University of New England

School of Economics

The Productive Efficiency Of Singapore Banks: An Application And Extension Of The Barr Et Al (1999) Approach

by

WAI HO LEONG and BRIAN DOLLERY

No. 2002-9

Working Paper Series in Economics

ISSN 1442 2980

http://www.une.edu.au/febl/EconStud/wps.htm

The Productive Efficiency Of Singapore Banks: An Application And Extension Of The Barr Et Al (1999) Approach *

Wai Ho Leong and Brian Dollery **

Abstract

While a voluminous literature exists on the measurement of financial institution efficiency, little work has been directed at investigating the properties of data envelopment analysis (DEA) scores by examining the relationships between these scores and traditional measures of bank performance. Following the seminal work of Barr, Killgo, Siems and Zimmel (1999), this paper employs data on Singapore financial institutions for the period 1993 to 1999 to develop efficiency scores for Singapore banks. It then examines the manner in which derived DEA efficiency scores interact with traditional measures of profitability, size, risk and soundness.

* The opinions expressed in this paper do not necessarily reflect the views of the Singapore Ministry of Trade and Industry. The preliminary empirical work for this paper was undertaken by Wai Ho Leong at Melbourne University.

** Wai Ho Leong, is Senior Economist/Deputy Director, Economics Division, Ministry of Trade and Industry, 100 High Street, Singapore 179 434. Brian Dollery is a Visiting Foreign Researcher, International Graduate School of the Social Sciences, Yokohama National University, 79-4 Tokiwadai, Hodogaya-ku, Yokohama 240-8501, Japan, and Professor of Economics, University of New England. Contact information: School of Economics, University of New England, Armidale, NSW 2351, Australia.
Email: bdollery@pobox.une.edu.au.

The productive efficiency of Singapore banks: An application and extension of the Barr et al (1999) approach

I. INTRODUCTION

Economists have invested considerable effort into the empirical measurement of the productive efficiency in financial institutions using non-parametric frontier models. Nevertheless, although the literature on financial institution efficiency using data envelopment analysis (DEA) is voluminous, surprisingly little attention has been focussed on the properties and consistencies of efficiency scores. Given the potential relevance of efficiency measures as a guide for financial regulators, this oversight should obviously be addressed.

Two seminal empirical papers have sought to tackle this question. Firstly, Bauer, Berger, Ferrier and Humphrey (1997) 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. Secondly, Barr, Killgo, Siems and Zimmel (1999) explored the properties of DEA efficiency scores by investigating the relationship between efficiency scores and some of the more traditional measures of bank performance. But to the best of our knowledge these pioneering efforts have not been pursued further in the literature. The present paper seeks to expand this nascent literature by applying and extending the work of Barr *et al* (1999) in institutional context of Singapore, where we employ three alternate DEA specifications and Singaporean data for the period 1993 to 1999.

The paper itself comprises seven main sections. Section 2 seeks to briefly describe the Singaporean institutional background to the empirical analysis in the paper. Section 3 provides a brief synopsis of the empirical analysis of financial services efficiency. Section 4 discusses the determinants of bank efficiency. Section 5 deals with data considerations, variable specification and other methodological issues. Section 6 discusses the DEA efficiency scores that derive from the three models employed. The relationship between efficiency scores and traditional measures of bank performance is examined in section 7. The paper ends with some brief concluding remarks in section 8.

II. FINANCIAL SERVICES IN SINGAPORE

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, banks disclosed for the first time 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, and 92 had offshore licences. Another 80 merchant banks provide services not covered by commercial banks, including asset management, equipment leasing, factoring and underwriting.

III. THE EMPIRICAL ANALYSIS OF FINANCIAL SERVICES DELIVERY

The empirical analysis of financial institution efficiency is a relatively recent phenomenon. In their review of 130 DEA studies on bank efficiency across 21 countries, Berger and Humphrey (1997) indicate that, of these, 116 papers were published between 1992 and 1996. Most research has an American institutional flavour, where the large number of banks has favoured econometric modelling (Avkiran, 1999), and most work has focused on the effects of scale and scope economies. Despite the plethora of empirical studies there is still no consensus on the best method for measuring efficiency in financial institutions. Four main approaches have been followed, including the stochastic econometric frontier approach, the thick frontier approach, the distribution-free approach and the DEA approach (Worthington, 1998).

