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by

Wai Ho Leong, Brian Dollery and Tim Coelli

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Abstract

Although considerable effort has been invested in the measurement of financial institution efficiency, hardly any empirical research has focussed on the properties and consistency of efficiency rankings derived from the data envelopment analysis (DEA) methodology. Following the seminal work of Bauer, Berger, Ferrier and Humphrey (1997), this paper employs data on Singaporean banking for the period 1993 to 1999 to develop efficiency scores and rankings for Singapore banks. It then invokes the five consistency conditions developed by Bauer et al (1997) to examine these scores and rankings. Our approach allows researchers to experiment with different models and select the most appropriate model for policy purposes.

Key Words:data envelopment analysis; bank efficiency; consistency conditions

** Wai Ho Leong, Department of Economics, University of Melbourne Brian Dollery School of Economics, University of New England and International Graduate School of the Social Sciences, Yokohama National University and Tim Coelli School of Economics, University of New England. Contact information: School of Economics, University of New England, Armidale, NSW 2351, Australia. Email: bdollery@metz.une.edu.au.

MEASURING THE TECHNICAL EFFICIENCY OF BANKS IN SINGAPORE FOR THE PERIOD 1993 TO 1999: AN APPLICATION AND EXTENSION OF THE BAUER *Et Al* (1997) TECHNIQUE

1. Introduction

Over the past two decades, the measurement of financial institution efficiency using non-parametric frontier models has received considerable attention. However, while the literature on the application of data envelopment analysis (DEA) to the area of bank efficiency measurement is burgeoning, research on the salient properties of efficiency scores as a tool of policy is comparatively rare. The paucity of empirical research in this key area seems perplexing, especially when one recognises that policymakers need accurate assessments about the effects of their decisions on the institutions they supervise.

Only two studies have been identified to date within this tradition of the bank efficiency measurement literature. The first is Bauer, Berger, Ferrier and Humphrey (1997), which specified a formal set of conditions that efficiency rankings derived from various frontier methods should meet in order to be useful in a policy role. The second is Barr, Killgo, Siems and Zimmel (1999), which attempted to investigate the properties of DEA efficiency scores by studying the relationship between these scores and traditional measures of bank performance. It is surprising that DEA researchers elsewhere have not paralleled these developments in their work on efficiency measurement in financial services. In order to rectify this neglect, this paper attempts to examine the characteristics of DEA scores empirically, drawing on the approach of Bauer et al *(1997), using three alternate DEA specifications and Singaporean bank data for the period 1993 to 1999.*

Singapore has moved decisively to liberalise the banking sector, which until the financial crisis of 1997-98, was relatively sheltered from international competition. The Committee on Banking Disclosure *recommendations, which came in the wake of the crisis in 1998, was an important part of the financial reforms aimed at making Singapore a world-class financial centre.*

The success of these initiatives will determine whether Singapore is to remain a destination of choice for global investors. Nonetheless, with further freeing of trade and services imminent, it is clear that the current emphasis on microeconomic reform will continue. Key aspects of these reforms include those concerning comparative performance assessment and process benchmarking, optimum scale size and the impact of consolidation. The need for the application of improved productivity measurement in the realms of financial services is indisputable, especially as the interest in efficient outcomes has grown with the magnitude of the resources involved and the increasing national emphasis on microeconomic reform.

The paper itself is divided into seven main sections. Section 2 seeks to provide a synoptic overview of the empirical measurement of bank efficiency. Section 3 deals with the perplexing problems associated with defining bank output. The question of the determinants of bank efficiency is examined in section 4. Section 5 discusses the institutional characteristics of the Singaporean banking system. The research methodology is outlined in section 6 and section 7 analyses the results obtained from the estimation procedures. The paper ends with some brief concluding comments in section 8.

2. The Empirical Measurement of Bank Efficiency

The literature on financial institution efficiency is comparatively recent but nevertheless growing apace. In a comprehensive review of 130 DEA studies on bank efficiency across 21 countries, Berger and Humphrey (1997) showed that 116 scholarly papers were published between 1992 and 1996 alone. Research on financial institution efficiency is dominated by studies from the American institutional milieu, where the large number of banks has traditionally facilitated econometric modelling (Avkiran, 1999). The vast majority of these studies have focused on the cost effects of scale and scope economies.

Nonetheless, despite the volume of research in this area, there is still no consensus on the best method for measuring efficiency in financial institutions. At least four different approaches have been employed to date. These are the econometric (stochastic) frontier *approach, the thick frontier (TFA) approach, the distribution-free (DFA) approach and the linear programming (DEA) approach.*

Ferrier and Lovell (1990) evaluated the relative strengths of the econometric (stochastic) and linear programming techniques in the context of efficiency measurement. While they found that the DEA frontier enveloped the data more closely than a stochastic frontier, the magnitude of inefficiency reported by DEA was lower. Moreover, the rank correlation between both sets of technical inefficiency scores was not statistically significant.

These differences were attributed to three factors. First, if DEA reports noise as inefficiency, then random events may confound the efficiency ranking of a given sample. Second, imposing a parametric structure on the distribution of inefficiency will blend specification error with inefficiency. Hence the econometric approach may also potentially corrupt efficiency rankings. Finally, by incorporating categorical variables, the DEA approach may place observations in a small number of select categories, thus generalising inefficiency across non-homogeneous classifications.

