Are GCC Banks Efficient?

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This paper analyses the cost and profit efficiencies of the GCC banking sector over the period 1995-2000. Efficiencies are estimated using the most recent frontier technique, the Fourier Flexible form. The paper also uses a logistic regression model to estimate the determinants of GCC bank efficiency. The findings show that the level of inefficiencies in the GCC banking industry ranges between 8 and 10% for costs, and 30 and 32% for profits. There are no major differences in banks inefficiency levels among GCC countries. Moreover, inefficiencies show almost stable trends over 1995-2000. The main results from our logistic regression are that the strengthening of financial capital is a central element explaining bank efficiency in the GCC region; however, the erosion in loan quality reduces banking sector efficiency. Overall, the policy implication is that regulations need to focus on building a safe and sound banking system with adequate and prudential rules, and this should ultimately feed into improved banking sector efficiency levels.

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1. Introduction

This paper examines the efficiency of GCC banking system between 1995-2000. Generally, the interest in measuring X-inefficiency in banking has increased over the last decade as commentators have sort to examine the impact of increased competition on banking sector costs. While an extensive literature has developed to examine banking sector efficiency in the US and Europe (see Berger and Humphrey, 1997; Goddard et al. 2001) there is only limited literature on developing countries (e.g. Bhattacharyya, Lovell, and Shay, 1997; Isik and Hassan, 2002; Al-Jarrah, 2002).

The aim of this paper is to extend the established literature by examining the efficiency features of Gulf banking. Over the last decade, GCC banking systems have experienced many regulatory changes. The most important of these has been the gradual removal of interest rate ceilings on loans and deposits, which commenced from the mid 1990s onwards. The aim of these regulatory changes was to bring about a more competitive environment and to foster improved efficiency in the banking system. GCC banking systems will also be exposed to even more competition by the time they become more integrated within the recently announced GCC economic and monetary union or when the GATT's agreement (which all GCC countries have joined except Saudi Arabia) will come into effect. Given the ongoing deregulation process, it is important therefore to have an indication of the efficiency features of GCC banks in order to evaluate the influence of financial reforms that aim to improve the soundness and enhance competitiveness of the GCC financial systems overall.

In this paper, banking inefficiencies are examined by estimating both cost and profit functions, where these inefficiencies are depicted as the deviation of actual cost and profit of each bank from the optimal banking industry's cost and profit functions. This deviation is known as X-inefficiency, an important feature of operational inefficiency. The measurement of this deviation enables us to know the status of GCC banking inefficiency and how it is compared to banking sector inefficiency in other studies. In addition, this paper also takes into consideration the influence both risk and asset quality factors have on the levels of measured inefficiency in GCC banking markets. Generally, there is evidence that both risk and asset quality factors can influence both cost and profit efficiencies (Mester, 1996; Berger and Mester, 1997; Altunbas et al., 2000).

These factors are typically closely monitored by regulatory authorities so as to ensure that banks keep adequate levels of capital and have acceptable quality of loan portfolios. The links between efficiency, risk, and asset quality may therefore be important from a policy makers perspective. Especially, for instance if we find that efficient banks have high asset quality and are less risky. The paper also investigates the extent to which GCC banks exploit economies of scale in conducting banking operations. Knowledge of optimal bank size provides more information about the competitive status of GCC banking. Finally, we investigate the main determinant of efficiency in Gulf banking.

The paper is organised as follows. Section 2 discusses efficiency concepts and their functions. Section 3 describes the methodology of inefficiency calculation, the functional forms, and the data and variables used in the efficiency estimation. Section 4 introduces the logistic regression model, an approach used to evaluate inefficiency determinants in the GCC banking industry. Section 5 discusses the empirical results, and section 6 is the conclusions.

2. The X-Efficiency concepts

In a first step to measure efficiency in this paper, it is vital to identify the sort of efficiency upon which a banking industry is assessed. Here, our focus is to measure X-inefficiency, where X-inefficiency refers to the deviation from the frontier that gives the maximum attainable outcome, given the employed resources. In following Berger and Mester (1997), we estimate X-inefficiency in the GCC banking industry on the basis of three efficiency concepts: cost inefficiency, standard profit inefficiency, and alternative profit inefficiency. Cost efficiency is the widely used measure of bank efficiency from the input side (for example, Altunbas et al., 2000; Lang and Welzel, 1996; Kwan and Eisenbeis, Berger and Mester, 1997) and profit efficiency measures focus on the output side (incorporating both costs and revenues).

Measurement of profit efficiency is vital because it is believed that firms may not only err on the input side by choosing non-optimal input mix, but also err on the output side by producing output mixes that make them deviate from the optimal obtainable profit in the industry. Moreover, profit efficiency is ‘… based on [the] more accepted economic goal of profit maximization, which requires that the same amount of managerial attention be paid to raising a marginal dollar of revenue as to reducing a marginal dollar of cost' (Berger and Mester, 1997, p. 900). Therefore, it is important to examine both cost and profit inefficiencies as they provide a collective analysis of X-efficiency that helps explore more factors that may enhance or diminish banking efficiency from both the input and output sides of the production process.[1]

Cost inefficiency

Under the same market conditions and for the same output bundle produced, the cost inefficiency concept views inefficiency as the distance at which the estimated cost function of a financial firm is located away from the least cost function that belongs to the best practice firm in an underlying industry. Thus if the measured cost inefficiency for a banking industry is 15 per cent, this means that banks should use their inputs as efficiently as possible in order to gain a reduction of 15 per cent in their costs in order to make their cost functions reach the minimum cost function of the best practice bank.

Cost inefficiency is derived from the cost function.[2] Basically, the cost function describes a relationship between a cost variable and a set of explanatory variables plus the random and inefficiency factors. The cost function can be written in a natural logarithm form as

$$\ln TC = f(Q, P, Z) + \ln u_c + \ln v_c \tag{1}$$

where ln TC is the total cost variable, f stands for some functional form, Q is the vector of outputs, P is the vector of prices of input variables, Z is the set of other likely important exogenous variables, ln u_c is the inefficiency factor that reflects X-inefficiency and raises cost above the industry's optimal cost, and ln v_c is the random

[1] For example, ceilings on deposit and loan prices could affect both cost and profit functions of the banking industry.
[2] The formal calculation of the inefficiency is illustrated in the next section.

error incorporated to capture luck and measurement error, which may temporarily increase or decrease a bank's costs.

Standard profit inefficiency

Standard profit inefficiency focuses on how a bank's profits are compared to the profits of the best practice firm operating in a market where banks use the same inputs, produce the same output bundles, and face the same (market) conditions. In fact, standard profit inefficiency shows the percentage by which a bank needs to increase profits so that it moves to the profits of the best practice bank. Thus, if a standard profit efficiency average score is 60 per cent, this implies that bank *i* is losing 40 per cent of its profits, probably because of its excessive use of inputs and other deficiencies in generating revenues.

Calculation of standard profit inefficiency is derived from some specified profit function that can be written in a basic form with logs as

$$\ln(\pi,\theta) = f(PQ, P, Z) + \ln u_{\pi} + \ln v_{\pi} \tag{2}$$

where *PQ* is the vector of prices of output variables. Note that the standard profit function regresses profits on the same set of the explanatory variables that appear in the cost function, except that it takes output prices as given rather than output levels. This also makes it necessary to calculate the standard profit inefficiency on the basis of how banks choose output levels for the given output prices, a matter that allows for standard profits to capture inefficiency stemming from the non-optimal choice of outputs when responding to these prices.

Alternative profit inefficiency

Alternative profit inefficiency (as developed by Berger and Mester, 1997) reflects how far a firm's profit function is away from the maximum profit function earned by the best practice firm, given the same inputs used and outputs produced within the same prevailing market conditions. Generally, alternative profit efficiency is identical to standard profit efficiency, except that the concept of alternative profit efficiency is introduced to account for the effects of output prices on profit efficiency. That is, because output quantities are held constant in the alternative profit function, the level of inefficiency in the alternative profit model differs in response to the prices of output, which are set free to vary.

The calculation of alternative profit inefficiency is based on the profit function written in the log form as

$$\ln(\pi,\theta) = f(Q,P,Z) + \ln u_{\pi} + \ln v_{\pi} \tag{3}$$

where the explanatory variables in Eq. 3 are the same as for the standard profit function (of Eq. 2), except that the output quantities, *Q*, replaces prices of outputs, *PQ*.

The usefulness of the alternative profit inefficiency concept stems from several factors. Alternative profit inefficiency alleviates the problem of scale bias and avoids the problem of output price inaccuracy, which are problems related to the standard profit method. The problem of scale bias usually emerges from differences in bank sizes and outputs levels because the standard profit method does not control output levels. With alternative profit inefficiency measures, this problem is less severe because comparisons are made between a bank's ability to generate profits for a given level of outputs.

With regard to output price information, proxy measures are usually used for the output prices. Since it is often difficult to obtain prices for the outputs, the standard profit inefficiency measures may have an inherent price inaccuracy problem that affects the reliability of the inefficiency estimates. For the same reason, taking output levels instead of output prices allows the alternative profit efficiency measures to avoid this problem of price inaccuracy.

The alternative profit function could be a more appropriate measure of inefficiency when banks have market power that enables them to set higher prices for given output levels. On the other hand, in a more competitive market, the standard profit function seems also plausible since banks tend to be price takers, regardless of the output level they produce. In both cases, it is advisable to estimate both the standard and alternative profit functions together as they provide insights into the level of profit inefficiency given the prevailing condition of market competitiveness.

It should, however, be noted that profit inefficiency is expected to be greater than cost inefficiency since profit inefficiency accounts for inefficiencies on both the input and output sides of financial production. Moreover, alternative profit inefficiency is expected to be greater than standard profit inefficiency because the former captures a wider source of inefficiencies such as those related to output qualities and market power.

Having explained the efficiency concepts to be used in the empirical part of this paper, the following outlines the methodology used to estimate these efficiency concepts.

3. Methodological approach to estimating efficiency

In this section we discuss the methodology as well as the data and variables used to estimate inefficiency in the GCC banking industry. There are two main approaches to estimate inefficiency: parametric and non-parametric approaches (see also the review by Berger and Humphrey, 1997). Each of these also includes various modelling techniques: for example, the stochastic frontier, distribution-free, and thick frontier are parametric techniques used to derive efficiencies; data envelopment analysis and the disposal hull technique are the main non-parametric approaches. Our choice in estimating GCC banking sector efficiency is the parametric approach. In our opinion, the parametric approach adds more statistical sense to the efficiency estimation because the stochastic nature (or randomness), representing deviation from the true population path, is always present when a random sample is tested to obtain a general inference about a population.

Regarding the choice of techniques among the parametric approaches, we use the stochastic frontier technique because it has the advantage of considering the distribution on both error term composites. Non-consideration of distributional assumptions may lead to an inexact separation of the inefficiency and the random error terms, which may in turn produce an overestimation of inefficiency, especially when the random error term is not cancelled out over time. This problem is present also, to some extent, in the distribution-free technique (see Allen and Rai, 1996). Moreover, the thick frontier technique may encounter bias when ordering banks to construct the quartiles according to input prices. Because these prices are not the same across banks, inefficiency measures might be overestimated as well (Kaparakis et al., 1994).

Therefore, to estimate X-inefficiency in the GCC banking industry, we use the stochastic frontier technique, the methodology of which we discuss below in more detail.

A stochastic frontier, as typically explained for the cost function (i.e. stochastic cost frontier) can be constructed to estimate a theoretical least cost function for the industry, which will be attributed as the efficient cost function that belongs to the best practice firm. Accordingly, the estimated best practice firm is said to employ the minimum amount of inputs to produce the given level of outputs.

In a formal way, the single equation stochastic cost function can be given in a logarithmic form for N firms as[3]

$$\ln TC_i = f(Q_i, P_i) + \ln \varepsilon_i, \qquad i = 1, \ldots, N, \tag{4}$$

where $\ln TC_i$ is the observed total cost of bank i, Q_i is the vector of its output levels, and P_i is the vector of input prices the bank i pays. The cost function $\ln TC_i = f(Q_i, P_i)$ gives an indirect representation of the feasible technology; it relates the firm's cost to output levels and input prices, and shows the minimum cost of producing the output vector Q, given the price vector P (Varian, 1992). So, the minimum predicted cost for the industry is explained by $f(Q_i, P_i)$, which is the cost frontier portion in Eq. (4) and is considered to be the industry's benchmark of the most efficient firm. The deviation of banks' costs from the cost frontier is explained by the error term ε_i, which consists in a logarithmic form of

$$\varepsilon_i = v_i + u_i, \tag{5}$$

where v_i is the statistical noise that represents random fluctuations due to measurement error and luck factors and u_i is the inefficiency term which is presumed to result from mistakes in the choices of input mix that are specific to the firm's practice.

It should be noted that the inefficiency factor, *u*, is the X-inefficiency measure representing both technical inefficiency, which occurs when employing excessive inputs beyond the level needed to produce the given output level, $Q_{i;}$; and allocative

[3] While the analysis here describes the methodology used to calculate the efficiency measure for some frontier function given in Eq.4, the functional form for the frontier function specification used to estimate efficiencies will be discussed in the following subsection.

inefficiency, which occurs when failing to react optimally to relative prices of inputs, P_i.[4]

In order to obtain the measurement of inefficiency estimates, u_i, for the cost function mentioned above, [5] it is essential to determine how both error term components, v_i and u_i, are assumed to be distributed. Following Aigner, Lovell, and Schmidt (1977), we assume the distribution of the error term v_i has an identical two-sided normal distribution representing statistical noise which is believed to be independently distributed with zero mean and σ_v^2 variance, that is, $v_i \sim IIN(0,\sigma_v^2)$. The rationale behind this type of distribution is to allow for a pure randomness of the v component upon which this component can either take positive or negative values according to the nature of luck and factors out of management control that can affect bank performance.