One of the major difficulties in the measurement of bank output resides in the fact there is no consensus in the literature on how to define or measure these services. In broad terms, bank output should encompass the portfolio management and advisory services that banks usually provide to depositors in their intermediation capacity. Moreover, the absence of an explicit price also causes significant problems in the measurement of financial services. Without an explicit price, economists must impute their value. Whereas banks are viewed as producers of financial services in this study, not all financial services constitute output.

A fundamental difficulty arises in the treatment of bank deposits and much heated debate in the literature focuses on the input-output status of these deposits. Broadly speaking, deposits were seen as the main inputs for loan production and the acquisition of other earning assets. However, high value-added deposit products, such as integrated savings and checking accounts, investment trusts, and foreign currency deposit accounts, emphasise the output characteristics of deposits. Indeed, high value-added deposit services are an important source of commissions and other fee revenue for specialised commercial banks. Accordingly, in these specialised institutions, the output nature of deposits cannot be overlooked. Deposits are thus “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).

This argument can be extended *mutates mutandis* to hold that the classification of deposits should therefore depend on the nature of the financial institutions in any given representative sample and the regulatory regime of the particular nation. For instance, in the context of Singapore the quantum of high value-added deposits is relatively small compared to time and savings deposits, and there may thus be more reason to regard deposits as inputs. Similarly, because most foreign banks operating in Singapore are legally restricted in their ability to accept Singapore dollar deposits, their revenue share of interest-bearing loans far exceeds that of deposit services.

Three major methods have been developed to define the input-output relationship in financial institutions in the literature. In the first place, the production approach (Sherman and Gold, 1985) models financial institutions as producers of deposit and loan accounts, and defines output as the number of these accounts and transactions. Inputs are typically characterised as the number of employees and capital expenditures on fixed assets. Secondly, the intermediation approach (Berger and Humphrey, 1991) focuses on the role of financial institutions as intermediaries that transfer funds from surplus to deficit units. Following this approach, operating and interest costs generally represent the major inputs, and interest income, total loans, total deposits and non-interest income form the most important outputs. Finally, the asset approach sees financial institutions as quintessentially creators of loans. Outputs defined as the stock of loan and investment assets (Favero and Papi, 1995).

Perhaps the most damaging criticism of the production approach resides in its neglect of interest costs since interest costs are a major expense at any bank. For instance, among the banks in our Singaporean sample, interest expenses represent some 60-75% of total costs on average. This may explain why the intermediation approach seems to have dominated empirical research. The intermediation approach is also extremely adaptable since categories of deposits, loans, financial investments and financial borrowings may be assigned as either inputs or outputs (Colwell and Davis, 1992).

IV. THE DETERMINANTS OF FINANCIAL SERVICES EFFICIENCY

The problem of identifying causal factors of efficiency becomes is exceedingly difficult in the milieu of international banking. Under the influence of global competition, banks are continuously trying to find ways to diversify income, whilst keeping capital intensity as low as prudently possible. The drive to achieve optimal business diversification has also fuelled mergers and acquisitions. Four factors seem to influence bank efficiency: (1) agency problems; (2) structure of regulation and organisation; (3) effective risk management; and (4) size and technology.

Firstly, the agency problem has been examined in some detail. Pi and Timme (1993) examined empirical evidence on the impact of the disjunction between ownership and control in US commercial banks. They found *inter alia* that banks where the positions of chairman of the board and the chief executive officer were conflated into a single individual were generally less efficient. It was only through mechanisms that disperse the concentration of authority, such as CEO stock ownership, outside institutional ownership and board membership, that this effect was constrained.

Secondly, 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 example, 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 investigators have attempted to account for differences in regulation within a single institutional type. For instance, Fecher and Pestieau (1993) examined technical efficiency variation in banks across five OECD countries.

Thirdly, the impact of risk management practices is also clearly important. Given informational asymmetry, successful identification of risk can allow banks to adopt 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 pursuing good investor relations, ready access to capital markets and a lower cost of capital, these factors may reflect higher operating efficiency.

