70 | Bank of Jordan Plc | Jordan | Other | 0.8042 | 0.7776 | 0.7778 |
| 71 | Attijari Bank | Tunisia | Other | 0.8970 | 0.8477 | 0.7351 |
| 72 | Capital Bank of Jordan | Jordan | Other | 0.8472 | 0.8710 | 0.7809 |
| 73 | Arab Tunisian Bank | Tunisia | Other | 0.8801 | 0.8784 | 0.8352 |
| 74 | BLOM Bank Egypt SAE | Egypt | Other | 0.9056 | 1.0000 | 0.9222 |
| 75 | Banque de Tunisie | Tunisia | Other | 0.9479 | 1.0000 | 0.9375 |
| 76 | Jordan Commercial Bank | Jordan | Other | 0.8127 | 0.8835 | 0.7686 |
| 77 | Société générale de Banque-Jordanie | Jordan | Other | 1.0000 | 1.0000 | 1.0000 |
| 78 | Banque BEMO Sal | Lebanon | Other | 1.0000 | 0.9616 | 0.9154 |
| 79 | Union Bancaire pour le Commerce et l'Industrie SA UBCI | Tunisia | Other | 1.0000 | 1.0000 | 1.0000 |
| 80 | Arab Turkish Bank-Arap Turk Bankasi | Turkey | Other | 0.9049 | 1.0000 | 1.0000 |
| 81 | Arab Banking Corporation (Jordan) | Jordan | Other | 0.9025 | 0.8879 | 0.8525 |
| 82 | Al Ahli Bank of Kuwait-Egypt | Egypt | Other | 0.6595 | 0.6907 | 0.6019 |
| 83 | Jammal Trust Bank SAL | Lebanon | Other | 0.9061 | 0.9926 | 0.8394 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 84 | Bankpozitif Kredi ve Kalkinma Bankasi AS-C Bank | Turkey | Other | 1.0000 | 1.0000 | 1.0000 |
| 85 | Turkish Bank A.S. | Turkey | Other | 1.0000 | 1.0000 | 1.0000 |
| 86 | CSCBank SAL | Lebanon | Other | 1.0000 | 1.0000 | 1.0000 |

Table 4 presents the efficient scores assigned to the sample Islamic banks over the years 2014–2016. In the sample of Islamic banks, 17 out of 21 are GCC-based. Therefore, as expected, the majority of the efficient Islamic banks originate in GCC countries. The sample Islamic banks outside the GCC area have their headquarters in Jordan and Turkey. There are two efficient non-GCC-based Islamic banks; Albaraka bank (#13) is regarded as efficient in 2014 and 2015, and Turkiye Finans bank (#10) is efficient in 2016. Most of the efficient sample Islamic banks have their main offices in Qatar (2014: 2 banks; 2015: 3 banks; 2016: 4 banks), followed by the banks based in Bahrain (2014–2016: 2 banks).

