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The use of DEA in measuring efficiency in Arabian banking

Abstract

The Data Envelopment Analysis (DEA) approach is used to investigate cost efficiency levels of banks operating in Jordan, Egypt, Saudi Arabia and Bahrain over 1992-2000. The estimated cost efficiency is further decomposed into technical and allocative efficiency at both variable and constant return to scale. Later on, the technical efficiency is further decomposed into pure technical and scale efficiency. Our cost efficiency scores ranged from 50 to 70% with some variations in scores depending on bank's size and its geographical locations. These results suggest that the same level of output could be produced with approximately 50-70% of their current inputs if banks under study were operating on the most efficient frontier. This level of inefficiency is more than the range of 10-15% for the 130 studies surveyed by Berger and Humphrey (1997) and Berger and DeYoung (1997). This level is also more than the level of inefficiency found in European studies including Carbo et al.'s (2000) whose findings for a sample of banks from twelve countries, show mean cost inefficiency of around 22% for the period of 1989 – 1996.

Keywords: Data Envelopment Analysis (DEA), non-parametric technique, efficiency, Arabian banking, intermediation approach, cost efficiency, Jordan, Bahrain, Saudi Arabia, Egypt.
JEL Classification: G21.

Introduction

This study investigates the efficiency levels in the banking sectors of various Arabian countries: Jordan, Egypt, Saudi Arabia and Bahrain over the 1992-2000 period. The empirical evidence on bank efficiency aims to compare the performance of banks operating in these countries with their counterparties in more developed countries. In addition, this study will highlight the features associated with the role of economic development and financial reforms that have taken place in these countries over the past decade and their impact on banking industry performance.

The financial sectors of Jordan, Egypt, Saudi Arabia and Bahrain have witnessed major financial reforms over the last decade. These reforms include liberalizing the financial systems, boosting banks' capitalization in accordance with Basle standards, enhancing the systems of banking supervision and updating regulatory frameworks. The main aim of such deregulation is to improve the efficiency of banking firms as these reforms are expected to enhance competition leading to price falls, output increases, greater levels of innovation and improved productive efficiency. To date, however, empirical studies provide mixed evidence on the impact of deregulation on bank performance (European Commission, 1997; Cecchini, 1988; Gardener et al., 1988).

1. Cost Efficiency in literature

This section briefly describes how cost efficiency for decision-making unit (DMU) is estimated in banking literature. Then it describes how cost efficiency can be decomposed into technical and allocative efficiency. In addition, it describes how technical efficiency can be further decomposed into pure technical and scale efficiency.

Efficiency, in general, defines the relationship between production and some desirable objective function such as cost minimization or revenue and profit maximization given certain levels of technology. The firm normally faces a degree of competitiveness in input and output markets, and its rational economic behavior aims to maximize the production by choosing either optimal input mix under cost minimization or optimal outputs under the revenue maximization objective.

Forsund et al. (1980) express the transformation of inputs into outputs by the production function $f(x)$, which shows the maximum output obtainable from various input vectors. Under certain regularity conditions, an equivalent representation of cost function can be estimated as:

$$c(y, w) = \min_x \{wx / f(x) \geq y, x \geq 0\}.$$

This function shows the minimum expenditure required to produce output y at input prices w. This function depicts how effective are firms in using inputs to produce a given level of output.

In addition, cost efficiency can be decomposed into technical and allocative efficiency. Koopmans (1951) defined technical efficiency as an event when an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. Coelli et al. (1998) refer to Nunamaker (1985) who defines technical efficiency as a measure of a decision-making unit (DMU) ability to avoid waste by producing as much output as long as input usage will allow.

Allocative efficiency, on the other hand, measures the ability of a DMU to avoid waste by producing a level of output at the minimal possible cost (the ability to combine inputs and outputs in optimal proportions in the light of prevailing prices).

Technical efficiency can be investigated further and decomposed into pure technical efficiency and scale efficiency. Webster et al. (1998) define scale efficiency as the case where the firm can produce its current level of output with fewer inputs assuming constant return to scale (the measure of the ability to avoid waste by operating on the most productive scale). Pure technical efficiency measures the proportional reduction in inputs that could be achieved if the firm operated on the variable returns to scale frontier. If the firm is able to achieve this, then further input reductions could be achieved by operating on the constant returns to scale frontier.