Finally, size and technology are also crucial 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 variable returns to scale (VRS) variant of the DEA model). Moreover, scale economies were found to confer only a small cost advantage to larger banks. They found that allocative inefficiency derived largely from the excessive use of labour and an under-utilisation of capital. Indeed, the most efficient banks in their sample belonged to the smallest size class.

V. DATA, VARIABLE SPECIFICATION AND METHODOLOGY

Commercial banks operating in Singapore for the period 1993 to 1999 form the population for this study. Our empirical approach seeks to achieve two outcomes. Firstly, relative technical efficiency scores from three alternate DEA model specifications are calculated for our sample of 35 major banks. In the second stage, we will attempt to evaluate the salient properties of DEA efficiency scores over time by examining how these scores relate with traditional indicators of bank performance and the input and output variables of the parent model. In so doing, we employ the longitudinal efficiency analysis approach of Barr *et al* (1999), which involves measuring the strength of association between score quartiles and model variables.

In order to build a sample representative of the industry, Singapore banks were carefully selected on three criteria. First, elements of the sample are 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 remove smaller merchant banks, finance companies and other financial institutions with different operating characteristics. Second, only commercial banks focused on the corporate lending markets were included. Finally, only the largest banks within these categories were selected, where archival data was available from the official Singapore *Registry of Companies*.

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 should 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. Second, significant variation between the size of the largest banks and the smallest banks had already been achieved.

Audited financial statements of the 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 in compliance of the standards of the MAS. From these statements, it was possible to collect data on two main inputs (deposits and fixed assets) and two outputs (loans and risk-weighted assets) for the period 1993 to 1999.

Two additional assumptions are imposed. First, the measured coefficient or implied distance from the best practice efficient frontier is deemed to reflect technical efficiency. Second, we assume variable returns to scale in the banking industry, which is employed in the DEA-VRS model of Banker, Charnes and Cooper (1984).

We now turn our attention to variable specification. Model B, 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. 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 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 A, 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 contained in Table1.

Insert Table 1 here

Operating efficiency is defined as the ratio of operating expenses (non-interest) to non-interest income. 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, 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. 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.

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 to 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 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 will carry a 100% risk weight. However, transaction and trade-related contingencies (bid bonds, warrants and credits guaranteed by shipment performance bonds) 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.

Insert 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 A. 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 is a distinct improvement over Model A for three reasons. First, risk-weighted assets are a better output proxy than loans as the former includes 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, as 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. Third, 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 an area of concern for users of Model B.

Nonetheless, the risk-weighted asset approach may require a higher degree of financial disclosure that may exceed statutory requirements in many jurisdictions. This is especially relevant in the context of developing countries. In cases where information is lacking, the assignment of weights for risk assets falls largely on analyst discretion.

VI. ANALYSIS OF EMPIRICAL RESULTS

The major empirical objective of this paper is to investigate the properties of DEA scores over time. In order to achieve this objective, we employ the longitudinal efficiency analysis approach used in Barr *et al* (1999) in their study of US banks. In broad terms, this involves sorting derived DEA scores into quartiles and observing how these quartiles interact with traditional indicators of performance and model variables.

In accordance with model specifications set out in Tables 1 and 2, we estimated the data using three alternative DEA models. Score trends and descriptive statistics are presented in Figure 1 and Table 3 respectively.

Insert figure 1 here

Insert Table 3 here

The seven year range of this study encapsulates significant changes in economic climate, in which Singapore 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 Figure 1, both A and C identified 1997 as the year with the lowest scores (averaging 0.2[1]), 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 B reported a more modest improvement in efficiency scores than A 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 B to a greater extent than models A and C.

The trends in scores reported by models A and C in Figure 1 appear to be mutually consistent in the period 1996-99 and related by time lags in 1993-95. Model A, 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 A and C between 1993 and 1996, although we lack reliable data for a more detailed investigation.

VII. RELATIONSHIP BETWEEN EFFICIENCY SCORES AND BANK INDICATORS

The major empirical objective of this paper is to evaluate the properties of DEA scores over time. More specifically, we want to examine how derived DEA efficiency scores interact with traditional measures of profitability, size, risk attitude and soundness. We expect institutions with higher efficiency scores to differ significantly from those with lower scores in measurable ways. More efficient banks are likely to have higher return on average assets (ROAA) and lower loan-to-asset ratios. Finally, we expect positive correlation between efficiency scores and financial strength as determined by capital adequacy ratios.