The DFA assumes that the random error component will cancel out over time when panel data is used. This implies that the estimated average residual may be an appropriate measure of inefficiency (Allen and Rai, 1996). Based on a sample of international banks, Allen and Rai (1996: 670) found that "DFA overestimates the magnitude of X-inefficiencies relative to the stochastic frontier approach".

The TFA developed by Berger and Humphrey (1991) represented one way of avoiding the restrictive assumptions required in conventional approach to the estimation of cost efficiency. TFA holds that the lowest average cost quartile of firms is of greater than the average efficiency, while the reverse is true for the highest average cost quartile. Bauer, Berger and Humphrey (1993) found that the levels of bank inefficiency established were reasonably consistent on the basis of the stochastic frontier and thick frontiers, although the rankings of individual banks differed significantly.

3. The Definition of Bank Output

One of the main difficulties in the measurement of bank output is that there is no consensus in the literature on how to define or measure these services. Broadly speaking, bank output should also include the portfolio management and advisory services that international banks typically provide to depositors while acting as their intermediaries. The absence of an explicit price also causes significant complications in the measurement of financial services. Without an explicit price, economists must impute their value. While we generally regard banks as producers of financial services in this paper, not all financial services constitute output. More specifically, the role of the financial products in the context of banking operations should first be considered.

A fundamental difficulty arises in the treatment of bank deposits. Considerable debate in the literature surrounds the input-output status of deposits. Traditionally, deposits are regarded as the main ingredients for loan production and the acquisition of other earning assets. On the other hand, high value-added deposit products, like integrated savings and checking accounts, investment trusts and foreign currency deposit accounts, tend to highlight the output characteristics of deposits. Indeed, high value-added deposit services are an important source of commissions and fee revenue for specialised commercial banks such as trust and private banks. In the context of these specialised institutions, one cannot afford to ignore the output nature of deposits. Deposits are "therefore simultaneously an input into the loan process and an output, in the sense that they are purchased as a final product providing financial services" (Griliches, 1993: 222) to varying extents.

Extending this argument further, one might further contend that the classification of deposits should therefore depend on the structure and characteristics of banks in the representative sample and viewed in the regulatory context of the country in question. For example, since the magnitude of high value-added deposits is relatively small compared to time and savings deposits in Singapore, there may be more reason to regard deposits as inputs in these circumstances. Moreover, given that most foreign bank branches operating in Singapore are restricted in their ability to accept Singapore dollar deposits[i], their revenue share of interest-bearing loans far exceeds that of deposit services.

Three main approaches have been developed to define the input-output relationship in financial institution behaviour in the literature. Firstly, the production approach *(Sherman and Gold, 1985) views financial institutions as producers of deposit and loan accounts, defining output as the number of such accounts or transactions. This method usually defines inputs as the number of employees and capital expenditures on fixed assets. Second, the* intermediation approach *(Berger and Humphrey, 1991) stems directly from the traditional role of financial institutions as intermediaries that convert financial assets from surplus units into deficit units. Operating and interest costs are usually the major inputs, whereas interest income, total loans, total deposits and non-interest income form the principal outputs. Third, the* asset approach *recognises the primary role of financial institutions as creators of loans. In essence, this stream of thought is a variant of the intermediation approach, but instead defines outputs as the stock of loan and investment assets (Favero and Papi, 1995).*

The principal criticism of the production approach lies in its exclusion of interest costs and an overemphasis on the role of staff costs and rental costs in defining inputs. This appears to neglect the banking sectors traditional function as distributors of funds. Moreover, interest costs are a major expense to any bank. For instance, among the banks in our Singaporean sample, interest expenses typically represent some 60-75% of total costs on average.

Perhaps this is why the intermediation approach seems to have dominated empirical research in this area. A strong supporting factor appears to lie in adaptability – categories of deposits, loans, financial investments and financial borrowings may be assigned to either inputs or outputs by discretion, on the basis of a priori *reasoning alone (Colwell and Davis, 1992). A similar idea was advanced by Hancock (1991), who noted that category choices by researchers remained contentious: there appeared to be no mechanism within either the intermediation approach or the asset approach to determine the issue empirically. For empirical resolution, she suggested a "user cost of money" approach, which defined bank services as inputs or outputs simply according to the sign of its derivative in a bank profit function, which could be easily estimated. However, critics have* *argued that such methods are arbitrary and represent the sacrifice of conceptual purity on the altar of empirical convenience.*

Other approaches to the measurement of bank activity incorporate risk management, adverse selection and information asymmetry into the neoclassical theory of the firm. The latter stream of thought was inspired by Leland and Pyle (1977), who showed that information asymmetry – whether ex-ante *(adverse selection) or interim (moral hazard) - gave banks incentive to develop information-sharing coalitions in order to improve on imperfect market outcomes by providing cross subsidisation within these coalitions.*

4. Determinants of Bank Efficiency

It is often argued that competition induces managers to operate as closely as possible to the production frontier and encourages transparency in financial stewardship. These insights derive from Hayek (1945), who argued that under uncertainty and asymmetric information, competitive pressures are the most effective way of fostering productive efficiency. However, Fecher and Pestieau (1993), in their study of OECD financial services, noted that while it seemed that competition did indeed drive efficiency, it was not at all clear that in the process of deregulating the economy and increasing its competitiveness, efficiency always increased monotonically.