**Table 4.** Efficiency scores of Islamic banks for 2014–2016

| # | Bank name | Country of Origin | Region | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|
| 1 | Al Rajhi Bank Public Joint Stock Company | Saudi Arabia | GCC | 1.0000 | 1.0000 | 1.0000 |
| 2 | Kuwait Finance House | Kuwait | GCC | 0.9920 | 1.0000 | 1.0000 |
| 3 | Qatar Islamic Bank SAQ | Qatar | GCC | 1.0000 | 1.0000 | 1.0000 |
| 4 | Albaraka Banking Group B.S.C. | Bahrain | GCC | 0.8676 | 0.8784 | 0.8813 |
| 5 | Alinma Bank Public joint stock company | Saudi Arabia | GCC | 1.0000 | 0.8982 | 0.9959 |
| 6 | Masraf Al Rayan (Q.S.C.) | Qatar | GCC | 1.0000 | 1.0000 | 1.0000 |
| 7 | Bank AlJazira JSC | Saudi Arabia | GCC | 0.8598 | 0.9054 | 0.9955 |
| 8 | Emirates Islamic Bank PJSC | UAE | GCC | 1.0000 | 0.9632 | 0.9474 |
| 9 | Kuveyt Turk Katilim Bankasi A.S.-Kuwait Turkish Participation Bank Inc | Turkey | Other | 0.7621 | 0.6822 | 0.7991 |
| 10 | Turkiye Finans Katilim Bankasi AS | Turkey | Other | 0.9537 | 0.8426 | 1.0000 |
| 11 | Barwa Bank | Qatar | GCC | 0.9401 | 0.9434 | 1.0000 |
| 12 | Qatar International Islamic Bank | Qatar | GCC | 0.9741 | 1.0000 | 1.0000 |
| 13 | Albaraka Turk Participation Bank-Albaraka Turk Katilim Bankasi AS | Turkey | Other | 1.0000 | 1.0000 | 0.8779 |
| 14 | Ithmaar Bank B.S.C. | Bahrain | GCC | 0.9160 | 0.9498 | 0.9624 |
| 15 | Sharjah Islamic Bank | UAE | GCC | 0.7223 | 0.6968 | 0.8656 |
| 16 | Jordan Islamic Bank | Jordan | Other | 0.8315 | 0.9047 | 0.9300 |
| 17 | Al-Salam Bank-Bahrain B.S.C. | Bahrain | GCC | 1.0000 | 1.0000 | 1.0000 |
| 18 | Kuwait Finance House | Kuwait | GCC | 0.9920 | 1.0000 | 1.0000 |
| 19 | Bahrain Islamic Bank B.S.C. | Bahrain | GCC | 0.7028 | 0.8082 | 0.8869 |
| 20 | Albaraka Islamic Bank BSC | Bahrain | GCC | 0.7480 | 0.7858 | 0.7363 |
| 21 | Bank Alkhair BSC | Bahrain | GCC | 1.0000 | 1.0000 | 1.0000 |

By applying steps [2] and [3] of the algorithm discussed in Section 2.3, we obtain bias-corrected efficiency estimators of both actual and virtual conventional banks (Tables E1–E3 in the Electronic Supplement) and Islamic banks (Tables E4–E6 in the Electronic Supplement).

Table 5 presents the average efficiency scores of the actual conventional and Islamic banks (*sample* 1), the average efficiency scores of the same conventional and Islamic banks, which are obtained from an extended sample both of actual and virtual banks (*sample* 2 – left-hand column), the average efficiency scores of all (actual and virtual) conventional and Islamic banks (*sample* 2 – right-hand column), and the sample sizes.

The efficiency scores assigned to actual conventional banks after the extension of the sample (see *sample* 2 in Table 5) with virtual banks (potential M&A) were significantly lower than those obtained from the original samples of the 86 banks (see *sample* 1 in Table 5) (Wilcoxon test: (2014) $T = -4.762, p < 10^{-4}, KS_{sample1} = 1.831, p = 0.002, KS_{sample2} = 1.362, p = 0.049$; (2015) $T = -4.977, p < 10^{-4}, KS_{sample1} = 1.944, p = 0.001, KS_{sample2} = 1.493, p = 0.023$; (2016) $T = -4.298, p < 10^{-4}$, $KS_{sample1} = 1.720, p = 0.005, KS_{sample2} = 1.491, p = 0.023$). This represents a medium change in the efficiency scores of the conventional banks (Cohen (1988, 1992)'s criteria: (2014) $r = -0.3631$ medium-sized effect; (2015) $r = -0.3795$ medium-sized effect; (2016) $r = -0.3277$ medium-sized effect).

Similarly, a significant decrease in the efficiency scores of the actual Islamic banks in *sample* 2 (see Table 5) compared to the scores obtained from *sample* 1 (see Table 5) is present (Wilcoxon test (2014): $T = -2.482, p = 0.013$; $T-$test (2014): $t(20) = 2.770, p = 0.012, KS_{sample1} = 1.090, p = 0.186, KS_{sample2} = 0.839, p = 0.483$; Wilcoxon test (2015): $T = -2.912,\ p = 0.004$; $T-$test (2015): $t(20) = 3.558, p = 0.002, KS_{sample1} = 1.015, p = 0.254, KS_{sample2} = 1.051, p = 0.220$; Wilcoxon test (2016): $T = -2.628,\ p = 0.009, KS_{sample1} = 1.414, p = 0.037, KS_{sample2} = 0.952, p = 0.325$)[1]. This is regarded as a medium-to-large change

[1] Since the size of the Islamic banks is small (i.e., 21 banks), the use both of parametric (i.e., *T*-test) and non-parametric (i.e., Wilcoxon test) tests for comparing mean efficiency scores of Islamic banks, before and after the inclusion of potential M&A in the sample under review, increases the robustness of our findings.

in efficiencies of Islamic banks (Cohen (1998, 1992)'s criteria: (2014) $r = -0.3830$ medium-sized effect; (2015) $r = -0.4493$ medium- to large-sized effect; (2016) $r = -0.4055$ medium- to large- sized effect).