Do DEA Score Quartiles Perform as a Consistent Measure over Time?

To isolate their salient characteristics, the derived DEA efficiency scores from Model C for each annual cross section were sorted in descending order and divided into quartiles. In this fashion, we can examine how the higher score quartiles compare with lower score quartiles in terms of performance measures and model variables. How the quartiles interact with these variables over time should indicate if derived DEA scores are a useful abstraction of reality over time.

Insert Figure 2 here

The results indicate that the differences in mean scores between the most and least efficient quartiles are significant at the 1% level of confidence. This implies that the differences between the efficiency ranked quartiles are statistically meaningful and that the use of efficiency quartiles to evaluate DEA technical efficiency scores is statistically appropriate.

Does Institution Size Matter?

Another stated goal of this study was to investigate the role played by bank size in determining efficiency. Quartile analysis provided interesting results. Figure 3 shows that in six of the seven reference years, banks in the smallest size quartile (by total assets) had consistently higher mean technical efficiency scores than the largest size quartile. Consistent with Barr *et al* (1999), scores from our model also highlight the potential for greater inefficiencies in the operation of larger and more complex banking operations. This also implies that despite the differences in variables used, scores obtained from both DEA models share some common properties.

Insert Figure 3 here

Economic conditions have a marked impact on the extent of the differences in efficiency scores between largest and smallest size quartiles. Thus, the divergence in scores between the largest and smallest size quartile lines in Figure 3 appeared to be at its widest between 1993 and 1994, during which period the banking industry experienced robust asset growth. This gap narrowed progressively after 1997, which coincided with the onset of a sharp deceleration in loan advances and economic growth rates.

Do Mergers Improve Efficiency Scores?

Table 4 summarises the DEA scores for two cases of mergers identified in Singapore following the Avkiran (1999: 1006) approach. In each case, we compared the ranking of the entity in the sample implied by its DEA technical efficiency score in the period before and after merger.

Insert Table 4 here

In Case 1, although efficiency rankings based on DEA scores had improved steadily between 1997 and 1999, the merged entity was ranked lower in the first two years relative to one of its constituents (Keppel Bank) in the years before merger. In

Case 2, one of the constituent banks (Bank of Tokyo) before merger had generally higher efficiency rankings than the merged Singapore unit of the Bank of Tokyo-Mitsubishi. In both cases, DEA efficiency rankings for the merged banks are not always unambiguously better off than their constituents before merger. Neither of the two mergers produced banks large enough to control a dominant share of the market.

Overall, this exercise provided no conclusive evidence to support the hypothesis that merged financial institutions in the Singaporean context could at least maintain their pre-merger level of efficiency (based on DEA scores). These findings are consistent with Avkiran (1999), who found that acquiring banks could not always maintain pre-merger relative efficiency rankings.

Are Banks with Higher Efficiency Scores More Profitable?

Insert Figure 4 here

The results suggest that ROAA is generally positively related to our measure of efficiency. Banks in the highest efficiency quartile reported higher mean ROAA than banks in the lowest efficiency quartile in all years other than 1995 and 1998. With the exception of 1995 and 1997, the differences in mean ROAA between the most and least efficient quartiles in all other years were significant at the 5% level.

In Figure 4, the ROAA trends for the respective score quartiles are not rank distinct. Rank distinction is harder to achieve in quartile based studies using smaller samples due to the “outlier” problem. This phenomenon is also responsible for the general lack of smoothness in the trends in Figure 4. Barr *et al* (1999) were able to achieve rank distinction as a result of the relatively large sample used (which tends to mitigate the effects of data “outliers”). Another factor relates to the differences in model variables used. Since risk-weighted assets is a proxy for output (unlike interest income in Barr *et al*), we are not surprised to find a less direct linkage between the efficiency scores and industry measures of profitability.

ROAA appears to be a good indicator of the impact of varying economic conditions on the different efficiency quartiles. At the height of the financial crisis in 1998, mean ROAA for the most efficient quartile dropped to a low of –0.76%. This suggests that the banks with the higher efficiency scores had either sought to make full provisions for possible loan loss charges early or had simply written off bad assets ahead of their peers. If this is true, then this argument would also corroborate the sharp rebound in ROAA for the most efficient quartile in the subsequent year.