Applied to the realm of international banking, the problem of identifying causal factors of efficiency becomes more daunting. Characterised by globalisation, banks are continuously trying to find ways to diversify income, while keeping capital intensity as low as prudently possible. The drive to achieve optimal business diversification has also fuelled mergers and acquisitions. In emerging markets, the combination of systemic stress and regulatory reforms adds more weight to this trend. Against this backdrop, four factors seem to influence bank efficiency: agency problems, structure of regulation and organisation, effective risk management, and size and technology.

A number of studies have examined the agency problem. For example, Pi and Timme (1993) examined empirical evidence revolving around the impact of the disjunction between ownership and control in US commercial banks. They found that banks with the *chairman of the board and the chief executive officer (CEO) held by the same person were generally less efficient. It was only through mechanisms that dispersed the concentration of authority, such as CEO stock ownership, outside institutional ownership and board membership, that this effect was mitigated.*

Second, regulatory and institutional factors may also affect efficiency. As Berger, Hunter and Timme (1993: 243) have observed: "It seems likely that regulation has also had effects on efficiency by influencing a financial institution's organisational structure. For example, both state and Federal agencies regulate depository institutions' ability to operate branches, and engage in non-bank activities, such as investment banking". Some studies have been undertaken where the regulatory structure has varied significantly across the sample in question. For instance, Ferrier and Lovell (1990) analysed a sample consisting of several different types of deposit-taking institutions, including commercial banks, savings and loans, and credit unions. Other researchers have tried to account for differences in regulation within a single institutional type, like Fecher and Pestieau (1993), who examined technical efficiency variations in banks across five OECD countries.

The third factor relates to the impact of risk management practices. In the face of informational asymmetry, successful identification of risk can enable banks to determine effective protection strategies against unanticipated losses. A balanced risk-reward profile may lead managers to greater competitive flexibility in terms of pricing, capital allocation and business strategy. By fostering good investor relations, easier access to capital markets and a lower cost of capital, these factors may reflect higher operating efficiency.

Finally, size and technology are also important considerations. Research by Ferrier and Lovell (1990) on a sample of 575 US commercial banks found that 88% exhibited increasing returns to scale (a result which supports our choice of the VRS variant of the DEA model). Moreover, scale economies were found to confer only a small cost advantage to large banks. They found that allocative inefficiency stemmed largely from the excessive use of labour and an under-utilisation of capital. Somewhat surprisingly, the most efficient banks in the sample belonged to the smallest size class. This was attributed to the *successful application of technology, which allowed smaller banks to overcome capital cost disadvantages and distribute products more effectively.*

5. Institutional Characteristics of Singaporean Banking

With the inception of the Monetary Authority of Singapore (MAS) in 1970, the government introduced fiscal incentives, removed exchange controls and encouraged competition among banks to spur financial sector development. In addition, migration requirements for expatriate executives were substantially lowered to enrich the pool of banking talent. Moreover, a large number of foreign banks were also permitted entry into Singapore.

Singapore has moved decisively to liberalise the banking sector, which until the financial crisis of 1997-98, was relatively sheltered from international competition. The *Committee on Banking Disclosure* recommendations in 1998 aimed to raise the standard of financial disclosure closer to European and US standards. In 1998, for the first time banks disclosed doubtful loan provisions classified into specific and general, loan portfolio by industry, current market values of investments, sources of revenue and expenses, and details of off-balance sheet transactions.

Since these regulatory changes, markets for securities, derivatives and foreign currencies, which provide services for Singapore and the ASEAN region, have become better developed. As at July 1999, there were a total of 141 commercial banks, of which 132 were regional branches of foreign banks. This compared with only 99 commercial banks in 1981. Three types of commercial banks operate in Singapore, depending on the type of licence they possess. Out of the 141 banks in 1999, 34 were full-licence banks (of which only 5 were locally incorporated), 23 were banks with restricted licences[ii], and 92 had offshore licences. Another 80 merchant banks provide services not covered by commercial banks, including asset management, equipment leasing, factoring and underwriting.

6. Methodology

Commercial banks operating in Singapore for the period 1993 to 1999 form the population for this study. Our empirical approach may be described in two stages. First, relative *technical efficiency scores from three alternate DEA model specifications will be used to rank our sample of 35 major banks. In the second stage, the implied rankings from the results will then be tested under the five specific consistency conditions developed by Bauer et al (1997).*

In order to build a sample representative of the industry, banks were carefully selected on three criteria. Firstly, the sample was restricted to locally-incorporated commercial banks and foreign banks with full, restricted and offshore licenses. Using industry statistics compiled by the KPMG (1997) Survey of Financial Institutions, *we were able to filter out smaller merchant banks, finance companies and other financial institutions with different operating characteristics. Secondly, only commercial banks focused on the corporate lending markets were selected. Finally, only the largest players within these categories, where archival data was available from the official* Registry of Companies, *were chosen.*

The resulting sample accounted for over 60% of total banking assets in 1999. More importantly, bank size in terms of total assets in our sample ranged from S$1.9 billion to S$106.4 billion. This wide variance will facilitate more accurate analysis of the correlation between observed efficiency and institution size. There were two main reasons for not enlarging the sample further. First, the 35 banks chosen already account for a significant portion of industry assets. And second, significant variation between the size of the largest banks and the smallest banks had been achieved. Put differently, the marginal cost of enlarging the sample further began to exceed marginal benefit significantly beyond this point.

Audited financial statements[iii] of banks in our sample were purchased from the *Registry of Companies and Businesses* in Singapore. All accounts were prepared under the historical cost convention in accordance with the Companies Act and compliance standards of the MAS. From these statements, it was possible to collect data on two main input variables (deposits and fixed assets) and two output variables (loans, risk-weighted assets) for the period 1993 to 1999. Since data were archived on microfilm, the collection process proved excessively time consuming.