**Table 5.** Efficiencies of conventional and Islamic banks (2014–2016)

| | 2014 | | | 2015 | | | 2016 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Actual | Actual | Actual & Virtual | Actual | Actual | Actual & Virtual | Actual | Actual | Actual & Virtual |
| | (*sample*1) | (*sample*2) | | (*sample*1) | (*sample*2) | | (*sample*1) | (*sample*2) | |
| Conventional banks | | | | | | | | | |
| Average efficiency scores | 0.9295 | 0.8920 | 0.9092 | 0.9290 | 0.8873 | 0.9077 | 0.9080 | 0.8749 | 0.9042 |
| Sample size | 86 | 581 | | 86 | 680 | | 86 | 630 | |
| Islamic banks | | | | | | | | | |
| Average efficiency scores | 0.9172 | 0.7940 | 0.7957 | 0.9171 | 0.7924 | 0.7414 | 0.9466 | 0.8661 | 0.8209 |
| Sample size | 21 | 42 | | 21 | 45 | | 21 | 48 | |

*Sample* 1: Original sample of actual banks
*Sample* 2: Extended sample of actual and virtual banks (possible M&A)

In the case of Islamic banks, the simulated efficiency scores based on the extended sample of actual and virtual firms are significantly lower than those of the actual efficiency scores (*sample* 1) (Wilcoxon test (2014) $T = -3.424, p = 0.001$; $T - test$ (2014): $t(20) = 5.300, p < 10^{-4}, KS_{sample1} = 1.090, p = 0.186, KS_{sample2} = 0.536, p = 0.936$; (2015) $T = -3.875, p < 10^{-4}$; $T - test$ (2015): $t(20) = 7.949, p < 10^{-4}, KS_{sample1} = 1.015, p = 0.254, KS_{sample2} = 0.820, p = 0.512$; (2016) $T = -3.771, p < 10^{-4}$, $KS_{sample1} = 1.414, p = 0.037, KS_{sample2} = 0.787, p = 0.566$). According to Cohen (1988, 1992)'s criteria, the M&A effect on Islamic banks efficiency scores is large (i.e., (2014): $r = -0.7472$; (2015): $r = -0.8456$; (2016): $r = -0.8229$).

Concerning the Islamic banks, the measurement of the M&A effect on efficiency scores is unlikely to be free of sample size bias, despite the results obtained from simulated efficiency scores. The sample of Islamic banks is particularly small (21 firms) leading to considerable efficiency overestimations (i.e., *sample* 1) (Banker, 1993; Banker & Natarajan, 2011), which are reduced when the size increases with the inclusion of the consolidated banks. Further bias correction of the efficiency estimators is achieved by using the smoothed bootstrap (Section 2.2). In the case of conventional banks, the sample size is considered large (Banker et al., 2010), especially when both actual and virtual (consolidated) banks are evaluated together. Hence, the overestimations are limited.

Table 6 presents the average country- and firm-level DOEG for conventional banks over the period 2014–2016. In addition, it provides ranking of the dominant (efficient) conventional banks based on their average DOEG. Table 6 facilitates the identification of the most favorable target markets for potential M&A for the bidders listed in the second column of this table.

In particular, Qatar National Bank (Qatar) ranks first among the dominant banks reporting a mean DOEG of 0.1892 from potential M&A. This bank remains first in this ranking, even though the Egyptian banking market is not considered a target for consolidations due to the current diplomatic crisis. The First Gulf Bank (UAE) is ranked third, being assigned a mean DOEG score of 0.1295, and Emirates NBD holds the fourth position in this ranking, with a mean DOEG score equal to 0.1210. On the contrary, the dominant conventional banks with the lowest DOEG are Invest Bank (UAE) (i.e., −0.1304), National Bank of Umm Al-Qaiwain (UAE) (i.e., −0.0701), International Bank of Qatar (Qatar) (i.e., −0.0636[2] and −0.0612), and Commercial Bank of Kuwait (Kuwait) (i.e., −0.0106). These banks report a negative mean DOEG, indicating that M&A are likely to have negative impact on their operating efficiency and should be well considered.