On the other hand, we adopt the half-normal distribution for the inefficiency part for which we consider u_i to be a non-negative or one-sided error term representing inefficiency and assumed to be distributed independently of the v_i term.

Formally,

$$f(u) = \left(\frac{2}{\pi}\right)^2 \exp\left[-\tfrac{1}{2}\left(u/\sigma_u\right)^2\right], \tag{6}$$

$$E[u] = \left(\frac{\sigma_u \phi(0)}{\Phi(0)}\right) = \left(\frac{2}{\pi}\right)^2 \sigma_u, \tag{7}$$

$$Var[u] = \left[1 - \frac{2}{\pi}\right]\sigma_u^2, \tag{8}$$

[4] The studies of Berger and Humphrey (1997), Altunbas et al., (2000), as well as others have considered the inefficiency term as reflecting both technical and allocative inefficiencies without disentangling them from each other.

[5] The functional form from which the inefficiency, u, will be derived is the Fourier Flexible form explained in the following subsection.

where N is the number of banks, $f(.)$ is the distribution function, $E[.]$ is the mean, $Var[.]$ is the variance, $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$, and ϕ and Φ are the standard normal distribution and the standard normal density functions respectively.

The rationale behind using the half normal distribution lies in the perception that the deviation from the frontier should take one side off the cost frontier, and that the cost frontier would have no mean if there should exist observations that fall anywhere under the cost frontier.

It should be noted that the approach of Aigner, Lovell, and Schmidt (1977) does not, however, estimate the u term directly. Accordingly, Jondrow et al. (1982) developed Aigner et al.'s model by providing an explicit formula, which shows that the ratio of variability, σ, for both v and u can be used to calculate the firm's relative inefficiency. This ratio is utilized for the error term portion of the estimated cost function in a way that calculates the inefficiency term given the estimate of the whole error term for each firm in each observation. That is, the level of inefficiency for each bank is calculated by the mean of the conditional distribution of u_i given ε_i. The mean of this conditional distribution for the half-normal model can be shown as

$$E(u \setminus \varepsilon) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(\varepsilon_i\lambda/\sigma)}{1-\Phi(\varepsilon_i\lambda/\sigma)} + \left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right], \tag{9}$$

Greene (1993) claims that the mean of the conditional distribution $E(u \setminus \varepsilon)$ is unbiased. Nevertheless, this mean is an inconsistent estimator of u_i because, regardless of the number of observations, the variance of the estimator remains non-zero.

After defining the distributional assumption and the way inefficiency is calculated, we need to estimate the cost function (Eq. 4) in order to obtain the parameters that yield the frontier as well as the estimates of inefficiency explained above.

To estimate the cost function model (Eq. 4), we use the maximum likelihood estimation technique. In fact, this technique is widely implemented in efficiency parametric studies and is preferred over the ordinary least square method. Greene (1993) argues that the maximum likelihood technique is useful in treating the distributional models of the random noise and the inefficiency components. The log-likelihood function can be written as

$$\ln L = \frac{N}{2}\ln\frac{2}{\pi} - N\ln\sigma - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\varepsilon_i^2 + \sum_{i=1}^{N}\ln\left[\Phi\left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right], \tag{10}$$

where N is the number of banks, $\varepsilon_i = u_i + v_i$, $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$, $\lambda = \sigma_u / \sigma_v$, and ϕ and Φ are the standard normal distribution and the standard normal density functions respectively. The maximum likelihood estimation operates in a way that finds the minimum of the log likelihood function in order to obtain the estimates of the cost function (Eq. 4).

The cost function given in Eq. (4) is not our functional form from which to derive efficiency levels, however; it is only used here to simplify our explanation of the methodology used to derive efficiency estimates. The following discusses how to specify our functional form used to estimate the cost and profit frontiers from which cost and profit inefficiency measures are derived.

Functional Form Specification

As just stated, this subsection is devoted to showing how our stochastic cost and profit functional forms are constructed. Although most studies use the translog functional form to estimate inefficiency, this form is not applied here because of certain limitations. Instead, we use the Fourier Flexible model to specify the cost and profit functions and to obtain inefficiency measures. To arrive at this functional form some steps will also be explained.

A large number of banking studies have used the translog function expressed in a stochastic framework to estimate the cost frontier function (see, for example, Kwan and Eisenbeis, 1996; Altunbas et al., 2000). The translog model is a flexible functional form and is expanded by a second-order Taylor series (see Greene, 2000, p. 217). The flexibility of the translog model is demonstrated in its usefulness for approximating the second-order effect of an unknown functional form (Berndt and Christensen, 1973). This flexibility serves as an advantage for banking efficiency studies because it is difficult to identify exactly the functional form that fits the banking cost and production technology (Kaparakis et al., 1994). Moreover, the translog model allows homogeneity of degree one by simply imposing restrictions on the translog model parameter (McAllister and McManus, 1993).

However, since the translog form is said to be less global because of the bias that makes some observations follow the pattern of other dominant observations, the more recent semi-parametric functional form known as the Fourier Flexible form has been suggested to be the preferred approach that corrects for the translog model's ill fit on the true path of data (Gallant, 1981, 1982; Mitchell and Onvural, 1993). In essence, the Fourier Flexible functional form adds more global approximation and flexibility to the translog form by adding the trigonometric terms to the translog specification. This means that the frontier to be estimated will provide a greater flexibility 'by allowing for many inflection points and by including essentially orthogonal trigonometric terms that help the frontier fit the data wherever it is most needed' (Berger and Humphrey, 1997, p. 179).

On account of these advantages, the Fourier Flexible specification has recently become the more acceptable and increasingly applied parametric functional form in measuring banking inefficiency. Before we set the specification of the Fourier functional form, it should be noted that because the Fourier Flexible form is a translog form extended with trigonometric terms, it is appropriate to note certain features related to the translog form that also apply to the Fourier form as well.[6]

One thing to note regarding the translog function is that as the number of the inputs (also variables) increases, multicollinearity will likely be severe (Greene, 1980). Berndt and Christensen (1973) show how the use of factor demand equations may overcome this problem.[7] Moreover, some studies using the translog function drop the most likely interactive terms causing multicollinearity (see for examples Lang and Welzel, 1996). Doing this might not totally remove multicollinearity problems and its continuing presence may induce an increase in standard errors, which may yield a number of non-significant coefficients.

Second, we should note that (as in a number of studies) factor share equations are used along with translog models (see e.g. Noulas et al., 1990). However, in our estimation, we exclude factor share equations from our model as they embody Shephard's Lemma or Hotelling's Lemma restrictions, which make unfavourable assumptions regarding the allocative efficiency (see Berger and Mester, 1997). Moreover, since inefficiency decomposition (into allocative and technical inefficiency) requires restrictive distributional assumptions, we prefer to keep inefficiency estimation non-decomposed and assume that the whole inefficiency residual component, as noted before, is the X-inefficiency measure (see Kaparakis et al., 1994).

As the Fourier Flexible functional specification is used in constructing our Fourier functional model that consists of the standard translog specification and the trigonometric terms, as well as the terms of X-inefficiency and the random error, we first show the core functions of our model along with the residuals, which include both inefficiency and the random error terms. Then we write the function in a translog form, which includes its interactive terms. We then add the trigonometric terms in order to reach the stochastic Fourier Flexible form.

[6] However, Altunbas and Chakravarty (2001) note that although the Fourier Flexible form has a better fit than the translog, the former, they find, provides weaker predictive power.
[7] Econometricians generally suggest that one way of reducing the multicollinearity problem is to increase the number of observations.

To start building our Flexible functional form we recall the cost and profit functions explained in section 2. These functions are rewritten as

$\ln TC = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln Q_i + \sum_{j=1}^{n} \beta_j \ln P_j + \varepsilon_i$ is the cost function,

$\ln(\pi + \theta) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln PQ_i + \sum_{j=1}^{n} \beta_j \ln P + \varepsilon_i$ is the standard profit function, and

$\ln(\pi + \theta) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln Q_i + \sum_{j=1}^{n} \beta_j \ln P_j + \varepsilon_i$ is the alternative profit function,

where *TC* is the cost variable, π is the profit variable, θ is a constant added to the firm's profits so that its natural log is positive, *Q* is the vector of outputs, *P* is the vector of prices of input variables, *PQ* is the vector of prices of output variables, and ε_i is the stochastic error term where $\varepsilon_i = u_i + v_i$.

The basic functions given above are developed in a multi-product translog specification.

To save repetition, we typically continue showing the construction of our model using the cost function. The translog cost function is written as

$$\begin{aligned} \ln TC = \alpha_0 &+ \sum_{i=1}^{n} \alpha_i \ln Q_i + \sum_{j=1}^{n} \beta_j \ln P_j \\ &+ \frac{1}{2}\left[\sum_{i=1}^{n}\sum_{j=1}^{n} \delta_{ij} \ln Q_i \ln Q_j + \sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln P_i \ln P_j \right] \\ &+ \sum_{i=1}^{n}\sum_{j=1}^{n} \rho_{ij} \ln Q_i \ln P_j + \varepsilon_i \end{aligned} \tag{11}$$

In order to reach our Fourier Flexible form, we transform output variables into the Fourier first and second order trigonometric terms, and, because input prices are attributed with little variations, they are left to be separately described in the translog portion.

As a result of this transformation, which adds the trigonometric terms to the translog form, the model becomes the Fourier Flexible form shown as

$$\begin{aligned}\ln TC = \alpha_0 + \sum_{i=1}^{n}\alpha_i \ln Q_i + \sum_{j=1}^{n}\beta_j \ln P_j \\ + \frac{1}{2}\left[\sum_{i=1}^{n}\sum_{j=1}^{n}\delta_{ij}\ln Q_i \ln Q_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\ln P_i \ln P_j\right] \\ + \sum_{i=1}^{n}\sum_{j=1}^{n}\rho_{ij}\ln Q_i \ln P_j + \sum_{i=1}^{n}[a_i \cos(z_i) + b_i \sin(z_i)] \\ + \sum_{i=1}^{n}\sum_{j=1}^{n}[a_{ij}\cos(z_i + z_j) + b_{ij}\sin(z_i + z_j)] + \varepsilon_i\end{aligned} \tag{12}$$

where z_i is the adjusted value of the natural log of the output Q_i so that z_i span the interval [0.1 * 2π, 0.9 * 2π].[8]

Eq. (12) is the standard model used to estimate the cost function and derive efficiency levels within the Fourier Flexible specification form. At this point, it should be noted that recent studies have added additional sets of variables in their standard Fourier form, mainly financial capital, asset quality, and time trend variables. These variables are included to account for risk, loan quality, and technical progress respectively when measuring inefficiency.[9]

Financial capital variable has recently been included in cost and profit efficiency studies[10] because it is believed that an adequate level of financial capital in banks can indicate their ability to absorb losses and work as a cushion against any insolvency risks, resulting in more efficient performance. Moreover, in order to lessen cost inefficiencies, financial capital could be an alternative source to finance a bank's

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[8] The ends of the [0,2π] interval are cut off by 10% so that the z_n span [0.1 * 2π, 0.9 * 2π] to reduce the approximation problems near endpoints (Gallant, 1981). The formula for z_n is {0.2π - μ * *a* + μ * variable} where [*a*,*b*] is the range of the variable being transformed, and μ ≡ (0.9 * 2π - 0.1 *2π)/(*b*-*a*) (see Berger and Mester, 1997).

[9] In addition, environmental variables such as fixed assets and off-balance sheet variables have also been included in these studies (see e.g. Berger and Mester, 1997; Altunbas et al., 2000).

[10] Such as those of Altunbas et al., 2000; Berger and Mester, 1997; Mester, 1996.

portfolio instead of relying on debt finances, which incur interest payments.[11] Inclusion of financial capital can also take into account a bank's typical risk preferences (Berger and Mester, 1997). For example, banks' managements that obtain capital beyond their profit maximization schemes may be classified as risk averse banks. However, on the other hand, these banks may have more incentives to engage in riskier activities incurring volatile profits, which may result in inefficiency when negative profits dominate the outcomes of their operations.

Recent studies have shown the importance of considering asset quality in the efficiency measurement. Higher loan problems (proxied by non-performing loans or loan provisions) may mean that there is an amount of loans extended to low-quality borrowers that face repayment difficulty. Moreover, high loan problems can cast doubts on the screening and monitoring methods of a bank. For these reasons, the loan problems factor is expected to be a possible reason for distancing a bank from the efficient frontier.

A time trend variable has also been incorporated in various studies (such as those of Altunbas et al., 2000; and Lang and Welzel, 1996) to account for disembodied technical change. As the method of production changes over time, the time trend captures the factors of technological change, improvements in skills through learning by doing and training, as well as organizational and regulatory changes that may affect the efficient use of input resources (Altunbas, 2000; Baltagi and Griffin, 1988).

By considering the above-mentioned variables, we arrive at our preferred model, which can be written as[12]

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[11] Banks treat paid interest on debt as cost, but paid dividends on capital are not considered as costs (Berger and Mester, 1997).