Are Banks with Higher Efficiency Scores More Risk Averse?

Insert Figure5 here

In the context of US banks, Barr *et al* (1999) found that less efficient banks had higher loan asset ratios, which they interpreted as an indication of lower risk aversion. However, implicit in their inference is that the loan-to-asset ratio accurately portrays the attitude of a bank towards risk. It can be readily argued that a simple ratio like the loan-asset ratio is unlikely to capture fully a bank's attitude towards risk. A glaring omission, for instance, is OBS activity, which typically exceeds the on-balance sheet assets of major commercial banks operating in Singapore.

With the exception of 1995, the highest efficiency score quartile had lower loan-asset ratios than the lowest score quartile on average. This is evident from Figure 5. This finding may be interpreted in two conflicting ways. First, as Barr *et al* (1999) suggested, this could simply imply that less efficient banks (which tend to be less profitable) have a tendency to enhance profit margins by adopting higher credit risk profile. This means that more efficient banks are therefore more risk averse. On the other hand, it is also possible to show that more efficient banks can be less averse to risk, despite higher ROAAs and lower loan-asset ratios. For instance, these banks may have higher levels of OBS businesses (eg. fee-based and speculative activity like foreign exchange derivatives and contingent liabilities), which generate greater profitability and which the loan-asset ratio fails to capture.

Are Banks with Higher Efficiency Scores "Stronger" Institutions?

Insert figure 6 here

There is a noticeable tendency for banks with higher efficiency scores to have "stronger" capital structures measured in terms of the capital adequacy ratio (CAR). With the exception of 1998, a clear positive relationship exists between the CAR and efficiency scores for the duration of our study. However, this relationship does not seem to be independent of economic conditions. In Figure 6, the "most-to-least-efficient" differences narrow significantly during the difficult years of 1997 and 1998. Another possible factor explaining the drop in the mean CAR of more efficient banks was that Singapore's CAR requirements were modified in December 1998 to reduce the minimum Tier 1 capital requirement from 12% to 10%, and to allow for Upper Tier 2 capital to be used as regulatory capital for the remaining 2%.

These findings are consistent with Barr *et al* (1999), who also found evidence of a significant positive relationship between bank efficiency and bank examiner ratings (measured by the CAMELS rating[1]). This suggests that DEA models can be employed by regulators and banks as an “off-site” monitoring and internal benchmarking device.

Relationship Between Efficiency Scores and Model Variables.

Barr *et al* (1999) have observed that some of these differences would also manifest themselves in the input and output variables of the model. We would expect efficiency scores to correlate positively with risk-weighted assets (RWA) and negatively with deposits and fixed assets.

Risk Weighted Assets

Insert figure 7 here

RWA are broadly indicative of the level of earning assets or the ability of financial institutions to generate revenues. In tandem with expectations, it can be observed in Figure 7 that the highest score quartile has significantly higher levels of RWA (relative to assets) than the lowest score quartile in all years except 1996. This implies a positive relationship between efficiency scores and the mean RWA-to-total-asset ratio, although clear rank distinction between the mean RWA levels of different score quartiles was not achieved.[2]

Deposits

The longitudinal interaction between the mean adjusted deposits of the most and least efficient quartiles is more difficult to characterise. We had expected a tendency for efficiency scores to relate negatively to deposits as a percentage of assets, since deposits are an input variable in the model. However, as evident in Figure 8, no meaningful relationship may be inferred.

Insert figure 8 here

The results also suggest that the ratio of deposits to assets of the efficiency quartiles move independently with economic conditions over time. However, taking averages for the quartiles, one finds declining mean deposits as a percentage of total assets between 1993 and 1996, but a steady rising trend after 1996. This seems to concur with industry characteristics. Average growth in aggregate loans (16.44%) had outstripped deposits (10.82%) during the good years (1993-96), but deposit growth (14.42% versus 5.24%) was relatively higher during the difficult years (1997-99).

Fixed Assets

Insert figure 9 here

We observe no consistent relationship between efficiency scores and the level of fixed assets in Figure 9, although a general negative trend is noticeable if we limit the comparison to the highest and lowest score quartiles. It is generally expected that banks with higher efficiency scores will have lower levels of fixed assets (relative to assets). In five of the seven years of the sample period, banks with higher scores had lower levels of fixed assets (relative to assets). Whereas the trend between 1994 and 1998 is consistent with expectations, the reverse is true for the years 1993 and 1999.