Overall, the markets for the potential bidders regarded as favorable targets for M&A are Jordan (mean (aggregate) DOEG: 0.1328), Egypt (0.1036), Tunisia (0.0674), and Lebanon (0.0503). Unfavorable target markets for M&A are the Moroccan (i.e., mean (aggregate) DOEG: −0.0231) and Turkish (i.e., −0.0003). At a country level, on average Bahraini conventional banks are expected to have the highest operating efficiency gains from M&A, with conventional banks operating in other MENA countries (Egypt, Jordan, Lebanon, Morocco, Tunisia, and Turkey) as the mean DOEG

[2] Considering the Qatar diplomatic crisis, banks from Bahrain, Egypt, Saudi Arabia and United Arab Emirates have not been taken into account for the calculation of the mean DOEG as these countries have banned Qatari companies from doing any business in their territory.

is 0.0966, followed by Saudi Arabian and Qatari banks (i.e., mean country-level DOEG: 0.0685 and 0.0616 (0.0535), respectively).

The Qatar diplomatic crisis has had a considerable negative impact on the mean DOEG of the country's conventional banks as Egypt, the country reporting the second highest DOEG for Qatari banks (i.e., 0.1019), should not be regarded as a potential target market for M&A. In the context of this diplomatic crisis, Qatar National Bank cannot take advantage of an M&A with Credit Agricole Egypt SAE. This potential M&A would lead to a mean DOEG of 0.4831 for the Qatari dominant bank, the highest DOEG (ranking: #1) among those obtained from any other possible M&A (see Table E7 in the Electronic Supplement). As a result, the mean country-level DOEG for Qatari banks drops from 0.0616 to 0.0535.

A detailed firm-level analysis of the DOEG from potential M&A is found in Table E7 in the Electronic Supplement.

**Table 6.** Country- and firm-level analysis of DOEG for conventional banks

| Ranking | Dominant banks | Country | Mean (county level) | Mean (firm level) | Target markets | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Egypt | Jordan | Lebanon | Morocco | Tunisia | Turkey |
| 10 | Arab Banking Corporation BSC-Bank ABC | Bahrain | 0.0966 | 0.0927 | 0.1482 | 0.1778 | 0.0825 | 0.014 | 0.1042 | 0.0064 |
| 7 | Gulf International Bank BSC | | | 0.1080 | 0.1616 | 0.1985 | 0.1224 | 0.0252 | 0.1231 | -0.0048 |
| | Mean | | | | 0.1549 | 0.18815 | 0.10245 | 0.0196 | 0.11365 | 0.0008 |
| 11 | National Bank of Kuwait S.A.K. | Kuwait | 0.0302 | 0.0907 | 0.1281 | 0.1465 | 0.0697 | 0.0238 | 0.0342 | 0.0388 |
| 19 | Commercial Bank of Kuwait K.P.S.C. (The) | | | -0.0106 | 0.0364 | 0.0668 | -0.0237 | -0.0654 | -0.0116 | -0.081 |
| | Mean | | | | 0.08225 | 0.10665 | 0.023 | -0.0208 | 0.0113 | -0.0211 |
| 1 | Qatar National Bank | Qatar | 0.0616 | 0.1892 | 0.2323 | 0.2265 | 0.1788 | 0.1017 | 0.1311 | 0.147 |
| 13 | Al Khalij Commercial Bank | | | 0.0831 | 0.1204 | 0.1686 | 0.071 | -0.022 | 0.1173 | 0.0104 |
| 20 | International Bank of Qatar Q.S.C. | | | -0.0612 | -0.0471 | 0.0106 | -0.0606 | -0.1448 | -0.0047 | -0.1278 |
| 2 | Qatar National Bank[1] | | 0.0535[1] | 0.1805 | | 0.2265 | 0.1788 | 0.1017 | 0.1311 | 0.147 |
| 15 | Al Khalij Commercial Bank[1] | | | 0.0766 | | 0.1686 | 0.071 | -0.022 | 0.1173 | 0.0104 |
| 21 | International Bank of Qatar Q.S.C.[1] | | | -0.0636 | | 0.0106 | -0.0606 | -0.1448 | -0.0047 | -0.1278 |
| | Mean[1] | | | | 0.1019 | 0.1352 | 0.0631 | -0.0217 | 0.0812 | 0.0099 |
| 17 | National Commercial Bank (The) | S.Arabia | 0.0685 | 0.0437 | 0.0924 | 0.0773 | 0.0481 | -0.0424 | -0.0351 | 0.0025 |
| 5 | Samba Financial Group | | | 0.1122 | 0.1664 | 0.1759 | 0.0942 | 0.0104 | 0.0926 | 0.0527 |
| 6 | Riyad Bank | | | 0.1111 | 0.1587 | 0.1796 | 0.0921 | -0.0246 | 0.0926 | 0.0609 |
| 12 | Banque Saudi Fransi JSC | | | 0.0872 | 0.1303 | 0.1547 | 0.0491 | -0.0476 | 0.071 | 0.0538 |
| 16 | Saudi Investment Bank (The) | | | 0.0674 | 0.11 | 0.1448 | 0.0425 | -0.0321 | 0.0702 | 0.0133 |
| | Mean | | | | 0.13156 | 0.14646 | 0.0652 | -0.02726 | 0.05826 | 0.03664 |