[12] This preferred model is chosen from the feedback of our estimation experiment. In fact, the availability of data on the variables, how well the model behaves in the estimation process, and the validity of the model to pass the structural tests determined our model choice.

$$\begin{aligned}\ln TC = \alpha_0 &+ \sum_{i=1}^{2}\alpha_i \ln Q_i + \sum_{i=1}^{2}\beta_i \ln P_i \\ &+ \kappa_1 \ln E + \nu_1 \ln PROV + \tau_1 T \\ &+ \frac{1}{2}\left[\sum_{i=1}^{2}\sum_{j=1}^{2}\delta_{ij}\ln Q_i \ln Q_j + \sum_{i=1}^{2}\sum_{j=1}^{2}\gamma_{ij}\ln P_i \ln P_j + t_{11}T^2\right] \\ &+ \sum_{i=1}^{2}\sum_{j=1}^{2}\rho_{ij}\ln Q_i \ln P_j + \sum_{i=1}^{2}[a_i \cos(z_i) + b_i \sin(z_i)] \\ &+ \sum_{i=1}^{2}\sum_{j=1}^{2}[a_{ij}\cos(z_i + z_j) + b_{ij}\sin(z_i + z_j)] + \varepsilon_i,\end{aligned} \tag{13}$$

where E is equity capital, *PROV* is total loan provisions, and T is time trend. Since both risk and asset quality have been the variables under focus to measure the health of the banking system, we estimate Eq. (13) by including and excluding risk and quality factors in order to see how far these factors have an effect on the inefficiency estimates for our sample of Gulf banks. We call the model that excludes risk and quality factors the traditional model (and the one that includes them is the preferred model).

Note that, in Eq. (13), when estimating the profit functions, *TC* is replaced by profits (*PROF)* on the left-hand side for both the alternative and the standard profit functions. Moreover, the right-hand side of Eq. (13) is identical for both cost and alternative profit functions. However, for the standard profit function, we only replace the output quantities with output prices.[13]

Eq. (13) may be characterized by increasing, constant, or decreasing returns to scale, which means that because the degree of returns to scale is not known, the model might

[13] For instance, the standard profit function is shown as

$$\begin{aligned}\ln PROF = \alpha_0 &+ \sum_{i=1}^{2}\alpha_i \ln P_i Q_i + \sum_{i=1}^{2}\beta_i \ln P_i \\ &+ \kappa_1 \ln E + \nu_1 \ln PROV + \tau_1 T \\ &+ \frac{1}{2}\left[\sum_{i=1}^{2}\sum_{j=1}^{2}\delta_{ij}\ln Q_i \ln Q_j + \sum_{i=1}^{2}\sum_{j=1}^{2}\gamma_{ij}\ln P_i \ln P_j + t_{11}T^2\right] \\ &+ \sum_{i=1}^{2}\sum_{j=1}^{2}\rho_{ij}\ln Q_i \ln P_j + \sum_{i=1}^{2}[a_i \cos(z_i) + b_i \sin(z_i)] \\ &+ \sum_{i=1}^{2}\sum_{j=1}^{2}[a_{ij}\cos(z_i + z_j) + b_{ij}\sin(z_i + z_j)] + \varepsilon_i,\end{aligned}$$

where ln *PROF* is ln (π+θ) given that π is the profit variable, θ is a constant added to the firm's profit so that the natural log of profits is positive, and *PQ* is the output price variable.

be non-homogeneous. Thus, homogeneity restrictions are imposed on the translog portion of Eq. (13) to ensure that the cost function (as well as the profit functions) is linearly homogeneous in input prices. The homogeneity restrictions are shown as

$$\sum_{i=1}^{2} \beta_i = 1,$$

$$\sum_{i=1}^{2} \gamma_{ij} = 0 \text{ for all } j,$$

and $$\sum_{i=1}^{2} \rho_{ij} = 0 \text{ for all } j.$$

Moreover, Young's theorem requires symmetry of the second order parameters of the translog cost function, that is:

$$\delta_{ij} = \delta_{ji} \text{ for all } i,j,$$

and $$\gamma_{ij} = \gamma_{ji} \text{ fore all } i,j.$$

When solving for linear homogeneity restrictions, both the cost and the profit models are normalized by the price of labour (P_2) (see e.g. Greene, 1993; Berger and Mester, 1997; Altunbas et at., 2000). This can ensure that, on the efficient frontier, when input prices double, costs will exactly double by the same proportion as well, which would leave the input quantities unaffected.

Moreover, for the alternative profit function, homogeneity restrictions will serve to keep the relationship between input prices and profits in an equivalent fashion, although they need not to be imposed on the alternative profit function (Berger and Mester, 1997).

As explained, the Fourier functional form (Eq. 13) is the preferred model used to estimate cost, standard, and alternative profit functions. We obtain the parameters of these functions, as well as their inefficiency estimates, using Maximum Likelihood

Estimation (MLE) regression. The next subsection explains the derivation of economies of scale, which is based on our preferred model (Eq. 13).

Economies of scale

Economies of scale show by how much a proportional change in outputs level would lead to a change in total cost. In other words, economies of scale express the total cost elasticity with respect to output, which can be obtained by differentiating the cost function with respect to output variable. For the two outputs in our banking sample, economies of scale solved for Eq. (13) are given as

$$\begin{aligned} \textit{Scale economies} = \sum_{i=1}^{2} \frac{\partial \ln TC}{\partial \ln Q_i} &= \sum_{i=1}^{2} \alpha_i + \sum_{i=1}^{2}\sum_{j=1}^{2} \delta_{ij} \ln Q_j + \sum_{i=1}^{2}\sum_{j=1}^{2} \rho_{ij} \ln P_i \\ &+ \mu_i \sum_{i=1}^{2} \left[-a_i \sin(Z_i) + b_i \cos(Z_i) \right] \\ &+ 2\mu_i \sum_{i=1}^{2}\sum_{j=1}^{2} \left[-a_{ij} \sin(Z_i + Z_j) + b_{ij} \cos(Z_i + Z_j) \right]. \end{aligned} \tag{14}$$

If $\sum_{i=1}^{n} \frac{\partial \ln TC}{\partial \ln Q_i} = 1$, this shows that a proportional change in outputs yields the same proportional change in total cost. This is known as constant returns to scale or constant economies of scale. When the measurement $\sum_{i=1}^{n} \frac{\partial \ln TC}{\partial \ln Q_i} < 1$, this means that a proportional change in outputs leads to a change in the total cost with a proportional change less than that of output. In this case the relationship between output and total cost is said to exhibit increasing returns to scale, implying economies of scale. If $\sum_{i=1}^{n} \frac{\partial \ln TC}{\partial \ln Q_i} > 1$, this means that a proportional change in outputs leads to a more than proportional change in total cost. This relationship is known as decreasing returns to scale, which implies diseconomies of scale.

Having specified our methodology, the following details various aspects of the data and the variables used in our analysis of GCC bank efficiency.

Data and variables

Our study contains a balanced time series cross-sectional dataset, which consists of 93 GCC banks covering the six-year period from 1995 to 2000. The source of our data is mainly the London-based IBCA bank credit rating agency's database (Bankscope, Jan., 2002), the Financial Position of Commercial Banks in the UAE (1995-2000), published by the Emirates Bank' Association, and the annual financial statements of banks operating in Qatar. The majority of data in our sample relates to commercial banks, [14] with the exception of seven specialized banks, that are included to enhance the total number of observations in order to reduce the impact of multicollenearity among variables.

Table 1 shows the percentage of the total bank assets for each country included in the sample relative to the total assets of the banking industry in each country in the year 2000. The table indicates that the sample constitutes at least 89 per cent of the total banking industry's assets in Qatar, the UAE, Saudi Arabia, and Kuwait. However, the percentage of assets of Bahraini banks included in the sample is about half of the total bank assets of Bahrain's banking industry (as the rest belongs to the offshore banking units and other financial institutions for which data are unavailable). Moreover, the sample contains 64 per cent of the total Omani bank assets.

[14] According to the bank classification adopted in Qatar and by the UAE central bank authorities, Islamic banks are considered as commercial banks.

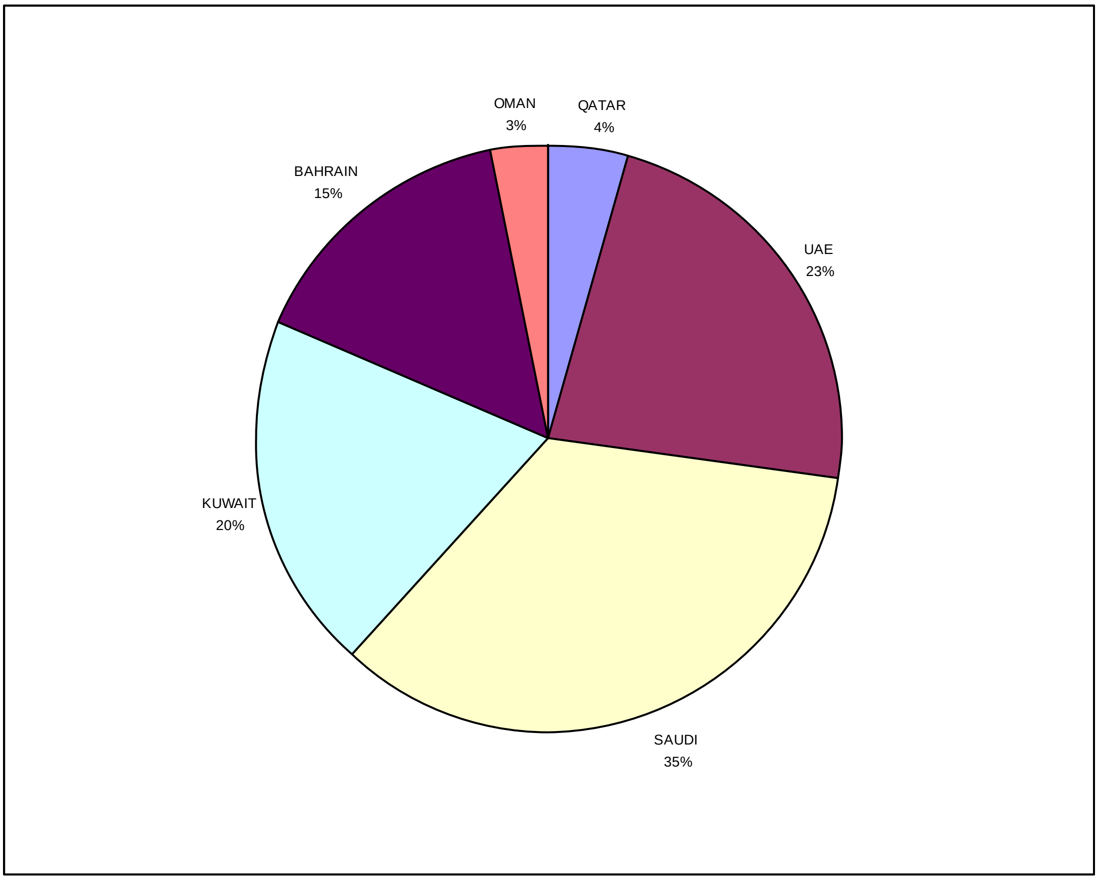
Table 1 Total assets of banks in each country in the sample relative to the total assets of the banking industry by country, 2000 - ('000 US dollars)

Country	Total assets of the sample	Total banking sector assets	%	No. of banks
QATAR	14,065,122	14,803,297	95%	14
UAE	71,967,905	75,504,087	95%	43
SAUDI ARABIA	108,197,277	121,195,722	89%	9
KUWAIT	62,552,718	70,413,140	89%	10
BAHRAIN	48,489,604	102,100,000	47%	11
OMAN	9,735,501	15,220,224	64%	6

Sources: Bankscope (Jan., 2002), financial reports of banks in the UAE and Qatar, and the annual reports published by the central banks in each country.

Figure 1 shows the share of the bank assets of each country included in the sample relative to the total bank assets of the whole sample in the year 2000. With only 9 Saudi banks, the figure indicates that the Saudi banks occupy the largest share of total assets of banks included in the sample. UAE banks occupy the second largest share in the sample, given that the number of UAE banks in the sample is 43, the highest among all GCC countries included in the sample.

Figure 1 Total assets of individual GCC country banks in the sample as a share in the total banking industry's assets for the underlying GCC country – Year 2000



Sources: Bankscope (Jan., 2002) and financial reports published by banks in the UAE and Qatar.

The variables

Table 2 defines the variables used in the specification of cost and profit functions of Eq. (13).

Table 2 Descriptive statistics of the outputs, inputs, and control variables used in the Eq. (13)

Variable	Description	Mean	St. Dev.	Min.	Max.
Dependent variables					
TC	Total cost includes interest expenses and operating costs ('000 US dollars)	155,717.4	262,769.4	1,736.9	1,728,938.2
PROF	Profits include revenues from loans and other earning assets less total cost ('000 US dollars)	62,480.4	81,198.4	6,472.7	522,098.6
Prices of inputs					
P1	Price of deposits	0.0469	0.0100	0.0218	0.0728
P2	Price of labour	0.0182	0.0078	0.0047	0.0530
Output quantities					
Q1	Total loans ('000 US dollars)	1256245	2090826	2807	1728938
Q2	Other earning assets ('000 US dollars)	1397850	2488464	13456	14409000
Prices of Outputs					
PQ1	Price of loans	0.1413	0.0394	0.0509	0.2000
PQ2	Price of other earning assets	0.0402	0.0333	0.0018	0.2959
Control variables					
E	Total equity ('000 US dollars)	307,501.8	451,200.0	0.3	2,297,223.0
PROV	Total provisions ('000 US dollars)	12,688.1	42,650.2	0.3	882,099.1
T	Time trend			5.0	10.0

Sources: Bankscope (Jan., 2002), financial reports of banks in the UAE and Qatar, and annual reports published by the central banks of the GCC countries.