2. Parametric and non-parametric approaches to measure efficiency

Berger and Humphrey (1997) note that efficiency estimation techniques can be broadly categorized into parametric and non-parametric methods. However, no consensus exists as to the preferred method for determining the best-practice frontier against which relative efficiencies are measured. The most commonly used non-parametric methods are known as Data Envelopment Analysis (DEA) and the Free Disposable Hull (FDH). On the other hand, the most commonly used parametric methods are the Stochastic Frontier Approach (SFA), the Thick Frontier Approach (TFA) and the Distribution Free Approach (DFA).

The main advantage of the non-parametric approach over the parametric one for measuring bank efficiency relates to the ability of the former to characterize the frontier technology in a simple mathematical form, and the ability to accommodate non-constant returns to scale. However, the non-parametric frontier method makes no accommodation for noise (Fried et al., 1993).

Alternatively, the parametric approach requires the specification of a production, cost, revenue, or profit function as well as assumptions about the error term(s). Cummins and Zi (1997) mention that the advocates of the parametric approach disagree about distributional assumptions imposed on the error term and note that debate still exists as to the most appropriate choice. In addition, the parametric method has also been criticized for confounding estimation of efficiency with specification errors.

Nonetheless, an argument in favor of the parametric approach is that it allows for random error, so these methods are less likely to misidentify measurement error, or transitory differences in cost, or specification error as inefficiency. The main parametric methods are the stochastic frontier approach (SFA), thick frontier approach (TFA) and distribution free approach (DFA).

The choice of estimation method has been an issue of debate with some researchers preferring the parametric approach (e.g., Berger, 1993) and others the non-parametric method (e.g., Seiford and Thrall, 1990). Despite dispute over the preferred methodological approach, the emerging viewpoint suggests that it is not necessary to have a consensus as to one single (best) frontier approach for measuring firm-level efficiency. Instead, there should be a set of consistency conditions for the efficiency measures derived from various approaches to meet. If efficiency estimates are consistent across different methodologies then these measures will be convincing and therefore valid (or believable) estimates for regulators and other decision-makers (Bauer et al., 1997).

In this study the non-parametric DEA technique will be use to estimate efficiency scores in banking industries under study. Other features of this technique are addressed in the following section.

3. The use of DEA approach in measuring efficiency

The DEA mathematical programming approach is an alternative method to estimate efficiency in the financial sector. This approach was originally proposed by Farell (1957) and received wider attention after Charnes et al. (1978) developed an estimable model that had an input orientation assuming constants returns to scale (CRS). Charnes, Cooper and Rhodes (1978) reformulated Farrell's original idea into a mathematical programming problem that construct a non-parametric piece-wise frontier that envelops the input and output data relative to which costs are minimized allowing for the calculation of efficiency' scores for each observation in the sample.

DEA constructs the frontier of the observed input-output ratios by linear programming techniques (Fare, Grosskopf, and Lovell, 1985). This procedure is not based on any explicit model of the frontier or the relationship of the observations to the frontier other than the fact that observations cannot lie below the frontier. This approach shows how a particular decision-making unit (DMU) operates relative to other DMUs in the sample and so it provides a benchmark for best practice technology based on the experience of the banks in the sample.

DEA can estimate efficiency under the assumption of constant return to scale and variable returns to scale. The CRS assumption is only appropriate when all DMUs are operating at optimal scale. However, factors like imperfect competition and constraints in finance may cause a DMU not to operate at optimal scale. As a result, the use of the CRS specification, when some DMUs are not operating at optimal scale, confuses measures of technical and scale efficiency. Banker et al.'s (1984) seminal work proposed a variable returns to scale and an output-oriented model.

Bauer et al. (1997) note that the usual radial form of DEA is based on technological efficiency where efficient firms are those for which no other firm or linear combination of firms produces as much or more of every output (given inputs) or uses as little or less of every input (given outputs). The efficient frontier is composed of these undominated firms and the piecewise linear segments that connect the set of input/output combinations of these firms, yielding a convex production possibility set.

To match firms in so many dimensions, other constraints are often imposed on DEA linear programming problems. Other constraints specified in the financial institutions research can include such factors like quality controls (such as the number of branches or average bank account size) or environmental variables (such as bank ownership or state regulatory controls).

However, matching firms in so many dimensions can result in firms being measured as highly efficient solely because no other firms or few other firms have comparable values of inputs, outputs or other constrained variables. That is, some firms may be self-identified as 100% efficient not because they dominate other firms, but because there are only a few other observations, with which they are comparable. The problem of self-identifiers or near self-identifiers most often arises when there are a small number of observations relative to the number of inputs, outputs.