[1]: Considering the Qatar diplomatic crisis, banks from Bahrain, Egypt, Saudi Arabia and United Arab Emirates have not been taken into account for the calculation of the mean DOEG as these countries have banned Qatari companies from doing any business in their territory.

**Table 6.** Country- and firm-level analysis of DOEG for conventional banks (*Continued*)

| Ranking | Dominant banks | Country | Mean (county level) | Mean (firm level) | Target markets | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Egypt | Jordan | Lebanon | Morocco | Tunisia | Turkey |
| 4 | Emirates NBD PJSC | UAE | 0.0402 | 0.1210 | 0.1785 | 0.1841 | 0.0918 | -0.0323 | 0.1147 | 0.0625 |
| 18 | National Bank of Abu Dhabi | | | 0.0362 | 0.0752 | 0.0715 | 0.0446 | -0.021 | -0.0305 | -0.0057 |
| 8 | Abu Dhabi Commercial Bank | | | 0.0968 | 0.14 | 0.1645 | 0.0718 | 0.0083 | 0.0875 | 0.0415 |
| 3 | First Gulf Bank | | | 0.1295 | 0.1762 | 0.1945 | 0.1161 | 0.0276 | 0.1272 | 0.0665 |
| 14 | HSBC Bank Middle East Limited | | | 0.0825 | 0.1452 | 0.1669 | 0.0817 | -0.0075 | 0.0932 | -0.0191 |
| 9 | Union National Bank | | | 0.0957 | 0.1772 | 0.2068 | 0.0528 | 0.0247 | 0.1388 | 0.0019 |
| 22 | National Bank of Umm Al-Qaiwain PSC | | | -0.0701 | -0.1033 | 0.012 | -0.0686 | -0.1078 | 0.0215 | -0.1458 |
| 23 | Invest Bank P.S.C. | | | -0.1304 | -0.1549 | -0.0719 | -0.1508 | -0.1494 | 0.0097 | -0.1803 |
| | Mean | | | | 0.0793 | 0.1161 | 0.0299 | -0.0322 | 0.0703 | -0.0223 |
| | Mean (aggregate) | | | 0.0638 | 0.1036 | 0.1328 | 0.0503 | -0.0231 | 0.0674 | -0.0003 |

Similar to Table 6, Table 7 displays the average country- and firm-level DOEG for Islamic banks over the review period (i.e., 2014–2016).

A bank from Qatar, Masraf Al Rayan, is assigned the highest mean DOEG (i.e., 0.1363) from potential M&A, followed by the Emirates Islamic Bank (UAE) (i.e., mean firm-level DOEG = 0.0896) and Qatar Islamic Bank (Qatar) (i.e., mean firm-level DOEG = 0.0688). Only four out of ten Islamic banks report a positive mean DOEG from M&A with other Islamic banks. As a result, the mean (aggregate) firm-level DOEG for Islamic banks is negative (i.e., -0.0321), while the corresponding score for the conventional banks is positive (i.e., 0.0638). This is a statistically significant difference between the DOEG of the conventional and Islamic banks (Mauchly's test is significant: $\mathcal{X}^2(2) = 93.353, p = 10^{-4}$; therefore, the assumption of sphericity is violated. The Greenhouse-Geisser corrected test ($\varepsilon = 0.875$) shows the presence of a statistically significant difference between the DOEG of the two types of banks: $F(1.75), 4.25 = 11.99, p = 10^{-4}$). Hence, M&A should not be considered as a strategy for expansion for most Islamic banks.