Two additional assumptions are imposed. First, the measured coefficient or implied distance from the best practice efficient frontier reflects technical efficiency. Second, we assume variable returns to scale (VRS) in the banking industry (Banker, Charnes and Cooper (1984))[iv]*.*

Three models were employed. We label these as Models A, B and C. Model A, which regards banks as optimisers of interest income and other income subject to interest expenses and other expenses, would have been our model of choice (see Table 1). Unfortunately, only two years of data are available for this model. Until the new disclosure laws in 1998, foreign bank branches operating in Singapore were not required to file interest expense, operating expense and interest income in their annual financial statements: the convention in the earlier years was simply to aggregate all income as total turnover. This meant that data categories like interest income and interest expense for most of our sample were not publicly available prior to 1998.

A "second-best" specification is Model B, which has one output variable (loans) and two inputs (deposits and fixed assets). To ensure comparability in financial data in 1993 and 1994, minor accounting reclassifications were made to reconcile the differences in the manner banks reported their earnings. Details of both models are summarised in Table 1.

[Table 1 here]

Operating expenses are defined as total costs less interest expenses, while operating income is given as net interest income plus non-interest income. We define shareholder's funds as the sum of common equity, share reserves and retained earnings; less intangible assets, asset revaluation reserves and equity in unconsolidated subsidiaries; plus minority interests, preference shares issues and other hybrid capital instruments.

As more financial services are moved off the balance sheet, the traditional measures of on-balance sheet outputs that have been used to evaluate banking performance and efficiency fail to capture banking activities occurring off the balance sheet. Put differently, the output variables used in conventional DEA models (like Models A and B) do not reflect the growth of off-balance sheet (OBS) services.

This leads us to the risk-weighted DEA approach, which models bank output explicitly in terms of risk-weighted assets[v]. Risk-weighted assets include OBS items that conventional output variables, such as loans, fail to capture. By weighting different asset classes by risk, the entire spectrum of revenue-generating assets can be included in the model. It is thus of considerable interest to observe how DEA scores reported under this methodology will differ from those obtained under conventional approaches. In this regard, an examination of the consistency and properties of DEA scores derived from different methods is crucial.

In accordance with the Basle convention, assets are weighted according to their inherent level of risk. Five weights - zero, 10%, 20%, 50% and 100% - are assigned to five broad asset classes. Relatively risk-free assets like cash, claims on sovereigns, central banks and OECD governments are assigned zero weighting. Securities issued by governments are assigned a 10-20% weight, depending on the residual time to maturity. Similar weights apply to loans guaranteed by multilateral agencies, public sector agencies and sovereigns.

Claims on the private sector with a residual maturity of over one year, both in the form of commercial loans and securities, are assigned 100% weights on account of relative credit and investment risk. Full-risk weights also apply to business premises, real estate, investment securities (corporate shares and bonds) and other fixed assets.

Contingent liabilities that substitute for loans, like general loan guarantees, bank acceptance guarantees and standby letters of credit for loans and securities, carry a 100% risk weight. Transaction and trade-related contingencies (such as bid bonds, warrants and credits collateralised by shipment performance bonds), however, will receive a lower 20-50% weight, depending on tenure. Shorter-term commitments or commitments which can be unconditionally cancelled at any time carry only low risk and therefore a nil weight.

[Table 2 here]

In Model C presented in Table 2, risk-weighted assets are explicitly regarded as the sole bank output, while inputs are represented by deposits and fixed assets (as in Model B). From the same set of audited financial statements, it was possible to calculate risk weighted assets for banks in 1993, 1994, 1998 and 1999, thus enabling us to track efficiency changes over the same reference period as before.

Model C represents a distinct improvement over Model B for three main reasons. Firstly, risk-weighted assets are a better output proxy than loans as the former include OBS items. Relative efficiency is likely to be significantly different when we take into account potential economies of scope between the swaps and forward books. Second, since risk-weighted assets encompass the entire spectrum of a bank's earning assets (e.g. securities, loans, investments and OBS items), Model C offers a more realistic abstraction of the bank's revenue function than either A or B. Thirdly, using risk-weighted assets instead of interest income or non-interest income as an output proxy allows us to avoid the problem of variations in product prices across banks. This is obviously an area of concern for Model A.

7. Discussion of Results

This study is neither an attempt to replicate the complex relationships embedded within a bank's production function, nor an effort aimed at creating an international comparison of efficiency. Rather we aim to investigate whether the nature and extent to which DEA-type analysis in its current state can supplement traditional measures of bank performance and function effectively as a tool of policy for industry regulators. Using alternate DEA model specifications and Singaporean data, this can be achieved by evaluating the salient characteristics of the derived DEA scores and rankings as a measure of efficiency over time. In order to investigate this largely unexplored area, material will be drawn from two related empirical contexts.

The empirical approach revolves around a central theme. Efficiency scores obtained from three separate DEA models will be analysed in terms of five specific conditions developed by Bauer et al (1997) in their research on measured efficiency derived from different frontier methods. Generally, if implied efficiency rankings behave consistently over time, identify best practice banks consistently and portray market reality, then this indicates robustness in the methodology.