VIII. CONCLUDING REMARKS

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. We would also have expected to establish a negative relationship between the percentage of gross loans that are non-performing and the efficiency score quartiles in accordance with Barr *et al* (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 relationships between traditional measures of bank efficiency and DEA efficiency scores.

In summarising the results of the analysis of Singapore bank efficiency, several points should be emphasised. We sought to evaluate the properties of DEA scores over time, using the longitudinal analysis approach of Barr *et al* (1999). Essentially, efficiency scores were sorted into quartiles and tested against traditional indicators of bank performance and with the input-output variables of our model. To varying degrees, the results indicate significant relationships between efficiency scores and traditional indicators of bank performance, namely capital adequacy, profitability, loan-to-asset ratio and institution size. Subsequently, we found evidence to support a positive association between scores and the output variable, but not between scores and the input variables.

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 by necessity and not choice to adhere to the present DEA methodology, given our data limitations.

REFERENCES

Avkiran, N.K. (1999) The evidence on efficiency gains: The role of mergers and the benefits to the public, *Journal of Banking and Finance*, **23**, 991-1013.

Banker, R.D. Charnes, A. and Cooper, W.W. (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, **30**, 1078–1092.

Barr, R.S., Killgo, K. A., Siems, T. F. and Zimmel, S. (1999) Evaluating the productive efficiency and performance of US commercial banks, *Financial Industry Studies Working Paper 99-3*, Federal Reserve Bank of Dallas, Dallas.

Bauer, P.W. Berger, A.N., Ferrier, G.D. and Humphrey, D.B. (1997) Consistency conditions for regulatory analysis of financial institutions: A comparison of frontier efficiency methods, *US Federal Reserve Financial Services,* Working Paper 02(97).

Berger, A.N. and Humphrey, D.B. (1991) The dominance of inefficiencies over scale and product mix economies in banking, *Journal of Monetary Economics*, **28**, 117–148.

Berger, A.N. and Humphrey, D.B. (1997) Efficiency of financial institutions :International survey and directions for future research, *European Journal of Operational Research,* (Special issue). http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2140

Berger, A.N. Hunter, W.C. and Timme, S.G. (1993) The efficiency of financial institutions: A review and preview of research past, present and future, *Journal of Banking and Finance*, **17**, 221–249.

Colwell, R.J. and Davis, E.P. (1992) Output and productivity in banking, *Scandinavian Journal of Economics*, **94**, 111–129.

Farrell, M.J. (1957) The measurement of productive efficiency, *Journal of the Royal Statistical Society*, Series A (General) **120**, 253–289.

Favero, C.A. and Papi, L. (1995) Technical efficiency and scale efficiency in the Italian banking sector: A non-parametric approach, *Applied Economics*, **27**, 385–395.

Ferrier, G.D. and Lovell, C.A.K. (1990) Measuring cost efficiency in banking: Econometric and linear programming evidence, *Journal of Econometrics*, **46**, 229–245.

KPMG (1997) *Survey of banking and financial institutions in Singapore*, KPMG Peat Marwick Consultants, Singapore.

Mester, L.J. (1993) Efficiency in the savings and loan industry, *Journal of Banking and Finance*, **17**, 267–286.

Pi, L. and Timme, S.G. (1993) Corporate control and bank efficiency, *Journal of Banking and Finance*, **17**, 515–530.

Sherman, H.D. and Gold, F. (1985) Bank branch operating efficiency: Evaluation with data envelopment analysis, *Journal of Banking and Finance*, **9**, 279–315.

Siems, T.F. (1992) Quantifying management's role in bank survival, *Federal Reserve Bank of Dallas Economic Review*, 20, 29–41.

Worthington, A. C. (1998) The determinants of non-bank financial institution efficiency: A stochastic cost frontier approach, *Applied Financial Economics*, **8**, 279–289.

Figure 1. Mean Scores By DEA Model.