In the MENA region (including Turkey), there are two markets where the GCC Islamic banks could expand their operations through M&A: Jordan and Turkey. However, as shown in Table 7, (i.e., mean (country level)), none of these markets is regarded as favorable for M&A, as the DOEG obtained from the consolidation of GCC-based and Jordanian Islamic banks is -0.0734 and GCC-based and Turkish Islamic banks is -0.0114, respectively. An exception to this negative outlook is UAE, which reports a positive mean DOEG from consolidations between local and overseas Islamic banks. However, it should be noted that this country-level score is biased, as it is based on a single Islamic bank/potential acquirer (i.e., Emirates Islamic Bank PJSC). A detailed firm-level analysis of DOEG from potential M&A between Islamic banks is available in Table E8 in the Electronic Supplement.

**Table 7.** Country- and firm-level analysis of DOEG for Islamic banks

| Ranking | Dominant banks | Country | Mean (country level) | Mean (firm level) | Target markets | |
|---|---|---|---|---|---|---|
| | | | | | Jordan | Turkey |
| 8 | Al-Salam Bank-Bahrain B.S.C. | Bahrain | -0.0319 | -0.1009 | -0.0434 | -0.1296 |
| 4 | Bank Alkhair BSC | | | 0.0463 | -0.0484 | 0.0937 |
| | Mean | | | | -0.0459 | -0.0180 |
| 9 | Kuwait Finance House | Kuwait | -0.2491 | -0.2036 | -0.3856 | -0.1126 |
| 3 | Qatar Islamic Bank SAQ | Qatar | -0.0452 | 0.0688 | 0.0355 | 0.0855 |
| 1 | Masraf Al Rayan (Q.S.C.) | | | 0.1363 | 0.0920 | 0.1585 |
| 10 | Barwa Bank | | | -0.2683 | -0.3767 | -0.2140 |
| 7 | Qatar International Islamic Bank | | | -0.0738 | -0.0634 | -0.0790 |
| | Mean | | | | -0.0782 | -0.0123 |
| 5 | Al Rajhi Bank Public Joint Stock Company | S.Arabia | -0.0124 | -0.0056 | -0.1145 | 0.0488 |
| 6 | Alinma Bank Public joint stock company | | | -0.0094 | 0.0602 | -0.0442 |
| | Mean | | | | -0.0272 | 0.0023 |
| 2 | Emirates Islamic Bank PJSC | UAE | 0.0948 | 0.0896 | 0.1106 | 0.0791 |
| | Mean (aggregate) | | | -0.0321 | -0.0734 | -0.0114 |

## 5. Conclusion

In this study, we developed a new smoothed bootstrap GDDF DEA measure for estimating efficiencies in the presence of both desirable and undesirable variables and positive and negative values in the data set. The objective of this work is the estimation of operating efficiency gains from possible M&A between banks. Our empirical analysis is based on two samples of banks: conventional and Islamic banks located in the MENA region and Turkey. The number of conventional and Islamic banks under review is 86 and 21, respectively, for the period 2014–2016. The two samples expand significantly after the inclusion of consolidated banks.

Our findings, in line with the extant literature, identify higher efficiencies for the conventional banks than their Islamic counterparts throughout the review period. It is noteworthy that this discrepancy applies in spite of the incorporation of non-performing loans in the efficiency measurement, which are regarded as a critical weakness of conventional banks. However, the average efficiency scores of the conventional and Islamic banks converge over the years 2014–2016. The gradual downward trend in the average efficiency of the conventional banks is neutralized by M&A. Consolidations have a positive effect on the efficiency of this type of banks. On the contrary, M&A are not recommended for Islamic banks, as the estimated efficiencies after consolidations are lower than those found before consolidations. As expected, most of the efficient sample banks are in the GCC. These financial institutions are most likely to be the bidders, while banks from the remaining MENA region and Turkey are most likely to be the targets. The most favorable markets for M&A for the GCC-based banks are Jordan and the Egypt.