These variables are given along with their descriptive statistics including sample means and standard deviations. Both cost and alternative profit functions specify two outputs, two inputs, two input prices, and two output prices variables used in the standard profit functions, as well as risk, asset quality, and technical progress variables.

The specifications of outputs and inputs are viewed from the assets and liabilities sides respectively, which conforms with the intermediation approach to modelling banking production (Sealey and Lindley, 1977). The output variables are total loans, denoted by Q_1; and other earning assets, denoted by Q_2, which reflects investments or securities categories.

Two prices of inputs are considered: prices of borrowed funds, denoted by *P1*; and prices of labour, denoted by *P2*. These are calculated as follows. *P1* is obtained by the division of interest paid by the borrowed funds, where borrowed funds are the total of all interest bearing deposits. *P2* is a proxy of labour price computed as the ratio of staff costs to total assets.[15 & 16]

The dependent variable of the cost function, denoted by *TC*, is obtained from the sum of interest expenses and the staff costs, where both of these comprise the vast majority of the banking total cost. Variable profits, denoted by *PROF*, are calculated as the revenues from loans and other earning assets less total cost.

To control for bank risk, we use financial capital, denoted by *E*. The variable *PROV* is the loan loss provisions taken as a proxy for loan (or assets) quality.[17] The model also includes time trend, denoted *T,* which accounts for technical progress.

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[15] Price of labour is usually computed by the division of staff cost by the number of staff. However, owing to the non-availability of data on staff numbers we follow Altunbas et al. (2000) to calculate the price of labour as a ratio of staff cost to the total assets.

[16] The majority of studies also include the price of fixed assets. However, for many banks considered in this paper (especially foreign banks in the UAE) there are no data on fixed assets expenses (for example, depreciations) to calculate the price of fixed assets. We are therefore forced to confine the number of inputs to borrowed funds and labour.

[17] Among categories of loan loss provisions, loan loss level and the non-performing loan data, only the loan loss provisions category is available for the entire sample.

Inefficiency determinants & logistic regression

After explaining the methodology measuring cost and profit inefficiency levels in the GCC banking sector, one may need to go a step further and investigate the sources or the possible determinants of inefficiency in the industry. In order to do this, we need to employ the most likely influential variables and the appropriate econometric technique. Table 3 presents the descriptive statistics of the variables that are examined as possible inefficiency determinants. Most of these variables have been used in studies such as those of Mester (1996), Altunbas et al. (2000), and Girardone et al. (2000).

Table 3 Descriptive statistics of the variables used in the logistic regression model

Variable	Description	Mean	St. Dev.	Min	Max
CN	Cost inefficiency half-normal	0.0839	0.0469	0.0144	0.4467
SN	Standard profit inefficiency half-normal	0.3312	0.1849	0.0361	.9897
EQUITY	Total equity ('000 US dollars)	307,501	451,200	0.3000	2,297,223
ROA	Rate of return on assets	0.0480	0.0404	0.0064	0.2841
PROV	The ratio of provisions to total loans	0.0170	0.0361	0.0000	0.3735
FOREIGN	Foreign banks – dummy variable	-	-	0	1
LTA	Ratio of loans to total assets	0.4966	0.1926	0.0105	0.9059
FIX	Fixed assets ('000 US dollars)	39,767	103,297	1	899,873
TA	Total assets ('000 US dollars)	2,832,011	4,704,465	31,616	26,699,785
TBGDP	Total bank assets as a ratio to GDP	1.7739	1.8609	0.1935	7.3626

Sources: Bankscope (Jan., 2002), financial reports of banks in the UAE and Qatar, and annual reports published by the central banks authorities in the GCC countries.

The inefficiency variables (CN and SN) are the measured cost and profit inefficiencies derived from the traditional Fourier Flexible cost and profit functions that exclude risk and asset quality variables. We use inefficiency estimates derived from the traditional rather than the preferred model because we want to avoid double consideration of the risk and quality factors.

Basically, the authors of various studies (e.g. Mester, 1996; Altunbas et al., 2000) believe that factors of risk and quality are important variables determining inefficiency levels. Accordingly, our inefficiency determinant model mainly includes *EQUITY*(=financial capital) and *PROV*(=loan loss provisions); these variables are used again as proxies for risk and loan quality respectively.

Here, it is expected that the sign of *EQUITY* is negative, indicating that the more inefficient banks have more risk that may be attributed to inadequate capital maintained in their operations. In other words, efficient banks have lower risk and are more able to generate profits that help in accumulating more retained earnings added to the financial capital (this assumes that dividends are unchanged).

In relation to bank capital, risk, and bank returns, we also include the variable ROA(=rate of return on assets), which is used as a proxy for performance. ROA is expected to be inversely related to cost and profit inefficiency on the grounds that the more inefficient firms are believed to employ their inputs in non-productive outputs that earn low returns.

With regard to the loan quality variable, the sign of the loan quality (*PROV*) is expected to be positive, showing that the more inefficient firms have higher provisions, indicating that they face loan problems and, thus, regulations force them to increase their loan provisions in accordance with deteriorating loan quality.

Moreover, because we wish to consider whether foreign banks are more efficient than their domestic competitors in the GCC, we include the dummy variable FOREIGN(=foreign banks), which consists of a value of one if the bank is foreign and zero otherwise. With regard to the GCC banking data of our sample, the foreign bank dummy variable and inefficiency variables are expected to be positively related since foreign banks operate under restrictions relating to bank size and branching limits, as well as tax impositions that may add to their costs.

Other independent variables are also considered in order to capture additional characteristics of bank and industry specifics. These are: L/TA(=net loans/total assets), FIX(=fixed assets), (TA=total assets), and TBGDP(=total banking assets/GDP). Variables L/TA, FIX, TA, and TBGDP respectively, control for balance sheet mix, bank size, and market size factors that may be influential in influencing banking sector inefficiency.

Overall, in order to investigate the determinants of GCC bank inefficiency we estimate the following model

$$INEFF = f\ (EQUITY, ROA, PROV,\ FOREIGN,\ LTA, FIX, TA,\ TBGDP) \quad (15)$$

As mentioned, this model will be estimated using the logistic functional form. The general form of the logistic model is written as

$$\hat{E}(u_i \setminus \varepsilon_i) = \frac{\exp(X_i^{'}\gamma)}{1+\exp(X_i^{'}\gamma)} + \xi_i \quad (16)$$

where X_i is a vector of independent variables for the ith firm, γ is the parameter vector, and ξ_i is a normally distributed error term.

Since the inefficiency variables are the dependent variables with values falling between zero and one, the logistic functional form is preferred here (compared with ordinary least squares methods) because the former is generally used to estimate models where the dependent variables are bounded between zero and one.

Following Mester (1996), the interpretation of the logistic function results only tells us about correlation relationships and do not tell us anything about causality. Nevertheless, the logistic regression is also preferred over the simple correlation method because it is possible to take other variables into consideration when estimating inefficiency determinants.

5.The empirical results on GCC banking efficiency [18]

Following the methodology of Berger and Mester (1997), we evaluate three inefficiency concepts: cost inefficiency, profit inefficiency, and alternative profit inefficiency. The results are based on two specifications: the preferred model and the traditional model. For both the preferred and the traditional models we use the Fourier Flexible form; however, the preferred model differs from the traditional specification by including the equity and loan provisions variables, which are considered in this research as proxies for risk and loan quality factors respectively.

Structural tests

Undertaking the estimation of the model (Eq. 13) using pooled time series cross-section data usually requires a test to check if it is permissible to pool both dimensions of the data, an issue that arises when one is using panel data (Baltagi, 2001). The checking of the data poolability is performed in order to detect whether or not the parameters of the model are the same (or stable) across time and bank observations, especially when data are pooled. This can be tested using the poolability test, which is an application of a generalized Chow's (1960) test. The residual sum squared of the restricted model,

[18] The estimation is carried out using *LIMDEP* econometric software version 7.0.

which is obtained from the OLS pooled model estimated for Eq. (13), and the total value of the unrestricted residual sum of squares, which is obtained from individual OLS regressions of 93 banks across each year of the study period, are calculated to carry out Chow's poolability test. As shown in Tables (5a to 5c), the test which is undertaken for the cost, standard profit, and alternative profit functions yields observed F-statistics of 1.05, 0.96, and 0.63 respectively, which are distributed as F(120, 414). Under the null hypothesis: $H_0 : \beta_t = \beta$ for t = 1, …, T, the test does not reject poolability at the 1 per cent level of significance. Therefore, our poolability test suggests that pooling our data in order to estimate Eq. (13) is valid, which also implies that the estimated model parameters are stable over time and bank observation.

As our data sample has a 'panel' dimension with a large cross-section (93 banks estimated over 6 years), the inclusion of banks of different sizes in the sample may give rise to concern of heteroskedasticity in the error term. We apply the Goldfeld-Quandt test (1965) to check whether or not the heteroskedasticity problem is present in the model. If not, then the test indicates that disturbance variances are homoskedastic, or, in other words, constant across observations. For the cost, standard profit, and alternative profit functions, Tables (5a to 5c) show that because the calculated test values are less than the critical value, the Goldfeld-Quandt test does not reject the null hypothesis of homoskedasticity at 1 per cent level of significance

As it is widely recommended to conduct more than one test for checking heteroskedasticity, the LM test for dependent-variable heteroskedasticity is another useful test to carry out here. [19 & 20] At the 1 per cent level of significance, Tables (5a to 5c) show that the LM test does not reject the null hypothesis of homoskedasticity in both standard and alternative profit functions; however, for the cost function the test is rejected. Assuming homoskedasticity in the disturbance term when heteroskedasticity is present would still produce consistent but not inefficient estimates (Baltagi, 2001).

Overall, the heteroskedasticity tests of these models tend to indicate that the estimation may be viewed as free from heteroskedasticity since both the Goldfeld-Quandt test and

[19] White's (1980) test of heteroskedasticity is not appropriate for our model since this test causes a loss in the degree of freedom if applied.
[20] See Thomas, 1997, Chapter 10.

the LM test, if taken together, suggest that the error term is apparently not positively correlated with any of the explanatory variables. This implies that the various model specifications do not have serious heteroskedasticity problems.

Given that we are estimating models using panel data, it is also important to investigate whether fixed or random effects estimation must be undertaken. A number of studies that estimate translog and Fourier Flexible models suggest that it is not appropriate to work under the framework of the panel fixed effects model since this induces a substantial loss in the degree of freedom, especially when the number of cross-sections is large (see e.g. Lang and Walzel, 1996; Altunbas et al., 2000). However, before dismissing the fixed effects model, it is important to undertake the random effects test since it can, at least, provide information as to whether individual effects are present or not. The test undertaken here to check the existence of random effects is the Lagrange Multiplier test, devised by Breusch and Pagan (1980). Tables (5a to 5c) show that the LM test rejects the hypothesis of no individual effects at the 1 per cent level of significance, for the cost, standard profit, and alternative profit functions. In this case, the LM test suggests that there is considerable heterogeneity across banks and that the random effects model is the method to be used to control for the effects of the differences across bank observations in our sample. Based on the LM test, we conclude that the random effects model is the appropriate panel estimation approach.

With regard to the choice of the functional form, the Fourier Flexible form is tested against the translog model. Using the F-test, Tables (5a to 5c) show that the hypothesis that the translog model is valid was rejected at the 1 per cent significance level for the cost, standard profit, and alternative profit functions. The results show the superiority of the Fourier Flexible form over the translog model since the presence of the Fourier trigonometric terms in the model is compelling.

Additional tests are also undertaken to check if the exclusion of the risk (E) and asset quality (PROV) variables, as well as the technical progress variables (T and TT), has no statistical significant effects on the model specification shown in Eq. (13). The F-test evaluated at the 1 per cent level of significance rejects the null hypothesis that these variables have a zero effect on the dependent variables in each efficiency concept function. In other words, the existence of these variables in the model are important for our inefficiency analysis.

Generally, as the structural tests imply, this section concludes that Eq. (13) for the cost, standard profit, and alternative profit functions (that have the Fourier Flexible functional form and incorporate banks' asset quality, risk, and time trend variables) are econometrically valid for our efficiency analysis. The inefficiency measures derived from estimating the aforementioned model are discussed in the following section.