DEA uses sample data to derive the efficiency frontier against which each firm (in the sample) is evaluated. No explicit functional form for the production needs to be specified. Instead, the production frontier comprises piecewise linear segments that assign relative efficiency scores for each firm. Another important feature of DEA scores is independency of units of measurement (of both inputs and outputs) as long as these units are the same for all observations.

Siems and Barr (1998) point that the DEA methodology is a valuable tool for strategic, policy, and operational decision problems, particularly in the service and non-profit sectors. They argue that this approach provides an analytical, quantitative benchmarking tool for measuring relative efficiency. In contrast to statistical procedures that are based on central tendencies, DEA reveals best-practice frontiers by analyzing each decision-making unit DMU separately and then measures relative productive efficiency with respect to the entire population being evaluated.

Cummins and Zi (1997) and Cummins and Weiss (1998) note that DEA considers the technological aspects of production function and therefore, it is utilized to estimate cost and revenue frontiers. It provides a convenient way for decomposing cost efficiency into pure technical, scale and allocative efficiency without requiring estimates of input and output prices. If estimates of input prices are available, cost efficiency can also be measured (e.g., Aly et al., 1990; and Ferrier and Lovell, 1990).

4. Methodology: measures of cost efficiency

This section describes the steps utilized to derive cost efficiency in the countries under study using the linear programming DEA approach.

4.1. Constant returns to scale DEA model. Efficiency measures derived using DEA are based on maximizing the ratio of all output over all the inputs. Assuming a data set that includes K inputs (k = 1,..., K), M outputs (m = 1,..., M) for N firms (j =1,..., N). Then for the ith observation, the set of input and output can be represented by the column of input vector x_i and the column of output vector y_i and the sets of inputs and outputs for the ith observation are x_{ik}, and y_{im}. The input matrix X = [K×N], and the output matrix Y = [M×N] represent the data for all N firms. The optimal weights are obtained by solving the mathematical programming problem:

$$\max_{u,v}(u'y_i / v'x_i),$$
$$\text{s.t. } u'y_j / v'x_j \le 1, j = 1,2,..., N, \quad (1)$$
$$u, v \ge 0.$$

The aim is to obtain a measure of efficiency (the ratio of all outputs over all inputs) such as $u'y_i / v'x_i$ is maximized, where u is a vector of output weights [M×1], and v is a vector of input weights [K×1]. The inequality equation requires that the weights are positive. DEA selects the weights that maximize each firm's productive efficiency score as long as no weight is negative and the weights are universal.

To avoid the problem of the infinite number of solutions in the problem, the constraint $v'x_i = 1$ is imposed to provide the multiplier form of the DEA linear programming problem:

$$\max_{\mu,v}(\mu' y_i),$$
$$\text{s.t. } v'x_i = 1,$$
$$\mu' y_j - v'x_j \le 0, j = 1,2,...,N, \quad (2)$$

$\mu, v \geq 0$,

where the change of notation from u and v to μ and v is used to reflect the transformation.

The dual envelopment form of the input-oriented CRS DEA linear program of equation (2) can be written as:

$$\min_{\theta,\lambda},$$
$$\text{s.t.} \; -y_i + Y\lambda \geq 0, \quad (3)$$
$$\theta x_i - X\lambda \geq 0,$$
$$\lambda \geq 0,$$

where θ is a scalar, and λ is an N×1 vector of constants. The objective function seeks to minimize the efficiency score, θ, which represents the amount of radial reduction in the use of each input. The first constraint (the output constraint) implies that the production of the *r*th output by observation *i* cannot exceed any linear combination of output *r* by all firms in the sample. The second constraint involves the use of input *s* by observation *i*, and implies that the radially reduced use of input *s* by firm *i* cannot be less than the same linear combination of the use of input *s* by all firms in the sample. The value of θ obtained will be the efficiency score for the *i*th firm that satisfies: $\theta \leq 1$. When θ value is 1 (the point is on the frontier), the firm is technically efficient according to the Farrell's (1957) definition. Equation (3) must be solved *N* times, once for each firm in the sample, and then a value of θ is obtained for each firm (see Coelli et al., 1998).

Equation (3) above assumes that constant returns to scale are imposed on every observation in the sample. It does not take into account factors which make firms unique beyond the simple input-output mix (such as inefficiencies which result from operating in areas of increasing or decreasing returns to scale due to size constraints).