The three DEA model specifications set out in Tables 1 and 2 have been estimated using the sample data. Descriptive statistics are presented in Figure 1 and Table 3 respectively. The results are analysed in terms of the five specific conditions of Bauer et al (1997). The first three conditions compare and measure the degree to which derived rankings from different models are consistent with each other. The remaining conditions assess the stability of measured efficiency over time and the ability of different models to identify the same "best-practice" institutions.

[Figure 1 here]

[Table 3 here]

Relationship between Efficiency Rankings and Industry Conditions*The seven-year range of this study encapsulated significant changes in the Singapore economy, during which Singaporean banks experienced both difficult and profitable operating periods. 1993-1996 marked a period of robust growth in financial services output, followed by the "down" years of 1997 and 1998 and resurgent growth in 1999.*

All the models related well to competitive conditions in the banking industry. In Figure1, both A and C identified 1997 as the year with the lowest scores (averaging 0.2[vi]), when credit market conditions in the region deteriorated rapidly. All three models painted a consistent picture of steadily rising efficiency scores between 1997 and 1999. Model A reported a more modest improvement in efficiency scores than B or C between 1998 and 1999. We attribute this to the keener competition in the market, which generally meant that *net interest margins were being compressed. Due to the variables used, this affected Model A to a greater extent than models B and C.*

Moreover, the trends in scores reported by models B and C in Figure 1 appear to be mutually consistent in the period 1996-99 and related by time lags in 1993-95. Model B, which measures output by loans to non-bank customers, reports a sharp increase in mean efficiency scores in 1994, when credit conditions were buoyant. By contrast, Model C uses risk-weighted assets, which captures a broader spectrum of earning assets, including newer fee-based financial services occurring off the balance sheet. It is possible that OBS activities can explain much of the differences in reported efficiency scores in Models B and C between 1993 and 1996, although we lacked reliable data for a more detailed examination.

Comparing Efficiency Distributions With Each Other

Mean scores from models B and C averaged 0.38, significantly below the 0.53 reported by Model A. Part of this difference may be explained by the fact that Model A was based on a different time period due to the nature of the data. Skewness and kurtosis coefficients in Table 3 also indicate significant differences in the distribution of efficiency scores reported by Model B with the other two models. It is interesting to note that the average standard deviation of scores from B and C (0.16) are less than half that of Model A (0.35). On the other hand, the trends reported by B and C, which are closer in dimensions and variables, were also more consistent with each other.

The trends shown in Figure 1 also illustrate how mean efficiency scores from alternate model specifications can vary. These results concur with Avkiran (1999), who noted that derived DEA scores are sensitive to changes in input and output variables. The lack of consistency between alternate models can create problems for policymakers. More importantly, it underlines the importance of robustness checks and the need for DEA users to experiment with alternative specifications and variables.

Rank-Order Correlation of the Efficiency Distributions

As Bauer et al (1997) observed, the ordering of banks implied by the efficiency scores is usually of greater concern and usefulness to policymakers than the efficiency scores per se. *It is therefore desirable that efficiency scores generated by different models rank institutions in a* fairly *consistent fashion over time.*

We calculated the Spearman[vii] *rank-order correlation coefficients (r_s) to determine how close the implied rankings of banks are among each of the three DEA models for the given sample. The ranking for each model is based on the mean efficiency score derived for each bank in our sample over the seven-year period. The r_s is essentially a measure of association derived from the ranks of the observations between two series. A value of r_s = 1 (or –1) indicates perfectly positive (negative) rank-order association, whilst $r_s = 0$ indicates that no association exists (Kvanli, Guynes and Pavur, 1986).*

The matrix of rank-order correlation coefficients is presented in Table 3. A coefficient of 0.28, which is statistically significant at the 5% level, suggests that efficiency rankings implied by scores from Models B and C are fairly consistent with each other. In our view, one can accept differences in rankings between different models, if the association coefficient between them is at least statistically significant at the 5% level. We would thus be very surprised if rankings from two different models were perfectly or strongly related.

It is also noteworthy that the rank-order implied by scores from Model A correlates inversely with Models B and C, albeit with quite significant non-zero coefficients. As discussed earlier, one possible explanation might relate to the differences in model dimensions and variables used. On the other hand, average efficiency scores for Model A are based on only two years of data (compared to seven years for B and C) and thus may not reflect the similar diversity of economic climates and industry conditions implicit in the other scores. In this regard, Model A is therefore not strictly comparable with B and C.

Stability of Measured Efficiency Over Time

Baur, Berger, Ferrier and Humphrey (1997) proposed a measure to test the stability of measured efficiency over time. In other words, it was unlikely for a very efficient bank in one year to be ranked inefficient in the next period. This implied that measured efficiency *had to be reasonably stable over short periods of time in order to be useful for regulatory policy purposes. For instance, if it is thought that the policy implementation lags require three years to take effect, then the three-year apart average correlation is the best indicator as to whether the policy will hit the intended banks (Baur, Berger, Ferrier and Humphrey, 1997).*

More specifically, this process involves calculating the average Spearman rank-order correlation coefficients of efficiency scores reported by each DEA model between each pair of years *to determine its ability to report stable scores over time. If n represents the number of years in the study period, then average coefficients will be calculated for pairs of years from one to n-1 years apart. In this fashion, the relative stability of measured efficiency of each model may be compared. The average Spearman coefficients of t-year apart efficiency scores for Models B and C are presented in Table 4.*

[Table 4 here]

The results indicate generally lower levels of rank correlation (-39% to 14%) between the 38 pairs of years measured than the (16% to 76%) range reported in Bauer et al (1997)[viii]. Only 14 of these correlation coefficients were significantly non-zero at the 5% level. Like the US study, we also observed a tendency for coefficients to decline as the years apart increased. Taken together, our results imply a greater tendency for efficiency rankings to change relatively quickly over time.