Table 5 (a to c) Structural tests for model (13)

Table (5a) Structural tests of the cost function Eq. (13)

Test Performed		Test Statistics	Degrees of Freedom		Critical value		H0 Hypothesis	Decision
Poolability	Chow's test	1.0592	((T-1)K)=	120	F(.01,120,414)=	1.383	H0:Bt=B data is poolable or betas are stable	Not-rejected
			((N-K)T))=	414				
Heteroskedasticity	Goldfeld-Quant test	0.8299	n1=	253	F(a,N1-K,N2-K)=(.01,279-26,279-26)=	1.341	H0:Disturbances of the variances are constant	Not-rejected
			n2=	253				
Heteroskedasticity	LM test	18.391	k=	1	X2(0.01,1)=	6.635	H0:Disturbances of the variances are the constant	Rejected
Random effects	LM test	358.09	k=	1	X2(0.01,1)	6.635	H0:No individual effects	Rejected
Translog Form	F-test	3.397	K=	10	F(.01,10,536)	2.354	H0:Translogn form is valid or Fourier terms =0	Rejected
	Chi-squared test	33.993			X2(10)=	23.209		Rejected
DROP PROV,E,T,TT	F-test	13.327	k=	4	F(.01,4,532)=	3.355	H0:estimated model is better when these are dropped	Rejected
DROP PROV,E	F-test	25.059	k=	2	F(.01,2,532)=	4.645	H0:estimated model is better when these are dropped	Rejected
DROP PROV,T,TT	F-test	1.4102	k=	3	F(.01,3,532)=	3.819	H0:estimated model is better when these are dropped	Not-rejected
DROP E,T,TT	F-test	17.729	k=	3	F(.01,3,532)=	3.819	H0:estimated model is better when these are dropped	Rejected
DROP RPOV	F-test	0.1815	k=	1	F(.01,1,532)=	6.683	H0:estimated model is better when these are dropped	Not-rejected
DROP E	F-test	50.024	k=	1	F(.01,1,532)=	6.683	H0:estimated model is better when these are dropped	Rejected
DROP T,TT	F-test	1.9974	k=	2	F(.01,2,532)=	4.645	H0:estimated model is better when these are dropped	Not-rejected

Table (5b) Structural tests of the standard profit function Eq. (13)

Test Performed		Test Statistics	Degrees of Freedom		Critical value		H0 Hypothesis	Decision
Poolability	Chow's test	0.9676	((T-1)K)=	120	F(.01,120,414)=	1.383	H0:Bt=B data is poolable or betas are stable	Not-rejected
			((N-K)T))=	414				
Heteroskedasticity	Goldfeld-Quant test	0.7705	n1=	253	F(a,N1-K,N2-K)=(.01,279-26,279-26)=	1.341	H0:Disturbances of the variances are the constant	Not-rejected
			n2=	253				
Heteroskedasticity	LM test	6.4003	k=	1	X2(0.01,1)=	6.635	H0:Disturbances of the variances are the constant	Not-rejected
Random effects	LM test	400.64	k=	1	X2(0.01,1)	6.635	H0:No individual effects	Rejected
Translog Form	F-test	661.00	K=D101	10	F(.01,10,536)	2.354	H0:Translogn form is valid or Fourier terms =0	Rejected
	Chi-squared test	6610.0			X2(10)=	23.209		Rejected
DROP PROV,E,T,TT	F-test	19.025	k=	4	F(.01,4,532)=	3.355	H0:estimated model is better when these are dropped	Rejected
DROP PROV,E	F-test	35.174	k=	2	F(.01,2,532)=	4.645	H0:estimated model is better when these are dropped	Rejected
DROP PROV,T,TT	F-test	6.3979	k=	3	F(.01,3,532)=	3.819	H0:estimated model is better when these are dropped	Not-rejected
DROP E,T,TT	F-test	20.255	k=	3	F(.01,3,532)=	3.819	H0:estimated model is better when these are dropped	Rejected
DROP RPOV	F-test	14.096	k=	1	F(.01,1,532)=	6.683	H0:estimated model is better when these are dropped	Not-rejected
DROP E	F-test	56.348	k=	1	F(.01,1,532)=	6.683	H0:estimated model is better when these are dropped	Rejected
DROP T,TT	F-test	2.0251	k=	2	F(.01,2,532)=	4.645	H0:estimated model is better when these are dropped	Not-rejected

Table (5c) Structural tests of the alternative profit function Eq. (13)

Test Performed		Test Statistics	Degrees of Freedom		Critical value		H0 Hypothesis	Decision
Poolability	Chow's test	0.6303	((T-1)K)=	120	F(.01,120,414)=	1.383	H0:Bt=B data is poolable or betas are stable	Not-rejected
			((N-K)T))=	414				
Heteroskedasticity	Goldfeld-Quant test	0.9854	n1=	253	F(a,N1-K,N2-K)=(.01,279-26,279-26)=	1.341	H0:Disturbances of the variances are the constant	Not-rejected
			n2=	253				
Heteroskedasticity	LM test	2.8519	k=	1	X2(0.01,1)=	6.635	H0:Disturbances of the variances are the constant	Not-rejected
Random effects	LM test	375.520	k=	1	X2(1)	6.635	H0:No individual effects	Rejected
Translog Form	F-test	6.9483	K=	10	F(.01,10,532)	2.354	H0:Translogn form is valid or Fourier terms =0	Rejected
	Chi-squared test	69.4850			X2(10)=	23.209		Rejected
DROP PROV,E,T,TT	F-test	25.5201	k=	4	F(.01,4,532)=	3.355	H0:estimated model is better when these are dropped	Rejected
DROP PROV,E	F-test	50.1498	k=	2	F(.01,2,532)=	4.645	H0:estimated model is better when these are dropped	Rejected
DROP PROV,T,TT	F-test	12.7859	k=	3	F(.01,3,532)=	3.819	H0:estimated model is better when these are dropped	Not-rejected
DROP E,T,TT	F-test	20.5604	k=	3	F(.01,3,532)=	3.819	H0:estimated model is better when these are dropped	Rejected
DROP RPOV	F-test	36.8296	k=	1	F(.01,1,532)=	6.683	H0:estimated model is better when these are dropped	Not-rejected
DROP E	F-test	60.6521	k=	1	F(.01,1,532)=	6.683	H0:estimated model is better when these are dropped	Rejected
DROP T,TT	F-test	0.55111	k=	2	F(.01,2,532)=	4.645	H0:estimated model is better when these are dropped	Not-rejected

Parameter estimation analysis

The estimates in Tables (4a to 4c) show the maximum likelihood parameter estimation (MLE) of the Fourier Flexible cost, standard profit, and alternative profit functions, which are estimated for both the traditional and preferred model specifications (Eq. 13). The estimates of the model parameters are quite similar across model specifications (traditional and preferred model, as well as models excluding only risk variable [equity] or loan quality variable [provisions] from the preferred model).

The results in Tables (4a to 4c) also show that the functions' estimated coefficients mostly have consistent signs. To be specific, the input prices (P_1 and P_2) have positive effects on costs, implying that higher input prices lead to greater costs [see Table (3a)]. Moreover, in Table (3c), the positive relationship between the prices of inputs (P_1) and alternative profits may be explained by the fact that when the price of deposits increases, loan prices also increase, resulting in higher profits. Because output quantities are set as given in the alternative profit function and prices of output are left to move freely, changes in output prices induced by input price movements may bring the latter and profits into a close relationship.

Table 4 (a to c) Maximum likelihood parameter estimation for cost, standard, and alternative profit functions

Table 4 a

Maximum likelihood parameter estimation for the cost function using the half-normal model

		Traditional model			Preferred model Eq. (13)			No Equity			No Provisions		
Variable	Parameter	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value
Constant	α_0	-5.6534	10.7210	-0.5270	-4.8803	15.6330	-0.3120	-5.7154	10.5360	-0.5420	-4.7678	15.1940	-0.3140
lnQ1	α_1	-0.8054	1.3327	-0.6040	-0.5292	2.3481	-0.2250	-0.7993	1.3166	-0.6070	-0.5465	2.2376	-0.2440
lnQ2	α_2	2.7250	1.2191	2.2350	2.4391	1.0588	2.3040	2.7296	1.2320	2.2160	2.4317	1.0610	2.2920
lnP1	β_1	0.5019	0.0428	11.7340	0.4970	0.0434	11.4650	0.5017	0.0435	11.5440	0.4989	0.0428	11.6620
lnE	κ	-	-	-	-0.0225	0.0025	-8.8460	-	-	-	-0.0228	0.0025	-9.0970
lnPROV	ν	-	-	-	0.0020	0.0028	0.7270	0.0019	0.0027	0.7110	-	-	-
T	τ	-0.0421	0.0443	-0.9500	-0.0458	0.0454	-1.0090	-0.0427	0.0442	-0.9680	-0.0454	0.0449	-1.0110
TT	τ^2	0.0055	0.0058	0.9510	0.0060	0.0060	1.0070	0.0056	0.0058	0.9660	0.0060	0.0059	1.0110
lnQ1 lnQ1	δ_{11}	0.2953	0.1067	2.7680	0.2824	0.1883	1.5000	0.2944	0.1055	2.7920	0.2847	0.1789	1.5910
lnQ1 lnQ2	δ_{12}	-0.1555	0.0130	-11.9200	-0.1704	0.0130	-13.1340	-0.1553	0.0133	-11.7000	-0.1706	0.0126	-13.5170
lnQ2 lnQ2	δ_{22}	-0.0456	0.0915	-0.4990	-0.0056	0.0791	-0.0710	-0.0460	0.0924	-0.4970	-0.0051	0.0792	-0.0640
lnP1 lnP1	γ_{11}	0.2491	0.0527	4.7240	0.2433	0.0502	4.8500	0.2513	0.0534	4.7040	0.2421	0.0490	4.9430
lnP1 lnP2	γ_{12}	-0.2115	0.0340	-6.2220	-0.2010	0.0343	-5.8670	-0.2123	0.0345	-6.1600	-0.2001	0.0339	-5.9030
lnP1 lnQ1	ρ_{11}	0.1004	0.0301	3.3320	0.0965	0.0291	3.3110	0.0990	0.0302	3.2740	0.0981	0.0294	3.3370
lnP1 lnQ2	ρ_{12}	-0.1043	0.0311	-3.3510	-0.0972	0.0303	-3.2090	-0.1024	0.0307	-3.3340	-0.0992	0.0310	-3.2030
lnP2 lnQ1	ρ_{21}	0.0154	0.0219	0.7050	0.0036	0.0205	0.1750	0.0163	0.0227	0.7180	0.0034	0.0204	0.1650
cos(z1)	a_1	-0.6970	0.5260	-1.3250	-0.5632	0.8861	-0.6360	-0.6931	0.5204	-1.3320	-0.5739	0.8453	-0.6790
sin(z1)	b_1	0.0153	0.1420	0.1080	-0.0244	0.2566	-0.0950	0.0130	0.1412	0.0920	-0.0178	0.2346	-0.0760
cos(z2)	a_2	0.7306	0.3138	2.3280	0.6695	0.2817	2.3770	0.7317	0.3159	2.3170	0.6661	0.2811	2.3700
sin(z2)	b_2	0.0744	0.0828	0.8980	-0.0358	0.0633	-0.5660	0.0757	0.0863	0.8770	-0.0304	0.0640	-0.4750
cos(z1+z1)	a_{11}	-0.1552	0.0681	-2.2790	-0.1374	0.1131	-1.2150	-0.1544	0.0678	-2.2790	-0.1393	0.1067	-1.3060
sin(z1+z1)	b_{11}	0.0668	0.0452	1.4790	0.0227	0.0739	0.3080	0.0656	0.0450	1.4580	0.0260	0.0685	0.3800
cos(z1+z2)	a_{12}	0.0059	0.0273	0.2180	0.0522	0.0342	1.5250	0.0057	0.0270	0.2120	0.0493	0.0331	1.4880
sin(z1+z2)	b_{12}	-0.0627	0.0346	-1.8120	-0.0269	0.0348	-0.7740	-0.0626	0.0347	-1.8030	-0.0269	0.0349	-0.7710
cos(z2+z2)	a_{22}	0.1444	0.0472	3.0600	0.0970	0.0453	2.1390	0.1453	0.0463	3.1380	0.0968	0.0458	2.1140
sin(z2+z2)	b_{22}	0.0414	0.0270	1.5330	0.0055	0.0234	0.2330	0.0422	0.0273	1.5460	0.0064	0.0237	0.2700
	λ	1.5721	0.3254	4.8320	1.5728	0.2800	5.6170	1.5601	0.3198	4.8780	1.5697	0.2860	5.4890
	σ	0.0061	0.0003	19.6390	0.0056	0.0003	21.7900	0.0060	0.0003	19.7230	0.0056	0.0003	22.2840
	θ	-	-	-	-	-	-	-	-	-	-	-	-
	σ_v	-	-	-	-	-	-	-	-	-	-	-	-
lnP2	β_2	0.4981			0.5030			0.4983			0.5011		
lnP2 lnP2	γ_{22}	0.2115			0.2010			0.2123			0.2001		
lnP2 lnQ2	ρ_{22}	-0.0154			-0.0036			-0.0163			-0.0034		
Variance components	$\sigma^2(v)$	0.00606			0.0056			0.00603			0.00565		
	$\sigma^2(u)$	0.00953			0.0089			0.00940			0.00886		
Log Likelihood function		527.3			542.4			527.9			541.2		
Function converged at iteration		11			20			12			19		
R^2		0.996			0.996			0.996			0.996		

Traditional Model = Fourier Flexible form with two outputs, two inputs, and time trend

Preferred Model = Traditional model with the addition of risk and asset quality variables. This model is given in Eq. (13)

Table 4 b

Maximum likelihood parameter estimation for the standard profit function using the half-normal model