4.2. VRS model and decomposition of technical efficiency. Banker, Charnes and Cooper (1984) suggested an extension to the CRS model to account for variable returns to scale (VRS) when not all firms are operating at an optimal scale. If calculated technical efficiency (CRS) is different from the technical efficiency (VRS), then this indicates that the firm has scale inefficiency. Therefore, the use of the VRS specification permits the calculation of technical efficiency devoid of the scale efficiency effect (decomposing technical efficiency into pure technical and scale efficiency; that is $\theta_{CRS} = \theta_{VRS} \cdot \theta_{Scale}$). The CRS linear programming problem can be modified to account for VRS by adding the convexity constraint to provide:

$$\min_{\theta,\lambda}\theta,$$
$$\text{st} \quad -y_1 + Y\lambda \geq 0,$$
$$\theta x_i - X\lambda \geq 0,$$
$$N1'\lambda = 1 \quad (4)$$
$$\lambda \geq 0,$$

where *N*1 is an *N*×1 vector of ones. This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS. The convexity constraint $N1'\lambda = 1$ ensures that an inefficient firm is only benchmarked against firms of similar size.

4.3. Technical and allocative efficiency. If information about prices are available and we want to consider a behavioral objective such as cost minimization, then we can estimate measures of both technical and allocative efficiencies. For the case of VRS cost minimization, we run the input-oriented DEA model (defined by (4)) to obtain technical efficiency (TE), and then we need to solve the following cost minimization DEA:

$$\min_{\lambda, x_i^*} W_i' X_i^*, \quad (5)$$
$$\text{st} \quad -y_i + Y\lambda \geq 0,$$
$$x_i^* - X\lambda \geq 0,$$
$$N1'\lambda = 1,$$
$$\lambda \geq 0,$$

where w_i is a vector of input prices for the *i*th firm and x_i^* is the cost minimization vector of input quantities for the *i*th firm, given the input prices w_i and the output levels y_i. The total cost (economic) efficiency of the *i*th firm is calculated as: $EE = w_i' x_i^* / w_i' x_i$. (the ratio of minimum cost to observed cost , for the *i*th firm), then the allocative efficiency is calculated as *AE* = *CE* / *TE*.

To summarize, the above section describes how DEA will be utilized to derive the efficiency measures under the assumption of constant return to scale, variable return to scale, and shows how to identify whether firms are operating at increasing or decreasing returns to scale. Finally, the section shows how to split cost efficiency into technical and allocative efficiency measures.

5. The data

Our data comprise a representative sample of the banks operating in Jordan, Egypt, Saudi Arabia and Bahrain and consist of 82 banks over the 1992-2000 period. This sample represents around 78%, 88%, 63% and 55% of the financial systems of these countries (excluding the assets of foreign branches and central banks) (Table 1 below shows the details).

The financial systems of Jordan, Egypt, Saudi Arabia and Bahrain are characterized by the dominance of commercial banks in the financial system; for instance, their share of financial assets ranges from about 58% in Saudi Arabia to about 85% in Bahrain. In addition, the banking systems of these countries are concentrated (for instance, the share of the largest three banks ranged from about 49% of the banking sector in Saudi Arabia to about 79% in Jordan over the last decade).

Table 1. Size of the study sample relative to the banking sectors of Jordan, Egypt, Saudi Arabia and Bahrain over 1992-2000 (US$ million, figures rounded to nearest 2 digits)

	Bahrain			Egypt			Jordan			Saudi Arabia		
Country/Year	Sample assets	Total banking assets	%	Sample Assets	Total banking assets	%	Sample assets	Total banking assets	%	Sample assets	Total banking assets	%
1992	34,200	77,500	44	52,200	62,500	84	6,900	9,100	75	77,600	129,600	60
1993	34,300	68,400	50	54,300	60,900	89	7,100	9,600	74	82,700	142,800	58
1994	37,000	73,700	50	57,200	62,300	92	8,000	10,700	75	85,400	146,300	58
1995	40,000	73,700	54	63,900	69,800	92	9,100	11,900	77	89,600	150,100	60
1996	42,500	76,600	55	67,600	77,100	88	9,800	12,500	79	93,900	156,400	60
1997	44,900	83,500	54	77,200	89,100	87	11,100	13,700	81	105,000	163,900	64
1998	48,700	99,400	49	82,600	97,300	85	12,000	14,800	81	111,500	171,400	65
1999	55,200	102,100	54	88,700	103,300	86	13,000	16,300	80	121,700	172,200	71
2000	57,400	106,400	54	93,800	103,600	90	14,500	18,900	77	131,900	181,300	73
Average	43,800	84,600	52	70,800	80,600	88	10,200	13,100	78	99,900	157,100	63

Source: The total assets were extracted from the annual financial reports of the monetary agencies in the countries under study (the consolidated financial statements of the banks) while the sample was drawn from the London Bankscope database (January, 2000 & 2002).