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## References

Ahmad, M. F., & Lambert, T. (2019). Collective bargaining and mergers and acquisitions activity around the world. *Journal of Banking and Finance, 99*, 21–44.

Amel, D., Barnes, C., Panetta, F., & Salleo, C. (2004). Consolidation and efficiency in the financial sector: A review of the international evidence. *Journal of Banking and Finance, 28*, 2493–2519.

Arocena, P., Saal, D. S., Urakami, T., & Zschille, M. (2020). Measuring and decomposing productivity change in the presence of mergers. *European Journal of Operational Research, 282*(1), 319–333.

Avinadav, T., Chernonog, T., & Perlman, Y. (2017). Mergers and acquisitions between risk-averse parties. *European Journal of Operational Research, 259*, 926–934.

Banker, R. D. (1993). Maximum-likelihood, consistency and data envelopment analysis: A statistical foundation. *Management Science, 39*, 1265–1273.

Banker, R. D., & Natarajan, R. (2011). Statistical tests based on DEA efficiency scores. In W. W. Cooper, L. M. Seiford, & J. Zhu (Eds.), *Handbook on data envelopment analysis* (pp. 273–295). New York: Springer.

Banker, R. D., Zheng, Z., & Natarajan, R. (2010). DEA-based hypothesis tests for comparing two groups of decision making units. *European Journal of Operational Research, 206*, 231–238.

Beck, T., Demirguc-Kunt, A., & Merrouche, O. (2013). Islamic vs. conventional banking: Business model, efficiency and stability. *Journal of Banking and Finance, 37*, 433–477.

Berger, A. N., & Udell, G. F. (2002). Small business credit availability and relationship lending: The importance of bank organizational structure. *The Economic Journal, 112*, F32–F53.

Berger, A. N., Demsetz, R., & Strahan, P. (1999). The consolidation of financial services industry: Causes, consequences, and implications for the future. *Journal of Banking and Finance, 23*, 135–194.

Bernad, C., Fuentelsaz, L., & Gómez J. (2010). The effect of mergers and acquisitions on productivity: An empirical application to Spanish banking. *Omega, 38*, 283–293.

Casu, B., & Girardone, C. (2004). Financial conglomeration: Efficiency, productivity and strategic drive. *Applied Financial Economics, 14*, 687–696.

Casu, B., & Girardone, C. (2006). Bank competition, concentration and efficiency in the single European market. *The Manchester School, 74*, 441–468.

Casu, B., & Molyneux, P. (2003). A comparative study of efficiency in European banking. *Applied Economics, 35*, 1865–1876.

Chambers, R. G., Chung, Y., & Färe, R. (1998). Profit, directional distance functions, and Nerlovian efficiency. *Journal of Optimization Theory and Applications*, *98*, 351–364.

Chen, J. X., Deng, M., & Gingras, S. (2011). A modified super-efficiency measure based on simultaneous input–output projection in data envelopment analysis. *Computers and Operations Research, 38*, 496–504.

Cheng, G., & Zervopoulos, P. D. (2014). Estimating the technical efficiency of health care systems: A cross-country comparison using the directional distance function. *European Journal of Operational Research, 238*, 899–910.

Cheng, G., Zervopoulos, P., & Qian, Z. (2013). A variant of radial measure capable of dealing with negative inputs and outputs in data envelopment analysis. *European Journal of Operational Research, 225*, 100–105.

Chortareas, G. E., Girardone, C., & Ventouri, A. (2012). Bank supervision, regulation, and efficiency: Evidence from the European Union. *Journal of Financial Stability, 8*, 292–302.

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management, 51*, 229–240.

Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* (2nd eds.). New York: Routledge.

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*(1), 155–159.

Degl'Innocenti, M., Kourtzidis, S. A., Sevic, Z., & Tzeremes, N. G. (2017). Bank productivity growth and convergence in the European Union during the financial crisis. *Journal of Banking and Finance, 75*, 184–199.

DeYoung, R., Evanoff, D. D., & Molyneux, P. (2009). Mergers and acquisitions of financial institutions: A review of the post-2000 literature. *Journal of Financial Services Review, 36*, 87–110.

Färe, R., Grosskopf, S., & Lovell, C. (1994). *Production Frontiers*. Cambridge: Cambridge University Press.