		Traditional model			Preferred model Eq. (7.1)			No Equity			No Provisions		
Variable	Parameter	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value
Constant	α_0	10.6471	0.8133	13.0910	9.4045	0.8779	10.7120	10.3903	0.8179	12.7040	9.7141	0.8797	11.0420
lnPQ1	α_1	-1.9503	0.6740	-2.8940	-2.1203	0.6741	-3.1460	-2.0625	0.6749	-3.0560	-1.9997	0.6812	-2.9350
lnPQ2	α_2	0.1650	0.3629	0.4550	0.0711	0.3802	0.1870	0.1249	0.3662	0.3410	0.1215	0.3757	0.3230
lnP1	β_1	1.3330	0.0903	14.7610	1.3433	0.0965	13.9220	1.3263	0.0888	14.9400	1.3511	0.0993	13.6070
lnE	κ	-	-	-	0.0601	0.0064	9.4450	-	-	-	0.0585	0.0059	9.9780
lnPROV	ν	-	-	-	0.0117	0.0044	2.6860	0.0108	0.0038	2.7960	-	-	-
T	τ	0.1243	0.0662	1.8770	0.1202	0.0646	1.8600	0.1173	0.0644	1.8210	0.1276	0.0659	1.9350
TT	τ^2	-0.0158	0.0089	-1.7800	-0.0157	0.0086	-1.8250	-0.0150	0.0086	-1.7440	-0.0164	0.0088	-1.8700
lnPQ1 lnPQ1	δ_{11}	-0.7008	0.3586	-1.9550	-0.7884	0.3827	-2.0600	-0.7193	0.3805	-1.8910	-0.7702	0.3771	-2.0430
lnPQ1 lnPQ2	δ_{12}	0.0102	0.0403	0.2530	0.0073	0.0421	0.1740	0.0064	0.0407	0.1570	0.0134	0.0414	0.3230
lnPQ2 lnPQ2	δ_{22}	0.0971	0.0366	2.6510	0.0849	0.0370	2.2980	0.0935	0.0367	2.5450	0.0891	0.0364	2.4470
lnP1 lnP1	γ_{11}	0.4361	0.1215	3.5900	0.4413	0.1249	3.5340	0.4492	0.1249	3.5970	0.4285	0.1230	3.4850
lnP1 lnP2	γ_{12}	0.1597	0.0859	1.8590	0.1714	0.0829	2.0680	0.1615	0.0832	1.9410	0.1685	0.0854	1.9730
lnP1 lnQ1	ρ_{11}	-0.2994	0.1375	-2.1780	-0.2887	0.1435	-2.0120	-0.3139	0.1414	-2.2200	-0.2736	0.1415	-1.9330
lnP1 lnQ2	ρ_{12}	-0.0139	0.0705	-0.1970	-0.0267	0.0724	-0.3690	-0.0201	0.0704	-0.2850	-0.0202	0.0720	-0.2810
lnP2 lnQ1	ρ_{21}	0.0983	0.0576	1.7080	0.0946	0.0591	1.6020	0.0961	0.0577	1.6660	0.0964	0.0586	1.6450
cos(z1)	a_1	0.6841	0.0682	10.0280	0.6418	0.0783	8.1940	0.6707	0.0755	8.8870	0.6560	0.0688	9.5370
sin(z1)	b_1	-0.6949	0.0675	-10.3010	-0.6397	0.0755	-8.4780	-0.6815	0.0685	-9.9550	-0.6553	0.0726	-9.0220
cos(z2)	a_2	-0.0275	0.0477	-0.5760	-0.0237	0.0552	-0.4290	-0.0186	0.0486	-0.3830	-0.0323	0.0537	-0.6010
sin(z2)	b_2	-0.8446	0.0641	-13.1750	-0.7735	0.0654	-11.8280	-0.8414	0.0647	-13.0080	-0.7761	0.0640	-12.1180
cos(z1+z1)	a_{11}	0.0566	0.0483	1.1710	0.0530	0.0506	1.0490	0.0557	0.0495	1.1240	0.0530	0.0485	1.0930
sin(z1+z1)	b_{11}	-0.1611	0.0360	-4.4740	-0.1513	0.0390	-3.8760	-0.1607	0.0375	-4.2810	-0.1525	0.0366	-4.1640
cos(z1+z2)	a_{12}	0.0117	0.0585	0.2000	0.0007	0.0621	0.0110	0.0072	0.0600	0.1200	0.0051	0.0598	0.0850
sin(z1+z2)	b_{12}	-0.2043	0.0674	-3.0310	-0.2071	0.0741	-2.7940	-0.2117	0.0690	-3.0670	-0.1998	0.0713	-2.8040
cos(z2+z2)	a_{22}	0.0314	0.0392	0.8010	0.0455	0.0399	1.1410	0.0429	0.0395	1.0850	0.0341	0.0397	0.8580
sin(z2+z2)	b_{22}	-0.1402	0.0375	-3.7440	-0.1201	0.0421	-2.8530	-0.1357	0.0388	-3.4950	-0.1251	0.0401	-3.1200
	λ	7.2100	2.2215	3.2460	5.9792	1.6861	3.5460	7.0114	2.1344	3.2850	6.2850	1.8185	3.4560
	σ	0.0223	0.0011	20.0310	0.0213	0.0011	19.3230	0.0220	0.0011	19.7520	0.0216	0.0011	19.4130
	θ	-	-	-	-	-	-	-	-	-	-	-	-
	σ_v	-	-	-	-	-	-	-	-	-	-	-	-
lnP2	β_2	-0.3330			-0.3433			-0.3263			-0.3511		
lnP2 lnP2	γ_{22}	-0.1597			-0.1714			-0.1615			-0.1685		
lnP2 lnPQ2	ρ_{22}	-0.0983			-0.0946			-0.0961			-0.0964		
Variance components	$\sigma^2(v)$	0.02227			0.02129			0.02196			0.02165		
	$\sigma^2(u)$	0.16058			0.12732			0.15398			0.13604		
Log Likelihood function		116.6			136.6			121.9			130.2		
Function converged at iteration		29			29			30			29		
R^2		0.959			0.963			0.960			0.962		

Table 4 c

Maximum likelihood parameter estimation for the alternative profit function using the half-normal model

		Traditional model			Preferred model Eq. (13)			No Equity			No Provisions		
Variable	Parameter	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value	Coefficient	Std. Error	T-value
Constant	α_0	12.6909	37.4410	0.3390	16.5441	34.8460	0.4750	12.7897	38.0130	0.3360	16.3033	35.9250	0.4540
lnQ1	α_1	1.5433	3.7596	0.4100	1.3510	3.9883	0.3390	1.6818	4.5546	0.3690	1.2154	3.4139	0.3560
lnQ2	α_2	-1.9204	4.3169	-0.4450	-2.4241	3.5370	-0.6850	-2.0715	3.7442	-0.5530	-2.2559	4.1893	-0.5390
lnP1	β_1	1.0928	0.0896	12.1970	1.1120	0.0896	12.4100	1.0891	0.0892	12.2060	1.1151	0.0901	12.3740
lnE	κ	-	-	-	0.0656	0.0066	9.8890	-	-	-	0.0635	0.0071	8.9560
lnPROV	ν	-	-	-	0.0165	0.0038	4.3460	0.0158	0.0038	4.1330	-	-	-
T	τ	0.0997	0.0702	1.4190	0.0970	0.0692	1.4010	0.0923	0.0710	1.3000	0.1044	0.0688	1.5170
TT	τ^2	-0.0133	0.0094	-1.4100	-0.0134	0.0093	-1.4500	-0.0126	0.0095	-1.3280	-0.0141	0.0092	-1.5280
lnQ1 lnQ1	δ_{11}	-0.0810	0.3060	-0.2650	-0.0928	0.3205	-0.2900	-0.0931	0.3681	-0.2530	-0.0783	0.2776	-0.2820
lnQ1 lnQ2	δ_{12}	-0.0506	0.0313	-1.6190	-0.0273	0.0316	-0.8640	-0.0512	0.0325	-1.5730	-0.0285	0.0312	-0.9140
lnQ2 lnQ2	δ_{22}	0.2181	0.3352	0.6510	0.2313	0.2707	0.8550	0.2319	0.2872	0.8080	0.2178	0.3240	0.6720
lnP1 lnP1	γ_{11}	-0.2630	0.1665	-1.5800	-0.2534	0.1681	-1.5070	-0.2579	0.1685	-1.5300	-0.2555	0.1654	-1.5450
lnP1 lnP2	γ_{12}	0.1822	0.0746	2.4410	0.1861	0.0702	2.6500	0.1859	0.0707	2.6300	0.1827	0.0747	2.4470
lnP1 lnQ1	ρ_{11}	-0.0157	0.0692	-0.2270	-0.0364	0.0704	-0.5170	-0.0329	0.0700	-0.4700	-0.0169	0.0694	-0.2440
lnP1 lnQ2	ρ_{12}	-0.0711	0.0527	-1.3500	-0.0501	0.0550	-0.9110	-0.0514	0.0541	-0.9490	-0.0714	0.0533	-1.3380
lnP2 lnQ1	ρ_{21}	-0.0689	0.0427	-1.6110	-0.0530	0.0379	-1.3980	-0.0596	0.0376	-1.5840	-0.0623	0.0441	-1.4130
cos(z1)	a_1	1.0803	1.4067	0.7680	1.0522	1.4950	0.7040	1.1486	1.6888	0.6800	0.9759	1.2945	0.7540
sin(z1)	b_1	-0.2264	0.4882	-0.4640	-0.2525	0.4988	-0.5060	-0.1994	0.5814	-0.3430	-0.2772	0.4343	-0.6380
cos(z2)	a_2	-0.5098	1.0619	-0.4800	-0.6445	0.8681	-0.7420	-0.5554	0.9188	-0.6040	-0.5958	1.0187	-0.5850
sin(z2)	b_2	-0.0549	0.3099	-0.1770	-0.0741	0.2746	-0.2700	-0.0686	0.2795	-0.2450	-0.0583	0.3178	-0.1830
cos(z1+z1)	a_{11}	0.0891	0.1588	0.5610	0.0782	0.1781	0.4390	0.1018	0.1899	0.5360	0.0651	0.1549	0.4210
sin(z1+z1)	b_{11}	-0.0888	0.1106	-0.8030	-0.0805	0.1149	-0.7000	-0.0950	0.1295	-0.7330	-0.0742	0.1021	-0.7260
cos(z1+z2)	a_{12}	-0.0348	0.0679	-0.5130	-0.0259	0.0673	-0.3850	-0.0342	0.0669	-0.5110	-0.0294	0.0660	-0.4450
sin(z1+z2)	b_{12}	-0.0432	0.0913	-0.4730	-0.0993	0.0969	-1.0250	-0.0503	0.0987	-0.5100	-0.0914	0.0899	-1.0170
cos(z2+z2)	a_{22}	-0.0303	0.1303	-0.2330	-0.0279	0.1102	-0.2530	-0.0248	0.1150	-0.2150	-0.0325	0.1257	-0.2580
sin(z2+z2)	b_{22}	0.0346	0.0795	0.4350	0.0545	0.0674	0.8080	0.0369	0.0708	0.5210	0.0518	0.0805	0.6430
	λ	7.0035	2.0261	3.4570	5.7688	1.8094	3.1880	6.3914	2.0186	3.1660	6.3306	1.8600	3.4040
	σ	0.0276	0.0015	18.9990	0.0261	0.0014	18.5730	0.0270	0.0014	18.7780	0.0267	0.0014	18.6840
	θ	-	-	-	-	-	-	-	-	-	-	-	-
	σ_v	-	-	-	-	-	-	-	-	-	-	-	-
lnP2	β_2	-0.0928			-0.1120			-0.0891			-0.1151		
lnP2 lnP2	γ_{22}	-0.1822			-0.1861			-0.1859			-0.1827		
lnP2 lnQ2	ρ_{22}	0.0689			0.0530			0.0596			0.0623		
Variance components	$\sigma^2\ (v)$	0.02756			0.0261			0.0270			0.0267		
	$\sigma^2(u)$	0.19301			0.1505			0.1727			0.1690		
Log Likelihood function		58.4			81.6			67.7			71.1		
Function converged at iteration		46			43			42			39		
R^2		0.948			0.956			0.951			0.953		

In addition, the negative coefficients on the price of loans (PQ_1) in relation to standard profits clearly indicate that an increase in the price of loans would decrease the level of profits [see Table (4b)]. At first glance, this result might look odd since profits may be expected to increase as prices rise. However, because the standard profit function takes the price of output as given and leaves the quantity of output to move freely, this means that at higher prices banks face a lower demand for output; hence, at this given higher price of output, banks' profits may decrease. Thus, this negative relationship between loan prices and profits could indicate that the quantity of loans demanded (rather than the price of loans) is more influential in driving GCC banking profits. An alternative explanation suggests that an increase in loan prices may result in a reduction in the quantity of loans demanded, reducing profits by a greater proportion than would be added by any loan price increases The main finding is that an increase in prices results in lower levels of standard profits (all other factors remain the same).

The results also show that the risk variable (E) has consistent effects on both cost and profit functions. That is, since the estimated coefficient of equity is negative in the cost model, this might inform us that low levels of financial capital could contribute to increasing costs because of reliance on borrowed funds, while high levels of capital indicate the opposite.[21] Moreover, the positive coefficients of the (E) variable in the profit models indicate that as bank financial capital increases, banks secure greater profits as risk exposure lessens. Besides, the positive relationship between financial capital and profits may derive from the fact that profits add to financial capital in the form of retained profits, given that profits are not allocated as dividends. Thus, the stronger the financial capital base, the greater is banks' access to sources of internal finance, and therefore their opportunity of generating profits.

The coefficients reported in the tables also reveal some other interesting relationships. For example, Table (4a) shows that the loan quality proxy (PROV) has the expected relationship (though insignificant) with costs (indicating bad loans increase the cost burden of banks), and Tables (4b and 4c) indicate that PROV is positively related to

[21] High capital also means less risk exposure, which may place a low burden on the cost function compared to the case when capital is low and risk is high.

profits. This is probably because more profitable banks have the ability to make greater provisions. (However, one could also argue that one may expect an inverse relationship as banks tend to be more profitable when provisions fall.)

It may also be noted from Tables (4a to 4c) that the cost, standard profit, and alternative profit functions fit the data reasonably well. The adjusted R^2 reported over the six years for all model specifications ranges from 94.8 to 99.6 per cent. This means that the explanatory variables explain most of the variation in the dependent variables.