Our sample represents the major financial institutions that have consistently published their financial statements over the last ten years in the countries under study. The relative size of Bahrain's banks sample looks small and the reason is that the financial system in this country has been dominated by offshore banking units which are excluded from the sample as these belong to large international financial institutions and their data are unavailable. In Saudi Arabia, the specialized government institutions, while important, do not publish detailed financial statements and so these are not included in the sample.

Table 2 shows the specialization of the banks included in the sample. The number of commercial banks comprises around 66% of the total sample. The percent of commercial banks operating in each country varies; ranging from 42% in Bahrain to 77% in Saudi Arabia.

Table 2. Specialization of banks under study, 1992-2000

% of total	Bahrain	Egypt	Jordan	Saudi Arabia	All
Commercial	44	76	57	77	66
Investment	28	8	29	8	16
Islamic	17	5	7	0	7
Other	11	11	7	15	11
Total Number	18	37	14	13	82

Source: Bankscope (Jan. 2000 & 2002).

Table 3 shows that the size of total assets of all the banks included in the present study increased from about US$ 180 billion in 1992 to about US$ 310 billion in 2000 and averaged about US$ 235 billion over the whole period. Dividing these financial institutions into nine size categories, the share of the largest banks (with assets size greater than US$ 5 billion) constituted around 70% of the total assets of all the banks over the period of 1992-2000.

Table 3. Distribution of banks' assets in Jordan, Egypt, Saudi Arabia and Bahrain, 1992-2000

	1992	1993	1994	1995	1996	1997	1998	1999	2000	Avg.
	%	%	%	%	%	%	%	%	%	US$, mil.
1-99.9	0.11	0.08	0.14	0.16	0.14	0.10	0.06	0.02	0.02	202
100-199.9	1.16	1.05	0.78	0.35	0.31	0.18	0.21	0.29	0.27	1,073
200-299.9	1.76	1.35	1.10	1.78	1.04	0.80	0.67	0.36	0.32	2,173
300-499.9	3.78	4.08	3.47	2.79	2.92	2.75	2.49	2.04	1.58	6,422
500-999.9	2.56	2.73	4.64	4.57	4.51	3.53	3.67	3.47	3.29	8,569

Table 3 (continued). Distribution of banks' assets in Jordan, Egypt, Saudi Arabia and Bahrain, 1992-2000

	1992	1993	1994	1995	1996	1997	1998	1999	2000	Avg.
	%	%	%	%	%	%	%	%	%	US$, mil.
1,000-2,499.9	11.87	11.50	9.89	13.09	10.02	11.31	11.84	10.51	10.15	25,911
2,500-4,999.9	8.29	8.56	4.68	4.94	7.12	6.65	6.50	7.66	8.26	16,470
5,000-9,999	18.22	19.28	24.51	26.23	24.40	26.82	14.88	19.13	9.28	46,196
10,000+	52.26	51.37	50.78	54.22	49.54	47.85	59.67	56.53	66.83	129,190
T. Assets (US$, mil., nominal values)	179,033	186,975	197,046	213,044	225,426	250,325	267,943	292,855	313,209	

Source: Bankscope (Jan. 2000 & 2002).

This study employs the intermediation approach, as indicated earlier, for defining bank inputs and outputs. Following Aly et al. (1990), the inputs used in the calculation of the various efficiency measures are deposits (w_1), labor (w_2) and physical capital (w_3). The deposits include time and savings deposits, notes and debentures, and other borrowed funds. The price of loanable funds was derived by taking the sum of interest expenses of the time deposits and other loanable funds divided by loanable funds. Labor is measured by personnel expenses as a percent of total assets[1]. Bank physical capital is measured by the book value of premises and fixed assets (including capitalized leases). The price of capital was derived by taking total expenditures on premises and fixed assets divided by total assets. The three outputs used in the study include total customer loans (y_1), all other earning assets (y_2), and off-balance sheet items (y_3), measured in millions of US dollars.

The off-balance sheet items (measured in nominal terms) were included as a third output. Although the latter are technically not earning assets, these constitute an increasing source of income for banks and therefore should be included when modelling the banks' cost characteristics; otherwise, total banks' output would tend to be understated (Jagtiani and Khanthavit, 1996). Furthermore, these items are included in the model because they are often effective substitutes for directly issued loans, requiring similar information-gathering costs of origination and ongoing monitoring and control of the counterparts, and presumably similar revenues as these items are competitive substitutes for direct loans.