Fraisse, H., Hombert, J., & Lé, M. (2018). The competitive effect of a bank megamerger on credit supply. *Journal of Banking and Finance, 93*, 151–161.

Gattoufi, S., Al-Muharrami, S., & Al-Kiyumi, A. (2009). The impact of mergers and acquisitions on the efficiency of GCC banks. *Banks and Bank Systems, 4*, 94–100.

Halkos, G. E., & Tzeremes, N. G. (2013). Estimating the degree of operating efficiency gains from a potential bank merger and acquisition: A DEA bootstrapped approach. *Journal of Banking & Finance, 37*, 1658–1668.

Johnes, J., Izzeldin, M., & Pappas, V. (2014). A comparison of performance of Islamic and conventional banks 2004–2009. *Journal of Economic Behavior & Organization, 103*, S93–S107.

Kabir, M. N., Worthington, A., & Gupta, R. (2015). Comparative credit risk in Islamic and conventional bank. *Pacific-Basin Finance Journal, 34*, 327–353.

Kerstens, K., & Van de Woestyne, I. (2011). Negative data in DEA: A simple proportional distance function approach. *Journal of the Operational Research Society, 62*, 1413–1419.

Kneip, A., Simar, L., & Wilson, P. W. (2008). Asymptotics and consistent bootstraps for DEA estimators in nonparametric frontier models. *Econometric Theory, 24*, 1663–1697.

Kneip, A., Simar, L., & Wilson, P. W. (2011). A computationally efficient, consistent bootstrap for inference with nonparametric DEA estimators. *Computational Economics, 38*, 483–515.

Kounetas, K., & Zervopoulos, P. D. (2019). A cross-country evaluation of environmental performance: Is there a convergence-divergence pattern in technology gaps? *European Journal of Operational Research, 273*(3), 1136–1148.

Larkin, Y., & Lyandres, E. (2019). Inefficient mergers. *Journal of Banking and Finance, 108*, 105648.

Lozano, S., & Gutierrez, E. (2011). Slacks-based measure of efficiency of airports with airplanes delays as undesirable outputs. *Computers & Operations Research, 38*, 131–139.

Mobarek, A., & Kalonov, A. (2014). Comparative performance analysis between conventional and Islamic banks: Empirical evidence from OIC countries. *Applied Economics, 46*(3), 253–270.

Peyrache, A. (2013). Industry structural inefficiency and potential gains from mergers and break-ups: A comprehensive approach. *European Journal of Operational Research, 230*, 422–430.

Podinovski, V. V., & Kuosmanen, T. (2011). Modelling weak disposability in data envelopment analysis under relaxed convexity assumptions. *European Journal of Operational Research, 211*, 577–585.

Politis, D. N., Romano, J. P., & Wolf, M. (2001). On the asymptotic theory of subsampling. *Statistica Sinica, 11*, 1105–1124.

Sahut, J., & Milli, M. (2011). Banking distress in MENA countries and the role of mergers as a strategic policy to resolve distress. *Economic Modelling, 28*, 138–146.

Siganos, A. (2019). The daylight saving time anomaly in relation to firms targeted for mergers. *Journal of Banking and Finance, 105*, 36–43.

Simar, L. (2007). How to improve the performances of DEA/FDH estimators in the presence of noise? *Journal of Productivity Analysis, 28*, 183–201.

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science, 44*, 49–61.

Simar, L., & Wilson, P. W. (1999). Estimating and bootstrapping Malmquist indices. *European Journal of Operational Research, 115*, 459–471.

Simar, L., & Wilson, P. W. (2000). Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis, 13*, 49–78.

Simar, L., Vanhems, A., & Wilson, P. W. (2012). Statistical inference for DEA estimators of directional distances. *European Journal of Operational Research, 220*, 853–864.

Tarsalewska, M. (2015). The timing of mergers along the production chain, capital structure, and risk dynamics. *Journal of Banking and Finance*, *57*, 51–64.

Zervopoulos, P. D., Sklavos, S., Kanas, A., & Cheng, G. (2019). A multi-parametric method for bias correction of DEA efficiency estimators. *Journal of the Operational Research Society*, *70*(4), 655–674.

Zha, Y., Liang, N., Wu, M., & Bian, Y. (2016). Efficiency evaluation of banks in China: A dynamic two-stage slacks-based measure approach. *Omega*, *60*, 60–72.