Tables (4a to 4c) also present both inefficiency and random error variances, denoted as $\sigma^2(u)$ and $\sigma^2(\upsilon)$ respectively. Among all inefficiency concepts, the lowest inefficiency variance as a ratio in the total error term variance amounted to around 62 per cent (for the cost function estimated using the half-normal distribution). For the standard profit and alternative profit functions estimated using the half-normal distribution, the inefficiency term variance ratio accounted for around 86 per cent and 88 per cent of total variance respectively. These results suggest that the majority of the total variances of the stochastic error term ε is accounted for by the variances in the inefficiency component u, rather than the variances in the random error υ. This suggests that the deviations from the best practice bank's cost and profit functions have much more to do with managerial factors (represented by X-inefficiency) than with luck and other factors that are incorporated in the random error term.

Inefficiency estimates

The examination of how the mean inefficiency differs across model specifications gives us information on how the exclusion of the risk and quality variables from the preferred specification [Eq. (13)] would affect mean inefficiency estimations in the GCC banking industry.

As far as model specification is concerned, we notice from Table 6 that when estimating over each specification (traditional, preferred, preferred with no equity, and preferred with no provisions specifications), the inefficiency scores as well as the dispersions around inefficiency means tend to be similar. However, the elimination of equity and provisions variables from the preferred model resulted in a slight difference in the inefficiency means. For example, for the traditional model, Table 6 shows that the elimination of the E and PROV variables from the preferred model slightly increased the mean inefficiency for all efficiency concepts estimated using the half-normal distribution. Similarly, the individual elimination of E and PROV variables from the preferred model also resulted in a slight increase in the inefficiency levels across all efficiency concepts. This elimination process suggests that the control for risk and quality factors in the inefficiency models removes any over-estimation of inefficiency scores when these two factors are not taken into account. Moreover, the mean inefficiency results show that the exclusion of the E variable from the preferred specification results in higher inefficiency levels than does the exclusion of the PROV variable from the same specification.

Table 6 The mean inefficiency estimates

	Half-normal distribution model			
	Traditional model	Preferred model Eq. (13)	No Equity	No Provisions
Cost function	0.0839	0.0807	0.0837	0.0806
	(0.0469)	(0.0456)	(0.0468)	(0.0457)
Standard profit function	0.3312	0.2904	0.3235	0.3014
	(0.1849)	(0.1694)	(0.1813)	(0.1739)
Alternative profit function	0.3594	0.3138	0.3383	0.3345
	(0.2101)	(0.1865)	(0.1995)	(0.1974)

The mean cost efficiency from the preferred model is about 91 per cent. In other words, about 9 per cent of costs are wasted on average relative to a best-practice bank. The economic interpretation of the cost inefficiency level is that, given their particular output level and mix, on average, banks need to reduce their production costs by roughly 9 per cent in order to use their inputs as efficiently as possible. Overall, the levels of the mean cost inefficiency are consistent with inefficiency levels found by parametric studies on European, Japanese, and US banking markets. For example, Altunbas et al. (2000), Berger and Mester, (1997), Ferrier and Lovell, (1990), and

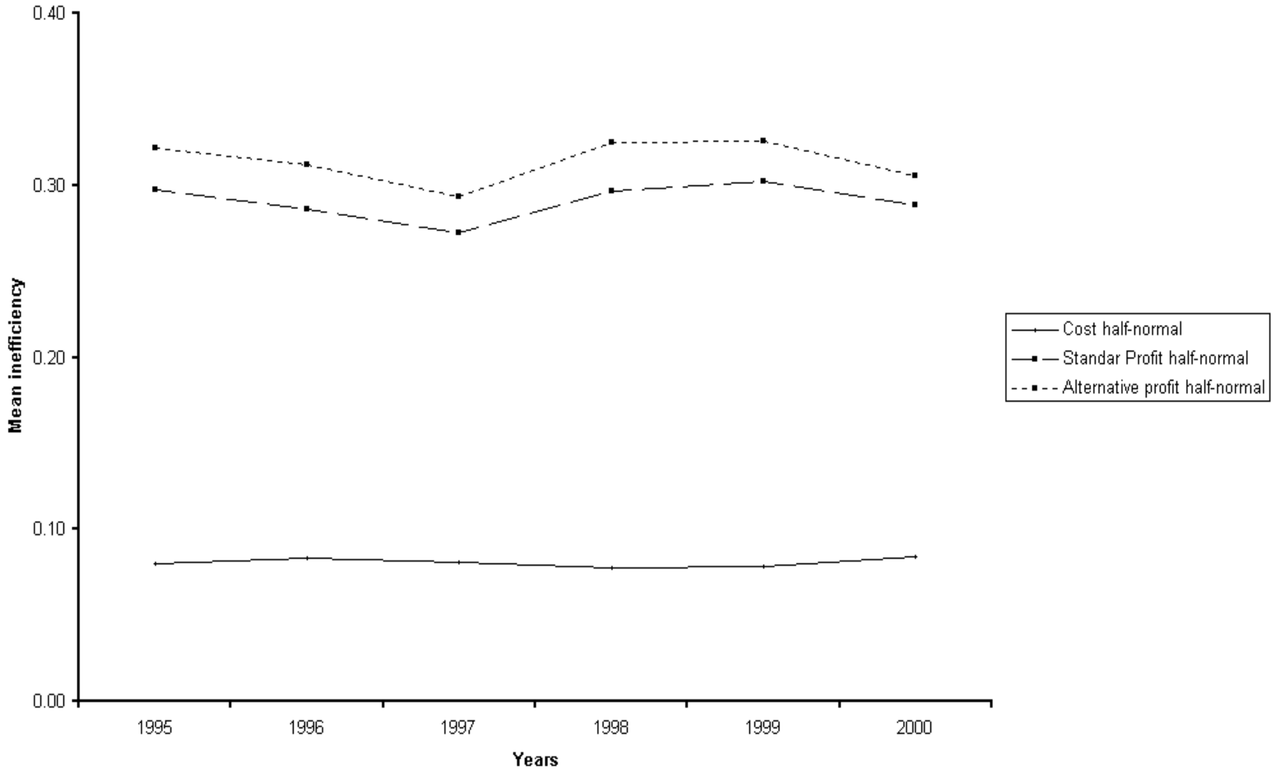
Berger (1993) found the average cost inefficiency of commercial banks to range from anywhere between 5 per cent (Altunbas et al., 2002 on European banks) and 40 per cent (Berger, 1993 on US banks). There is a general consensus, however, that cost inefficiency typically ranges between 5 per cent and 15 per cent (see Berger and Humphrey, 1997).

On the profit side, the mean inefficiencies derived from the standard and alternative profit functions are close to each other, given that the mean inefficiency of the alternative profit function is about 3 per cent higher than standard profit mean inefficiency scores. The interpretation of the inefficiencies on the profit side is not so different from the cost side. In both standard and alternative profit functions, the inefficiency results indicate that nearly one third of the profits that could be earned by the best practice bank are lost to inefficiency. The profit level of inefficiency is found to conform to the findings of a number of previous studies that found profit inefficiency to fall in the same range; for example, Lozano (1997) found that the average profit inefficiency of the Spanish depository institutions was 28 per cent. In contrast, profit inefficiency is found to be higher in the US banking sector. So, for instance, Berger and Mester (1997) report profit inefficiency ranging between 46 and 54 per cent. In general, profit inefficiency in US banking is found to be, on average, around 36 per cent (see the review by Berger and Humphrey, 1997). It is worth mentioning that, in accordance with previous profit efficiency studies (for example, those of Berger and Mester, 1997; and Al-Jarrah, 2002), the results in Table 6 show that profit inefficiencies are higher than cost inefficiencies. This finding is consistent across various model specifications. The cost inefficiency calculates wastes of resources only on the input side. Profit inefficiency accounts for inefficiencies on both the input and output sides. This generally results in higher inefficiency estimates on the profit side. Furthermore, when banks face higher operating costs that may be reflected in bank product prices, the profit function can also capture this source of inefficiency. In addition, profits are more variable than costs and can be affected more dramatically on account of economic downturns, unforeseen losses, and so on. Given the greater variation in profitability, it is therefore less surprising that inefficiency tends to be much larger compared to cost inefficiency.

In accordance with the literature, it is also observed from Table 6 that mean alternative profit inefficiencies are higher than standard profit inefficiencies. The standard profit function takes prices of outputs as given and leaves the output quantities to change freely. In contrast, the alternative profit function allows output prices to move freely and takes output levels as given. This implies that the alternative profit function may report inefficiency levels higher than standard profit inefficiencies because of market power conditions, service quality, and other endogenous or exogenous sources that may affect output prices and profitability. For markets with high levels of concentration, such as in the GCC banking industry, the standard profit function is less able to take into account the ability of banks to exercise market power without much change in output levels, whereas the alternative profit estimates are believed to capture this phenomenon. Moreover, when banks tend to offer services of low quality with low prices relative to the best practice bank, the alternative profit function can capture this source of inefficiency. Given these reasons, alternative profit inefficiency estimates are often likely to be higher than standard profit inefficiency estimates.

In the examination of how mean inefficiency levels change over the study period, Figure 2 shows the pattern of mean inefficiencies over time for all banks in our sample using the three different efficiency concepts. Generally, the figure shows a similar pattern in inefficiency levels over time with no discernable increase or decrease, although they tend to show a slight decrease in profit inefficiency over 1995-1997 and 1999-2000. The year 1998 witnessed a rise in loan loss problems (mostly due to the effect of a sharp oil prices decrease in 1998) resulting in a noticeable increase in profit inefficiency. Overall, however, both cost and profit efficiency seem to be relatively stable over time, indicating that market conditions, such as the competitive environment and regulatory changes, did not much affect industry’s cost and profit functions during the second half of the 1990s.

Figure 2 Inefficiency in the GCC banking industry over the study period



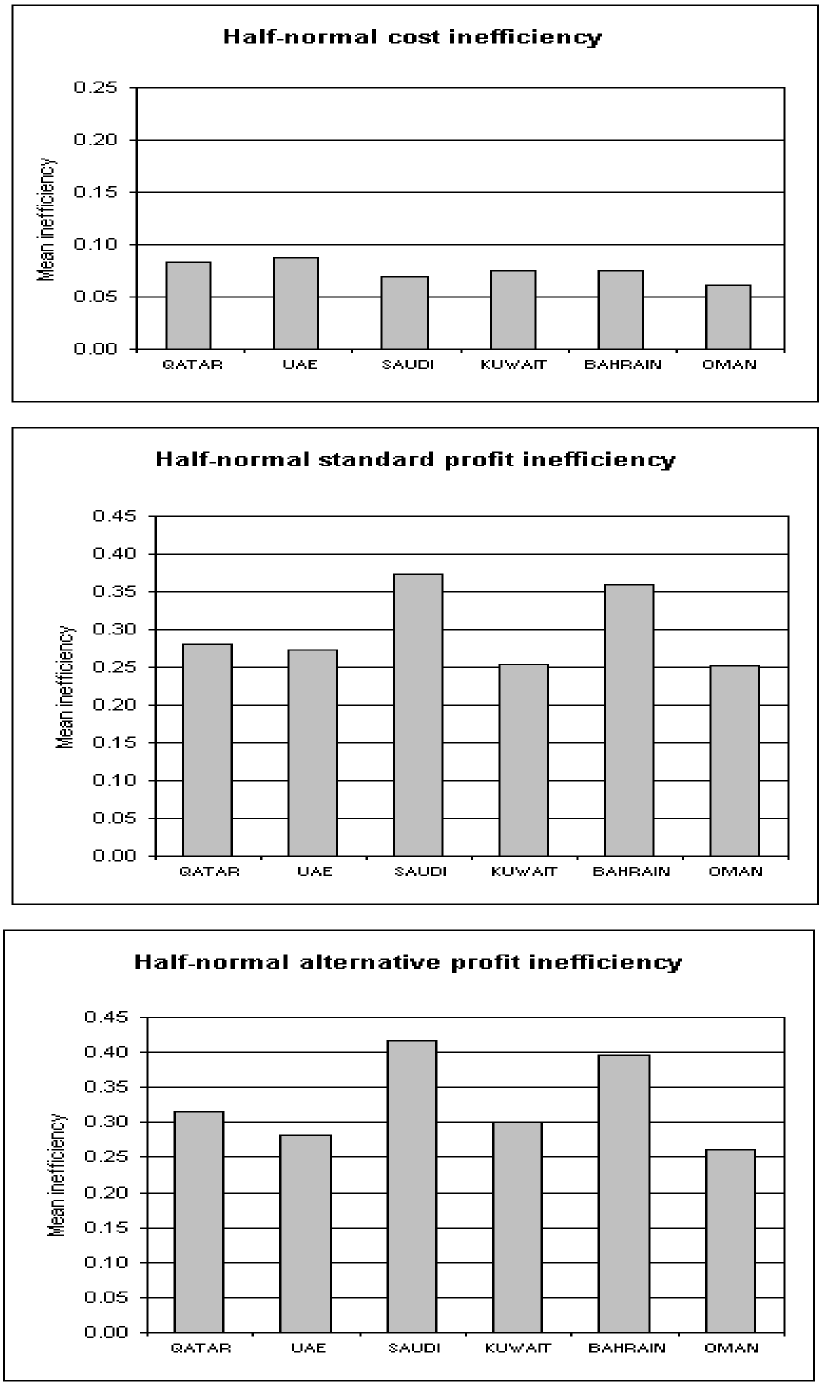
Regarding the efficiency comparisons across GCC countries, Figure 3 shows the mean inefficiencies for each country. These inefficiency measures are presented for the preferred Eq. (13) cost and profit inefficiencies estimated under the half-normal distribution.