The definitions, means, standards of deviation of the input and output variables used are reported in Table 4. The table shows that the average bank had US$ 1.26 billion in loans, US$ 1.39 billion in other earning assets, and US$ 1.32 billion in off-balance sheet items over 1992-2000. The cost of input variables averaged about 7.0 percent for purchased funds, 2.0 percent for labor and 1.0 percent for physical capital over the period of 1992-2000. On the other hand, the prices of banks output averaged about 15.0 percent for loans[2]; 5.0 percent for other earning assets and 1.0 percent for off-balance sheet items over the same period.

Results and conclusion

This section reports the efficiency measures obtained using DEA. As indicated earlier, DEA can be used to estimate efficiency under the assumptions of constant and variable returns to scale.

The cost efficiency estimated for the banks under study averaged 50% when the estimates are derived under constant return to scale while the estimates averaged around 70% under variable return to scale over 1992-2000. The efficiency scores vary across banks based on their relative size and across their geographical locations. Based on the size, the largest banks are found to be relatively the most cost efficient. Geographically, the Saudi banks are found to be the most efficient while the Jordanian banks are found to be the least efficient (Table 5 reports the details).

These cost estimates suggest that the same level of output could be produced with approximately 50-70% of their current inputs if banks under study were operating on the most efficient frontier. This level of inefficiency is more than the range of 10-15% for the 130 studies surveyed by Berger and Humphrey (1997) and Berger and DeYoung (1997). Further, this level is also more than the level of inefficiency found in European studies including Carbo et al.'s (2000) whose findings for a sample of banks from twelve countries, show mean cost inefficiency of around 22% for the period of 1989-1996.

When we decomposed the cost efficiency into technical and allocative efficiency, the allocative effi-

[1] As staff numbers were not available for the banks in the sample, we used this measure instead. This measure for staff costs has been used in various previous studies including Altunbas et al. (1996-1999).

[2] This may be an overstatement as interest earned on bonds is also included in this figure.

ciency scores in particular, vary considerably based on bank's size and bank's geographical location. The technical efficiency averaged around 90% for the banks under study with insignificant differences among the banks under study. This suggests that the banks under study might increase one or more of their current outputs by around 10% without reduction in their other outputs or without a need for more inputs. Bahraini averaged the highest technical efficiency of more than 90% while the Jordanian averaged the least of around 85%, under both constant and variable returns to scale.

When we further decomposed the technical efficiency into pure technical and scale efficiencies, we found that the scale efficiency estimates to be more than 90% for the banks under study. This suggests that the bank's size does not play a key role in differences among cost efficiency estimates for the banks' under study.

The allocative efficiency scores averaged around 70% for the banks under study with significant differences between banks based on the size and geographical locations. This score reflects that some banks under study have failed to combine inputs and outputs in their optimal proportions in the light of their prevailing prices. The Saudi banks are found to be the most allocative efficient and realized an efficient score of around 75% while the Egyptian banks are found to be the least (see Table 7 for details). Based on bank's size, the results are mixed but the larger banks have scored the highest allocative efficiency estimates.

Concerning scale efficiency (see Table 8), our results suggest insignificant levels of scale inefficiency across the banks under study. Furthermore, there were minor differences between scale efficiency scores across the banks under study.

Finally, while the countries under study have implemented many economic and financial reforms over the last decade or so, these do not appear to have noticeable positive impact on the efficiency of the respective banking systems under study. The estimated inefficiency levels of the banks under study are more than the range of 10-15% for the 130 studies surveyed by Berger and Humphrey (1997) and Berger and DeYoung (1997). Further, this level is also more than the level of inefficiency found in European studies including Carbo et al.'s (2000) whose findings for a sample of banks from twelve countries, show mean cost inefficiency of around 22% for the period from 1989 to 1996

Table 4. Descriptive statistics of the banks' inputs and outputs for Jordan, Egypt, Saudi Arabia and Bahrain over 1992-2000