One factor for this is that the seven-year span of our study period encapsulates both rapid and significant changes in economic conditions, in which Singapore banks experienced both extremely difficult and highly profitable operating periods. It is likely that these circumstances could have induced larger variations in the rankings of institutions over a relatively short space of time, thus resulting in weaker correlation coefficients than those obtained in North America.

Identification of Best-Practice Banks

Even if different models do not produce consistent rank orderings, they are still useful as policy tools if they are consistent in identifying the same "best-practice" or peer institutions. Rankings of banks in our sample based on average efficiency scores over the study period are summarised in Table 5. Of the nine best banks (the top quartile) identified by Model B, four (44.4%) are also ranked in the top quartile of Model C[ix]. Nearly all the rest are ranked in the second quartile of Model C. One fell short of the second quartile in Model C, but by only one slot. These findings suggest that both models (B and C) are generally able to identify the same efficient banks.

[Table 5 here]

On the other hand, the efficiency rankings from Model A are seen to differ quite significantly from both models B and C. This may be explained by the differences in the variable structure of the models. Model A is based on interest income and expense variables, which differ significantly from the balance sheet variables used in models B and C. Moreover, models B and C are generally similar in terms of variable structure. Put differently, the derived efficiency rankings are sensitive to variable changes.

Various shortcomings of our empirical study should be mentioned. Despite our best efforts, data constraints remained the largest impediment to the study. For instance, a broader and deeper sample base would have enabled us to experiment more rigorously with a larger number of alternative DEA model specifications. Limited by a maximum size of 35 observations in each of the seven annual cross-sections, a 1x2 functional form seemed appropriate. While shortcomings have been alleviated by our usage of novel OBS-inclusive variables like RWA, we would also have liked to expand Model C into a larger functional form, incorporating income statement variables, like interest income and interest expense, with risk-weighted assets. Unfortunately, public access to key income statement variables only became available after 1998. Not only should these general refinements result in smoother trends in the quartile-based studies, but we also expect to attain rank distinction in the quartile-based analysis with the same regularity that US-based researchers using large samples have been able to achieve.

Another concern relates to the inclusion of non-performing loans (NPL), which could potentially have significant impact on calculated efficiency scores and implied rankings. Based on the time trend of aggregate NPLs in the banking system, this impact is likely to be most apparent between 1997 and 1999.

A possible extension to this study is the Malmquist DEA technique, which uses pooled time series data to calculate changes in total factor productivity (TFP), technological effects, technical efficiency and allocative efficiency. Färe et al (1994) extended the Malmquist index of the TFP growth approach to illustrate how component distance functions can be estimated using DEA-like formulations. The resulting TFP indices could be decomposed into technical change and technical efficiency change components. Nonetheless, this represents a significant departure from our stated objectives, which focused on examining the salient properties of DEA efficiency scores.

8. Concluding Remarks

In summarising the results of the analysis of Singapore bank efficiency, several points should be emphasised. We evaluated DEA efficiency scores for banks obtained from three separate models in terms of five robustness tests developed by Bauer et al (1997). On the whole, the derived efficiency scores are reasonably consistent with competitive industry conditions, in identifying best-practice banks and across alternative DEA specifications. In terms of consistency over time, our results are somewhat less compelling than those obtained in Bauer et al (1997), suggesting there may be problems in drawing policy conclusions directly from any one model specification or approach. However, one should also take into consideration size limitations in the data set and rapid changes in economic climate over the study period.

While it is imperative that users understand its limitations, DEA models can offer much potential for a significant advance in the comparative analysis of financial institutions by enabling the concurrent study of the multiple variables that affect bank efficiency over time. DEA models could be employed to develop industry monitoring tools using time series data for policy inference and performance evaluation. For industry analysts, DEA offers a *multifaceted ranking methodology for benchmarking based on* a priori *economic reasoning, i.e. the efficiency measurement insights of Farrell (1957). This represents a significant improvement over traditional single ratio-driven rankings. In the absence of superior ranking alternatives, we are obliged to adhere to the present DEA methodology, given our data limitations, if only by necessity and not by choice.*

The present study sought to add to the literature surrounding microeconomic efficiency measurement in the banking industry in four main ways. Firstly, this study is the first empirical analysis of the nature of efficiency rankings of financial institutions using the DEA approach in Singapore. Moreover, in using a seven-year series of cross-sectional data, it examined the questions posed with regard to the significance and tenure of technical efficiency in banking.

Second, by investigating three different DEA model specifications and alternative means of incorporating contextual information into these analyses, the present study has also gone some way in addressing the limitations in our data set and the lack of consensus in the literature over what bank inputs and outputs should be.

Third, by incorporating risk-weighted assets in the model, our results capture the effects of off-balance sheet assets. This provides a more realistic abstraction of reality, since OBS can and typically do exceed on-balance sheet assets at major international banks.