In general, cost inefficiency estimates across GCC countries are more or less similar to each other. However, Figure 3 indicates that Omani banks appear to be the least cost inefficient (i.e. the most efficient), scoring a level of 7.1 per cent cost inefficiency. The next least cost inefficient banks are Saudi banks, with cost inefficiency levels of 7.9 per cent. Bahraini and Kuwaiti banks occupy the middle ground of GCC cost inefficiency with levels of 7.5 per cent. Qatari and UAE banks have been the most cost inefficient with cost inefficiency levels of 8.3 and 8.8 per cent respectively.

On the profit side, standard and alternative profit inefficiencies across GCC countries tend to vary. In general, Figure 3 shows that banks from Saudi Arabia and Bahrain are the most profit inefficient, with a profit inefficiency difference of at least 7 percentage points higher than for other GCC countries' banks.

Omani banks remain the least profit inefficient, while the rest of the GCC countries' banks fall in the middle positions. It may not be surprising that Omani banks are the least cost inefficient in the GCC banking industry, although the differences in inefficiency scores are relatively small between these countries. In addition, although the number of the Omani banks included in the sample is relatively small (6 banks), the Omani banking system witnessed the most active M & A (Merger and Acquisition) activity taking place in the GCC region over the study period, enabling Omani banks to show the highest cost and profit efficiency scores. These mergers have been stimulated by authorities' encouragements.

Figure 3 Cost and profit inefficiencies across GCC countries - Preferred model



The question why one country's banks are more cost or profit efficient than another can be related to the size of banks in a country. For instance, with reference to Figure 3, countries that have relatively small banks, such as the UAE and Qatar, tend to show higher cost inefficiency but lower profit inefficiency. On the other hand, banking industries that are dominated by larger banks, such as those in Saudi Arabia, Bahrain, and Kuwait, tend to show lower cost inefficiency but higher profit inefficiency. In fact, large banks may have lower cost inefficiencies because their per unit cost decreases as the scale increases. However, scale effects may induce profit inefficiency because large banks may face more difficulty in generating revenues efficiently. Berger and Mester (1997, p. 936) state that '[t]he cost and profit efficiency results together seem to imply that as banks grow larger, they are equally able to control costs, but it becomes harder to create revenues efficiently.' Moreover, this finding is consistent with the conventional fact that small banks typically have higher profitability ratios than larger banks. Having said this, however, the scale effects that induce profit inefficiency are unlikely to be large.

Economies of scale

Scale economies measure how a unit change in output affects total costs.[22] The economies of scale results shown in Table 7 are calculated for both the traditional and preferred specifications estimated using the half-normal models.

With reference to the cross-country scale economies comparisons, the results in Table 7 show that Saudi and Kuwaiti banks as realising scale economies over the period under study. Moreover, Bahraini banks experience constant returns to scale. However, UAE, Omani, and Qatari banks exhibit scale diseconomies.

[22] Scale economies are calculated using the following equation:

$$\begin{aligned} \textit{Scale economies} = \sum_{i=1}^{2} \frac{\partial \ln TC}{\partial \ln Q_i} &= \sum_{i=1}^{2} \alpha_i + \sum_{i=1}^{2}\sum_{j=1}^{2} \delta_{ij} \ln Q_j + \sum_{i=1}^{2}\sum_{j=1}^{2} \rho_{ij} \ln P_i \\ &+ \mu_i \sum_{i=1}^{2} \left[-a_i \sin(Z_i) + b_i \cos(Z_i) \right] \\ &+ 2\mu_i \sum_{i=1}^{2}\sum_{j=1}^{2} \left[-a_{ij} \sin(Z_i + Z_j) + b_{ij} \cos(Z_i + Z_j) \right]. \end{aligned}$$

If *scale economies* >1, < 1, or = 1, then there are diseconomies, economies of scale, or constant returns to scale respectively.

Table 7 Scale economies in the GCC banking industry - by country

	Half-normal	
	Traditional model	Preferred Eq. (13)
GCC	1.167	1.108
QATAR	1.288	1.222
UAE	1.228	1.166
SAUDI ARABIA	0.956	0.903
KUWAIT	0.924	0.886
BAHRAIN	1.072	1.027
OMAN	1.342	1.256

When risk and quality factors are taken into account, the preferred model again shows that Saudi and Kuwaiti banks exhibit scale economies at slightly higher levels. Bahraini banks are also close to unity, indicating constant returns to scale. UAE, Omani, and Qatari banks have not much been influenced by the introduction of risk and quality factors since these countries continue to exhibit scale diseconomies. In sum, closeness to unity of the scale estimates of banks in Saudi Arabia, Kuwait, as well as Bahrain may lead us to deduce that these countries' banks tend to show the range between economies and constant returns to scale, unlike banks in the UAE, Oman, and Qatar, that apparently show diseconomies of scale. Overall, on average, the sample shows that the GCC banking industry has been exhibiting scale diseconomies driven mostly by banks that belong to the GCC countries' exhibiting scale diseconomies (namely those in the UAE, Oman, and Qatar).

Logistic regression and efficiency correlates

This part of the paper examines the determinants of banking sector inefficiency in GCC banking systems over the study period 1995-2000. For this purpose, we use the logistic regression model, in which we regress inefficiency variables (cost inefficiency and profit inefficiency measures) on a variety of bank and market-specific variables that we believe are most likely to influence inefficiency levels.

As noted earlier, estimated coefficients of logistic regressions indicate relationships in terms of correlation rather than the power and size of impact or the causality relationship. The logistic regression model is preferred over the linear regression approach since the former is more appropriate to model the relationship between variables for which a dependent variable is bounded between zero and one, the range in which inefficiency scores fall.

In order to avoid double consideration of risk and asset quality variables when examining inefficiency determinants, the logistic model is estimated using inefficiency measures derived from the frontier estimation of the traditional model that does not incorporate equity and provisions. In addition, the estimates of inefficiency used here are for the traditional cost and profit functions estimated using the half-normal distribution.

As for the logistic parameters estimates, the results in Tables (8 and 9) show that the correlation between the cost and profit inefficiency measures regressed on the same set of the independent variables almost conform to expectations. [23]

Starting with the relationship between inefficiency and financial capital, in both cost and profit inefficiency determinants, the coefficient EQUITY is negative and is significantly different form zero. This indicates that banks with low inefficiency levels tend to hold higher levels of capital. Note that in our previous analysis in this section, we found that if we remove the capital variable from our preferred model, this results in a slight increase in the level of cost and profit inefficiency. This means that when financial capital is introduced in the model, it controls and takes into consideration the fact that banks with strengthened capital have a better cushion against risk and this

[23] Although R^2 has a low value, it is not an appropriate measure of closeness of fit in the context of logistic regressions (see Thomas, 1997).

seems to make them become more efficient. However, one must caution that this does not necessarily mean that efficient banks should always have higher capital and thus have lower risk (Mester, 1996). This is because higher levels of financial capital level may distort managers' incentives in a way that makes them keener to take riskier activities (moral hazard). Generally, in this analysis, the results suggest that more efficient GCC banks generate higher earnings, which are translated into higher levels of capital.

Table 8 The logistic regression parameter estimation

Dependent variable Cost inefficiency (CN)

Variable	Coefficient	Std. error	*T*-value
Constant	8.13E-02	7.71E-03	10.548
EIQUITY	-4.12E-08	1.33E-08	-3.108
ROA	-0.2483704	4.46E-02	-5.575
PROV	8.23E-02	4.27E-02	1.928
FOREIGN	2.59E-02	4.18E-03	6.203
LTA	-5.05E-02	8.63E-03	-5.857
FIX	2.42E-08	2.57E-08	0.943
TA	2.14E-09	1.35E-09	1.59
TBGDP	-3.45E-04	8.38E-04	-0.412
CN[-1][24]	0.4309832	3.61E-02	11.942
Durbin-Watson Statistic =	1.91243	Rho =	0.04379
Adjusted R-squared =	0.46058		
Observations =	558		

[24] The lagged dependent variable is used to remove auto-correlation.

Table 9 The logistic regression parameter estimation

Dependent variable	Standard profit inefficiency (SN)		
Variable	Coefficient	Std. error	*T*-value
Constant	0.2588479	3.13E-02	8.274
EQUITY	-2.66E-07	5.65E-08	-4.705
ROA	-1.006451	0.18616	-5.406
PROV	1.11E-02	0.18015	0.062
FOREIGN	8.52E-03	1.62E-02	0.527
LTA	-7.09E-02	3.53E-02	-2.005
FIX	-9.05E-08	1.08E-07	-0.838
TA	2.33E-08	5.74E-09	4.069
TBGDP	1.99E-03	3.53E-03	0.564
SN[-1][25]	0.5102705	3.46E-02	14.757
Durbin-Watson Statistic =	1.95567	Rho =	0.02217
Adjusted R-squared =	0.38476		
Observations =	558		

[25] The lagged dependent variable is used to remove auto-correlation.

The results also show that accounting profits (denoted as ROA) is negative and is significantly different form zero as well. The ROA coefficient in both cost and profit inefficiency regressions confirms that more efficient banks may be expected to achieve, on average, better accounting profits performance than less efficient banks. Therefore, this may underline the perception that more efficient banks can consolidate their capital through better profits performance, enabling them to accumulate higher capital, in turn making them less risky firms.

With respect to loan quality, both the cost and profit inefficiency dependent variables are positively correlated with the level of provisions (PROV); the PROV variable is significant at the 10 per cent level in the cost inefficiency regression but insignificant in the profit inefficiency regression. This positive correlation suggests that inefficient banks are forced by regulation to increase the level of provisions when their loans are facing defaults problems. In other words, a high level of provisions indicates loan quality deterioration and, as a result, inefficiency generally increases in response to the higher level of problem loans. This may also suggests that efficient banks with lower levels of loan provisions are better at evaluating credit risk (see Mester, 1996; Berger and Humphrey, 1997; Altunbas et al., 2000).

Turning to the issue of ownership, the binary variable FOREIGN shows a positive and statistically significant relationship with cost inefficiency but a statistically insignificant relationship with profit inefficiency. Taking at least the relationship between cost inefficiency and the variable FOREIGN, we infer that the existence of foreign banks has contributed to the inefficiency level in the GCC banking industry during the study period. In fact, regulatory restrictions on foreign bank business, such as restrictions on bank size, taxes, and bank branching, could also be the main factors inducing foreign banks to contribute to inefficiency in the GCC banking industry.

As for the rest of the control variables, the negative correlation between the loan to assets ratio (LTA) and the inefficiency levels indicate that banks with higher proportions of lending business in their balance sheets are more efficient. This result contrasts with previous studies' findings (for example, Altunbas et al., 2000, found a positive correlation between inefficiency and the loan to assets ratio in the case of Japanese banks). This result, however, may indicate that the GCC countries' larger banks have emphasized lending business during the second half of the 1990s in order to respond to market demand.

Moreover, total assets (TA), which approximates the size of a bank, shows a clearer relationship between bank profit inefficiency and bank size (than bank cost inefficiency and bank size). As we previously noted, large banks usually experience higher profit inefficiency than small banks, here, the statistically significant and positive relationship between TA and profit inefficiency indicate that as banks increase in size, their profit inefficiency increases. Nevertheless, this relationship is not evident in case of cost inefficiency since the TA coefficient is not significant, although its sign is positive.

Taken together, the main results from our logistic regression are that the strengthening of financial capital is a central element explaining bank efficiency in the GCC region. On the other hand, the erosion in loan quality reduces banking sector efficiency. Overall, the policy implication is that regulations in the region need to focus on building a safe and sound banking system with adequate and prudential rules, and this should ultimately feed into improved banking sector efficiency levels.

6. Conclusions

This paper empirically analyses the efficiency of the GCC banking sector over the period 1995-2000. It presents and compares the results using three efficiency concepts: cost efficiency, standard profit efficiency, and alternative profit efficiency.

The findings of the empirical analysis show that the level of inefficiency in the GCC banking industry ranges between 8 and 10 per cent for cost inefficiencies, and between 30 and 32 per cent for the profit inefficiencies. There are no major differences in banks efficiency levels among GCC countries. Moreover, the mean efficiency across countries shows almost a stable trend over the study period 1995-2000. With reference to the cross-country scale economies comparisons, the results show that Saudi and Kuwaiti banks are realising scale economies over the period under study. Moreover, Bahraini banks experience constant returns to scale. However, UAE, Omani, and Qatari banks exhibit scale diseconomies.

The findings show also that the risk and quality factors provide information influencing bank inefficiency levels when we use either the cost or profit function models. When risk and quality factors are considered, the mean inefficiency measures show a slight decrease. In the logistic regression, cost and profit inefficiency is found to be negatively related to risk. There is also evidence that inefficiency is positively related to loan quality variables, suggesting that banks with enhanced financial capital and high loan quality are more efficient.

Overall, the results suggest that greater consolidation in the industry could be encouraged between GCC banks. This may improve cost efficiency as costs are seen to decline with size. (While consolidation may increase profit inefficiency, these inefficiencies are unlikely to be much bigger than other sized banks). In essence, large GCC banks will be in a position to realise greater scale and X-efficiency. Moreover, larger bank size and levels of banking sector competition will help allay policy-makers fears concerning greater financial system openness. Moreover, GCC governments need to continue to implement financial reform packages that strengthen banking system soundness, foster banking competition, and also devise incentive schemes to improve managerial efficiency in order that GCC banks are better placed to meet the challenges of greater openness.

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