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

**Hussein A. Hassan Al Tamimi**

Department of Finance and Economics,  
University of Sharjah, Sharjah, United Arab Emirates

[hussein@sharjah.ac.ae](mailto:hussein@sharjah.ac.ae)

**Andi Duqi**

Department of Management, University of Bologna, Bologna, Italy

[andi.duqi@unibo.it](mailto:andi.duqi@unibo.it)

**Angelos Kanas**

Department of Economics, University of Piraeus, Piraeus, Greece

[akanas@unipi.gr](mailto:akanas@unipi.gr)

**Panagiotis D. Zervopoulos\***

Department of Management, University of Sharjah, Sharjah, United Arab Emirates

Tel.: +971 567159809

[pzervopoulos@sharjah.ac.ae](mailto:pzervopoulos@sharjah.ac.ae)

\* Corresponding author

**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 & Gutierrez, 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:

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

The assumptions met by the technology ( $T$ ) are: (T.1) closedness, (T.2) free disposability of inputs and desirable outputs:  $\forall (x, y) \in T$ , if  $x' \geq x$  and  $y' \leq y$  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:

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

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:

$$\begin{aligned} \vec{D}_T(x, y, b; g_x, g_y, g_b) = \min & \frac{1 - \frac{1}{m} \sum_{i=1}^m \beta |x_{io}| / x_{io}}{1 + \frac{1}{s+l} (\sum_{r=1}^s \beta |y_{ro}| / y_{ro} + \sum_{\eta=1}^l \beta |b_{\eta o}| / b_{\eta o})} \\ \text{s. t. } & \sum_{j=1}^n \lambda_j x_{ij} + \beta |x_{io}| \leq x_{io} \quad i = 1, \dots, m \\ & \sum_{j=1}^n \lambda_j y_{rj} - \beta |y_{ro}| \geq y_{ro} \quad r = 1, \dots, s \\ & \sum_{j=1}^n \lambda_j b_{\eta j} - \beta |b_{\eta o}| = b_{\eta o} \quad \eta = 1, \dots, l \\ & \sum_{j=1}^n \lambda_j = 1 \end{aligned} \tag{3}$$

## 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:

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

where  $\Psi' = \left( V \frac{\vec{g}}{\|\vec{g}\|} \right)$ ,  $V$  is a  $\mu \times (\mu - 1)$  matrix whose column  $\{v_\rho | \rho = 1, \dots, \mu - 1\}$  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:

$$\Gamma(w_o) = \{(z, u) | (z, u) = h_{w_o}(w), w \in T\} \quad (5)$$

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

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

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:

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

where  $(s_x, -s_y, 0)$  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:

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

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

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

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  $\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_n$  measured in step [1].

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

- [4] Construct a bootstrap sample  $Z_n^* = \{(z_j^*, u_j^*)\}_{j=1}^n$ , where  $z_j^* = z_j^{(naive)}$  and  $u_j^* =$

$$\begin{cases} \hat{\varphi}'_{z_j^{(naive)}} - \hat{\beta}_{z_j^{(naive)}}, & \text{if } \hat{\beta}_{z_j^{(naive)}} > h_1 \\ \hat{\varphi}'_{z_j^{(naive)}} - \hat{\xi}_{z_j^{(naive)}}, & \text{otherwise} \end{cases}; \hat{\xi}_{z_j^{(naive)}} \text{ is a random, independent draw}$$

from a uniform distribution on  $[0, h_1]$ ;  $z_n^{(naive)} = \{(z_j^{(naive)}, u_j^{(naive)})\}_{j=1}^n$  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  $\{z_{n,q}^{**}\}_{q=1}^Q$  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  $z_{n,q}^{**}, q = 1, \dots, Q$ .

- [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:

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

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:

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

### 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:

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

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

If  $\text{DOEG}_{(B1,B2)} > 0$  then the potential M&A is likely to be successful because of the potential operating efficiency gains. If  $\text{DOEG}_{(B1,B2)} < 0$  the M&A between firms is regarded as unfavorable while a  $\text{DOEG}_{(B1,B2)} = 0$  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
<b>Inputs</b>					
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	
<b>Desirable outputs</b>					
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	
<b>Undesirable output</b>					
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 ( $\cong 10\%$  of the total sample conventional banks) followed by the UAE-based ( $\cong 6.6\%$ ).

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

	Bankpozitif Kredi ve Kalkinma Bankasi					
84	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):  $T = -2.628, p = 0.009, KS_{sample1} = 1.414, p = 0.037, KS_{sample2} = 0.952, p = 0.325$ )<sup>1</sup>. This is regarded as a medium-to-large change

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<sup>1</sup> 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
	(sample1)	(sample2)		(sample1)	(sample2)		(sample1)	(sample2)	
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

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<sup>2</sup> 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 <sup>1</sup>		0.0535 <sup>1</sup>	0.1805		0.2265	0.1788	0.1017	0.1311	0.147
15	Al Khalij Commercial Bank <sup>1</sup>			0.0766		0.1686	0.071	-0.022	0.1173	0.0104
21	International Bank of Qatar Q.S.C. <sup>1</sup>			-0.0636		0.0106	-0.0606	-0.1448	-0.0047	-0.1278
	Mean <sup>1</sup>				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

<sup>1</sup>: 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:  $\chi^2(2) = 93.353, p = 10^{-4}$ ; therefore, the assumption of sphericity is violated. The Greenhouse-Geisser corrected test ( $\epsilon = 0.875$ ) 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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