Variables	Description	Mean	St. Dev.	Min.	Max.
TC	Total cost (includes interest expense, personnel expense, commission expense, fee expense, trading expense, other operating expenses) (US$ millions).	170	300	0	1,720
W1	Price of funds (%) (total interest expense/total customer deposits (demand, saving and time deposits)).	0.07	0.09	0.00	1.98
W2	Price of labor (%) (total personnel expense/total assets).	0.02	0.01	0.00	0.21
W3	Price of physical capital (non-interest expense/average assets).	0.01	0.01	0.00	0.21
Y1	The US $ value of total aggregate loans (all types of loans) (US$ millions).	1,260	2,280	1	15,060
Y2	The US $ value of total aggregate other earning assets (short-term investment, equity and other investment and public sector securities (US$ millions)).	1,390	2,470	1	13,600
Y3	The US $ value of the off-balance sheet activities (nominal values, US$ millions).	1,320	3,510	1	26,740
p1	Price of loans (%) (total earned interest/total loans).	0.15	0.07	0.01	0.87
p2	Price of other earning assets (%) (trading income and other operating income excluding commission and fees income/Other earning assets).	0.05	0.04	0.01	0.33
P3	Price of off-balance sheet items (%) (Commission and fees income/off-balance sheet items).	0.01	0.02	0.00	0.20

Source: Bankscope (Jan. 2000 & 2002).

Table 5. Cost efficiency average estimates over 1992-2000 (pooled data)

T. Asset (Mil. US$)	1-199	200-299	300-499	500-999	1,000-2,499	2,500-4,999	5,000-9,999	10,000 +	Avg.
Bahrain									
CRS	61	100	44	67	53	61	-	57	63
VRS	81	100	45	76	53	77	-	93	75
Egypt									

Table 5 (continued). Cost efficiency average estimates over 1992-2000 (pooled data)

T. Asset (Mil. US$)	1-199	200-299	300-499	500-999	1,000-2,499	2,500-4,999	5,000-9,999	10,000 +	Avg.
CRS	42	56	45	46	47	47	46	34	45
VRS	57	59	50	54	63	71	85	96	67
Jordan									
CRS	60	-	38	38	41	-	-	40	43
VRS	81	-	40	47	57	-	-	89	63
Saudi Arabia									
CRS	-	-	-	-	54	59	47	68	57
VRS	-	-	-	-	80	78	76	97	83
Average									
CRS	54	78	42	50	49	56	47	50	53
VRS	73	79	45	59	63	75	80	93	71

Source: Author's own estimation.

Table 6. Technical efficiency average estimates over 1992-2000 (pooled data)

T. Asset (Mil. US$)	1-199	200-299	300-499	500-999	1,000-2,499	2,500-4,999	5,000-9,999	10,000 +	Avg.
Bahrain									
CRS	95	100	88	87	85	83	-	88	89
VRS	100	100	97	88	87	90	-	100	95
Egypt									
CRS	92	88	75	89	86	89	100	80	87
VRS	100	90	78	90	91	95	100	100	93
Jordan									
CRS	78	-	74	76	74	-	-	82	77
VRS	100	-	82	78	80	-	-	100	88
Saudi Arabia									
CRS	-	-	-	-	75	97	85	85	85
VRS	-	-	-	-	90	100	92	97	95
Average									
CRS	88	94	79	84	80	90	92	83	86
VRS	100	95	86	85	87	95	96	99	93

Source: Author's own estimation.

Table 7. Allocative efficiency average estimates over 1992-2000 (pooled data)

T. Asset (Mil. US$)	1-199	200-299	300-499	500-999	1000-2499	2500-4999	5000-9999	10,000 +	Avg.
Bahrain									
CRS	63	100	50	75	67	71	-	65	70
VRS	81	100	46	85	65	85	-	93	79
Egypt									
CRS	48	64	61	53	54	53	46	44	53
VRS	57	66	65	61	69	75	85	96	71
Jordan									
CRS	81	-	52	49	57	-	-	49	58
VRS	81	-	50	61	72	-	-	89	70
Saudi Arabia									
CRS	-	-	-	-	73	61	56	80	67

Table 7 (continued). Allocative efficiency average estimates over 1992-2000 (pooled data)

T. Asset (Mil. US$)	1-199	200-299	300-499	500-999	1000-2499	2500-4999	5000-9999	10,000 +	Average
VRS	-	-	-	-	89	78	83	99	87
Average									
CRS	64	82	54	59	63	62	51	59	62
VRS	73	83	54	69	74	79	84	94	76

Source: Author's own estimation

Table 8. Scale efficiency average estimates/VRS over 1992-2000 (pooled data)

T. Asset (Mil. US$)	1-199	200-299	300-499	500-999	1000-2499	2500-4999	5000-9999	10,000 +	Avg.
Bahrain	95	100	90	99	98	92	-	88	94
Egypt	92	98	97	98	95	94	100	80	94
Jordan	78	-	91	98	93	-	-	82	88
Saudi Arabia	-	-	-	-	83	97	91	87	90
Average	88	99	93	98	92	94	96	84	93

Source: Author's own estimation.