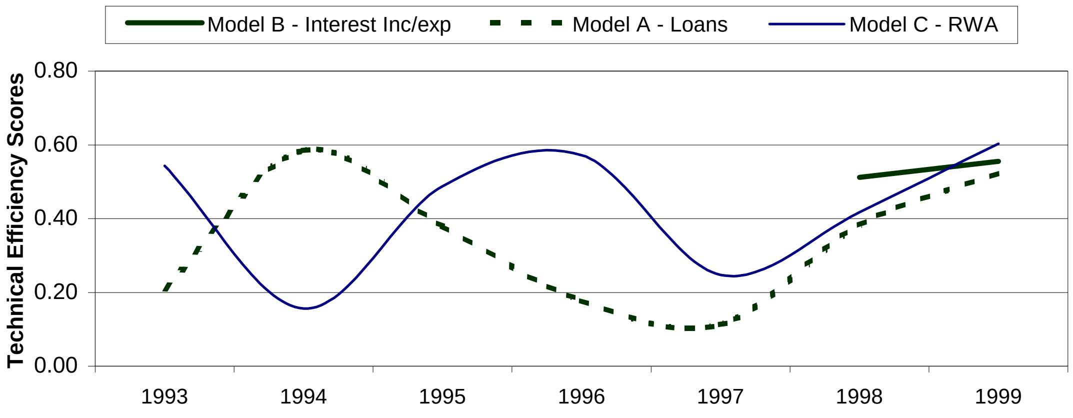

Figure 2. Score By Efficiency Quartile.

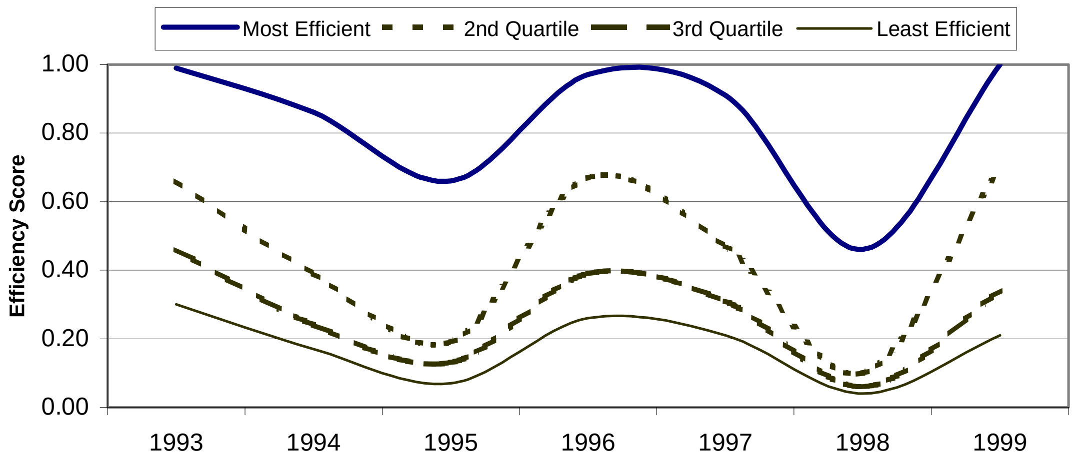

Figure 3. Efficiency Score By Size Quartile.

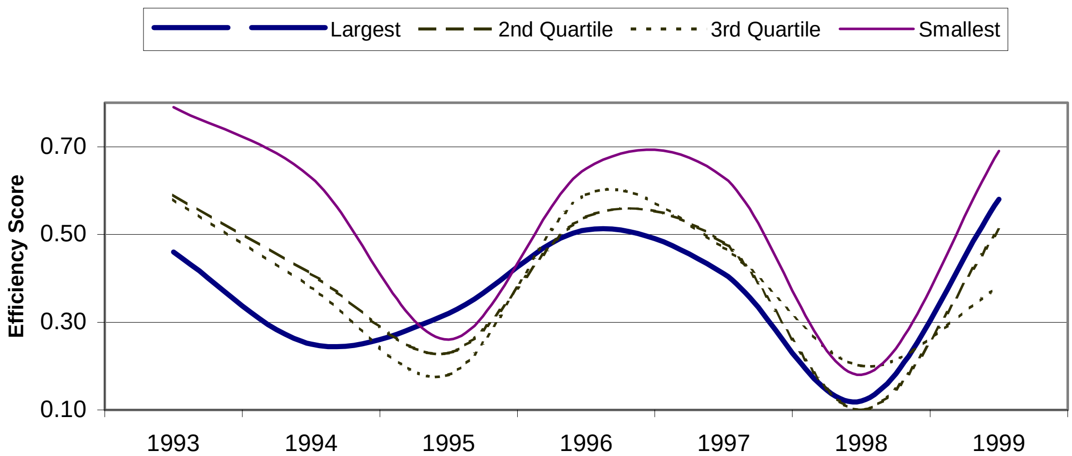

Figure 4. ROAA By Efficiency Quartile.