Finally, the empirical approach undertaken in this study provides a useful framework for evaluating the consistency of different DEA model specifications and frontier efficiency methods used in efficiency measurement. By providing more information on the characteristics of different models, this framework might facilitate research design and variable specification. This allows the user to experiment with a number of alternative models and select the one that behaves according to a priori *expectations.*

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TABLE 1: VARIABLES USED IN DEA MODELS A AND B – VRS DEA variants			
MODEL A (2 inputs, 2 outputs)		MODEL B (2 inputs, 1 output)	
Inputs	Outputs	Inputs	Outputs
Interest Expenses Operating Expenses	Interest Income Other Income	Deposits Fixed Assets	Loans
Data Years Available: 1998, 1999		Data Years Available: 1993-1999	

TABLE 2: VARIABLES USED IN DEA MODEL C	
Inputs	*Outputs*
Deposits *Fixed Assets*	*Risk Weighted Assets*
Aim: Cross-temporal Comparison *Reference Years: 1993, 1994, 1998, 1999*	

Table 3: Descriptive Statistics for the Average Efficiency Scores By DEA Model

	Model C	*Model A*	*Model B*
Mean Score	0.437	0.533	0.332
Standard Error	0.023	0.064	0.030
Median	0.436	0.512	0.302
Standard Deviation	0.133	0.352	0.178
Sample Variance	0.018	0.124	0.032
Kurtosis	0.752	-1.465	-0.553
Skewness	0.684	0.090	0.798
Range	0.598	0.987	0.600
Minimum	0.221	0.014	0.128
Maximum	0.819	1.000	0.728
Sample Size	35	30	35

Spearman Rank-Order Correlation

	Model C	*Model A*	*Model B*
Model C (2x1)	1.00	-	-
Model B (2x2)	- 0.69	1.00	-
Model A (2x1)	0.28	- 0.34	1.00

Notes:

1. Models B and C - Efficiency scores are calculated using 7 years of data for 35 observations and the descriptive statistics are based on the average efficiency for each bank over the study period
2. Model A – Efficiency scores are calculated using 2 years of data for 30 observations and the descriptive statistics are based on the average efficiency for each bank over the two-year period

Table 4: The Persistence of Efficiency – Correlation of t-year Apart Efficiencies						
	1Year Apart	2 Years Apart	3 Years Apart	4 Years Apart	5 Years Apart	6 Years Apart
Model B	0.10	0.02	0.08	-0.11	0.03	0.04
Model C	0.14	0.11	0.06	0.04	-0.38	-0.39

Notes:

1. Each entry in the table is the mean Spearman correlation coefficient of the n-year apart efficiencies for a particular model within the 7-year span. For example, the 1-year apart category include 6 correlation pairs - 1999-98, 1998- 97 and so on. The value of 0.10 for this category is thus the mean of the six coefficients.

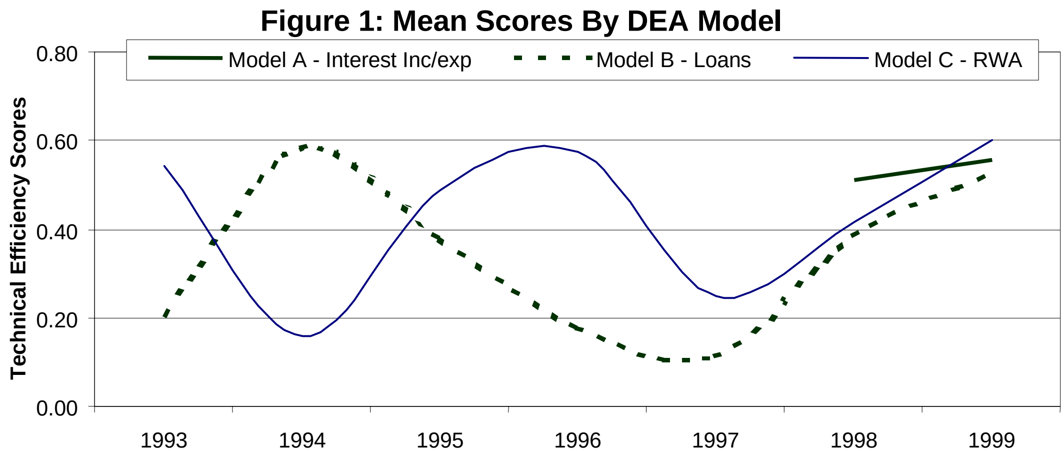
2. Model A is excluded since there are only two years of data.