References

1. Altunbas, Y., E. Gardener, and P. Molyneux (1996), "Cost Economies and Efficiency in EU Banking Systems", 'Journal of Economics and Business, 48, pp. 217-230.
2. Aly, H., R. Grabowski, C. Pasurka, and N. Rangan (1990), "Technical, Scale, and Allocative Efficiencies in U.S. Banking: An Empirical Investigation", The Review of Economics and Statistics, 72, pp. 211-218.
3. Banker, R., A. Charnes, and W. Cooper (1984), "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis", Management Science, 30 (9), pp. 1078-1092.
4. Bauer, P., A. Berger, G. Ferrier, and D. Humphrey (1997), "Consistency Conditions for Regulatory Analysis of Financial Institutions: A Comparison of Frontier Efficiency Methods", 'Finance and Economics Discussion Series, Federal Reserve Board, USA, 50, pp. 85-144.
5. Berger, A. (1993), " 'Distribution-free' Estimates in the US Banking Industry and Tests of the Standard Distributional Assumptions", Journal of Productivity Analysis, Vol. 4, pp. 261-292.
6. Berger, A. and D. Humphrey (1997), "Efficiency of Financial Institutions: International Survey and Directions for Future Research", European Journal of Operational Research, 98, pp. 175-212.
7. Charnes, A., W. Cooper and E. Rhodes (1978), "Measuring the Efficiency of Decision Making Units", European Journal of Operational Research, 2, pp. 429-444.
8. Coelli, T. (1998), "A Multi-stage Methodology for the Solution of Oriented DEA Models", Centre for Efficiency and Productivity Analysis (CEPA), Department of Econometrics, University of New England, Armidale, Australia (WP 1/98).
9. Coelli, T., D. Prasada, and G. Battese (1998), "An Introduction to Efficiency and Productivity Analysis", Kluwer Academic Publishers.
10. Cummins, J. and H. Zi (1997), "Measuring Cost Efficiency in the U.S. Life Insurance Industry: Econometric and Mathematical Programming Approaches", The Wharton School, University of Pennsylvania, (WP 03/97).
11. Cummins, J. and M. Weiss (1998), "Analyzing Firm Performance in the Insurance Industry Using Frontier Efficiency Methods", The Wharton School, University of Pennsylvania.
12. European Commission (1997), "The Single Market Review", Credit Institutions and Banking, Subseries II: Impact on Services, Vol. 3, (London: Kogan Page).
13. Fare, R., S. Grosskopf and C. Lovell (1985), "The Measurement of Efficiency of Production", Kluwer Academic Publishers, Boston.
14. Farrell, M. (1957), "The Measurement of Productive Efficiency", Journal of the Royal Statistical Society, Series A, CXX, Part 3, pp. 253-290.
15. Ferrier, G. and C. Lovell (1990), "Measuring Cost Efficiency in Banking: Econometric and Linear Programming Evidence", Journal of Econometrics, 46, pp. 229-245.
16. Fried, H., C. Lovell, and P. Eackaut (1993), "Evaluating the performance of US credit unions", Journal of Banking & Finance, 17, pp. 251-265.
17. Gardener, E. and P. Molyneux (1990), "Changes in Western European Banking: An International Banker's Guide", London, Unwin Hyman.
18. Jagtiani, J. and A. Khanthavit (1996), "Scale and scope economies at large banks: Including off-balance sheet products and regulatory effects (1984-1991)", Journal of Banking & Finance, 20, pp. 1271-1287.

19. Koopman, T. (1951), "An Analysis of Production as an Efficient Combination of Activities", in T. Koopman (Ed.) Activity Analysis of Production and Allocation, Cowles Commission for Research in Economics, Monograph No. 13, Wiley, New York.
20. Seiford, L. and R. Thrall (1990), "Recent Developments in DEA: The Mathematical Approach to Frontier Analysis", Journal of Econometrics, 46, pp. 7-38.
21. Siems, T. and R. Barr (1998), "Benchmarking the Productive Efficiency of U.S. Banks", Federal Reserve Bank of Dallas, Financial Industry Studies.
22. Webster, R., S. Kennedy, and L. Johnson (1998), "Comparing Techniques for Measuring the Efficiency and Productivity of Australian Private Hospitals", Commonwealth of Australia, (3/98).

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