Table 5: Rankings Implied by Average Efficiency Scores

Ranked – Model C 1993-1999	Peer Years	Peer Count	Mean Score	Ranked – Model A 1998-1999	Peer Years	Peer Count	Mean Score	Ranked - Model B 1993-1999	Peer Years	Peer Count	Mean Score
Credit Suisse First Boston	4	83	0.819	Bankers Trust	2	22	1.000	Royal Bank of Canada	3	76	0.728
ABN AMRO Asia Merchant Bank	4	28	0.674	Asahi Bank	2	14	1.000	Bankers Trust	3	58	0.629
Paribas Merchant Bank	2	36	0.555	Morgan Guaranty Trust	2	6	1.000	ABN AMRO Asia Merchant Bank	2	49	0.562
OUB Holdings	2	32	0.502	Deutsche Bank AG	1	13	0.519	Bank of America	2	35	0.711
Societe Generale Asia	2	6	0.520	Bank of Tokyo Mitsubishi	1	11	1.000	Paribas Merchant Bank	2	4	0.537
Indosuez Merchant Bank Asia	2	2	0.515	Citibank NA	1	6	0.705	Credit Suisse First Boston	2	2	0.538
Industrial Bank of Japan	1	24	0.413	DBS Holdings	1	5	1.000	Barclays Bank	1	26	0.576
The Fuji Bank, Ltd	1	22	0.379	Credit Agricole Indosuez	1	4	0.684	Credit Agricole Indosuez	1	23	0.404
Union Bank of Switzerland	1	21	0.352	ABN AMRO Asia Merchant Bank	1	3	0.502	OUB Holdings	1	19	0.313
Bank Nationale De Paris	1	19	0.353	Tokai Bank	1	1	1.000	Morgan Guaranty Trust	1	10	0.388
Credit Agricole Indosuez	1	19	0.395	Sumitomo Bank	0	0	1.000	Union Bank of Switzerland	1	5	0.576
Keppel Tatlee Bank	1	16	0.233	OUB Holdings	0	0	0.955	Bank of Tokyo	1	3	0.515
Royal Bank of Canada	1	11	0.465	OCBC Holdings	0	0	0.806	Deutsche Bank AG	1	2	0.262
Bankers Trust Company	1	6	0.436	Barclays Bank	0	0	0.679	HSBC Investment Bank	0	0	0.387
Tat Lee Bank	1	5	0.166	Royal Bank of Canada	0	0	0.581	Standard Chartered Bank	0	0	0.339
Citibank NA	1	4	0.547	Dresdner Bank AG	0	0	0.568	DBS Holdings	0	0	0.328
Bank of America	1	1	0.451	Keppel Tatlee Bank	0	0	0.504	Dresdner Bank AG	0	0	0.320
Barclays Bank	1	1	0.480	The Fuji Bank, Ltd	0	0	0.481	Sumitomo Bank	0	0	0.304
Deutsche Bank AG	1	1	0.376	Bank of America	0	0	0.397	Indosuez Merchant Bank Asia	0	0	0.302
The Sakura Bank	0	0	0.540	Bank Nationale De Paris	0	0	0.276	Asahi Bank	0	0	0.244
Dresdner Bank AG	0	0	0.457	Industrial Bank of Japan	0	0	0.248	OCBC Holdings	0	0	0.235
Standard Chartered Bank	0	0	0.354	UOB Holdings	0	0	0.260	Keppel Bank	0	0	0.214
DBS Holdings	0	0	0.346	Societe Generale Asia	0	0	0.158	Bank Nationale De Paris	0	0	0.211
Sumitomo Bank	0	0	0.310	Credit Suisse First Boston	0	0	0.141	Citibank NA	0	0	0.203
Morgan Guaranty Trust	0	0	0.308	Indosuez Merchant Bank Asia	0	0	0.124	Mitsubishi Bank	0	0	0.199
The Chase Manhattan Bank	0	0	0.308	HSBC Investment Bank	0	0	0.111	UOB Holdings	0	0	0.195
Asahi Bank	0	0	0.288	Paribas Merchant Bank	0	0	0.101	The Chase Manhattan Bank	0	0	0.190
Tokai Bank	0	0	0.272	The Chase Manhattan Bank	0	0	0.095	Tat Lee Bank	0	0	0.168
OCBC Holdings	0	0	0.257	Standard Chartered Bank	0	0	0.090	The Fuji Bank, Ltd	0	0	0.163
UOB Holdings	0	0	0.221	The Sakura Bank	0	0	0.014	Keppel Tatlee Bank	0	0	0.162
Bank of Tokyo Mitsubishi	0	0	0.207					Bank of Tokyo Mitsubishi	0	0	0.156
Bank of Tokyo	0	0	0.195					Societe Generale Asia	0	0	0.150
Keppel Bank	0	0	0.163					Tokai Bank	0	0	0.139
HSBC Investment Bank	0	0	0.144					The Sakura Bank	0	0	0.139
Mitsubishi Bank	0	0	0.068					Industrial Bank of Japan	0	0	0.128

Notes :

1. Peer Years - the number of years (out of seven) that a particular bank has been nominated as a best practice bank.
2. Peer Count - the number of times (in total) in all seven years that the bank has been nominated a peer for other banks.
3. Banks are ranked according to the following sequence of priority – (1) peer years (2) peer count and (3) mean score.



Footnotes

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i These restrictions apply only to Singapore dollar deposits. Only full licence foreign banks are allowed full access to the Singapore dollar deposit market.

ii Restricted banks are accorded the same privileges as full license banks but can only have one branch and have limits on accepting deposits from non-bank customers. Offshore banks have Singapore dollar-lending limits of up to S$1billion and are allowed to accept local currency funds from non-bank customers through swap transactions.

iii All banks operating in Singapore are required under the Companies Act to submit audited annual financial statements on their Singapore operations to the Registry of Companies and Businesses.

iv For a full discussion of DEA methodology, see Coelli, Rao and Battese (1998).

v This follows the formal definition of the Bank of International Settlements' Basle 1988 convention. "*International convergence of capital measurements and capital standards*", Basle Committee on Banking Supervision, July 1988.

vi A score of 0.2 implies that if the average firm were producing on the frontier instead of its current location, then only 20% of the resources currently being used would be necessary to produce the same output.

[vii] Since normality assumptions required by Pearson's (product-moment) correlation ~~will not hold~~are not appropriate in this case, a non-parametric ~~-~~measure like Spearman's (rank-correlation) coefficient is ~~applicable~~ preferred for statistical inference.

[viii] Incidentally, the authors also acknowledged that their coefficients were "surprisingly" high.

[ix] By comparison, the random chance of being in the top quarter has an expected value of 25%.