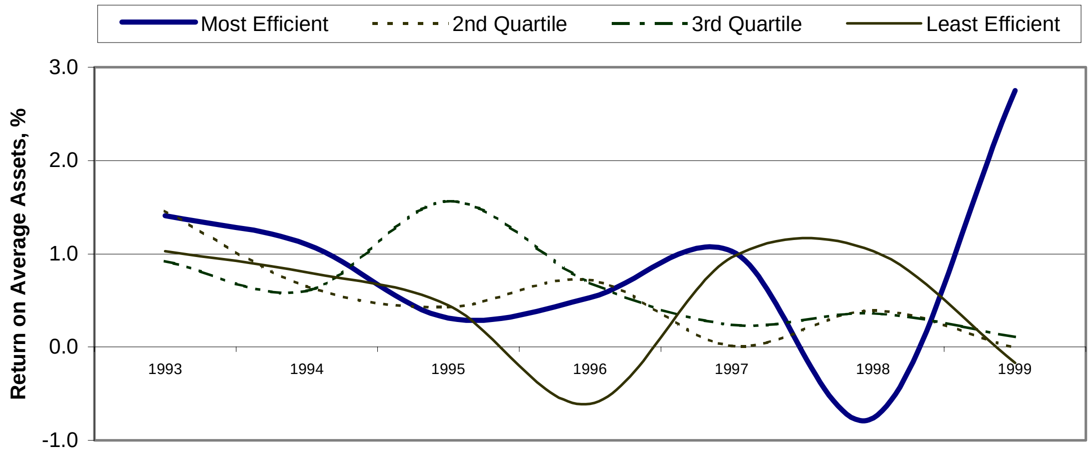

Figure 5. Mean Loan/Assets By Efficiency Quartile.

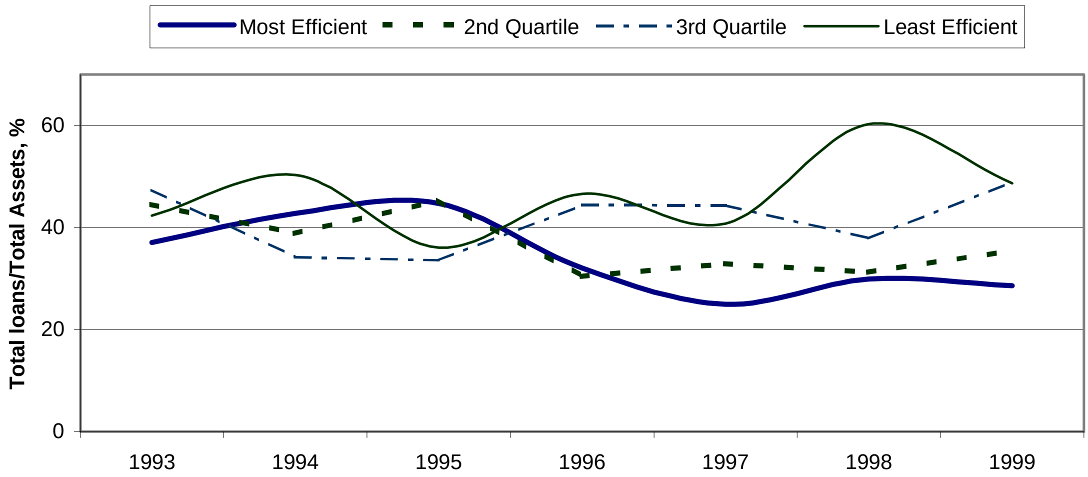

Figure 6. Mean Capital Adequacy Ratio By Efficiency Quartile.

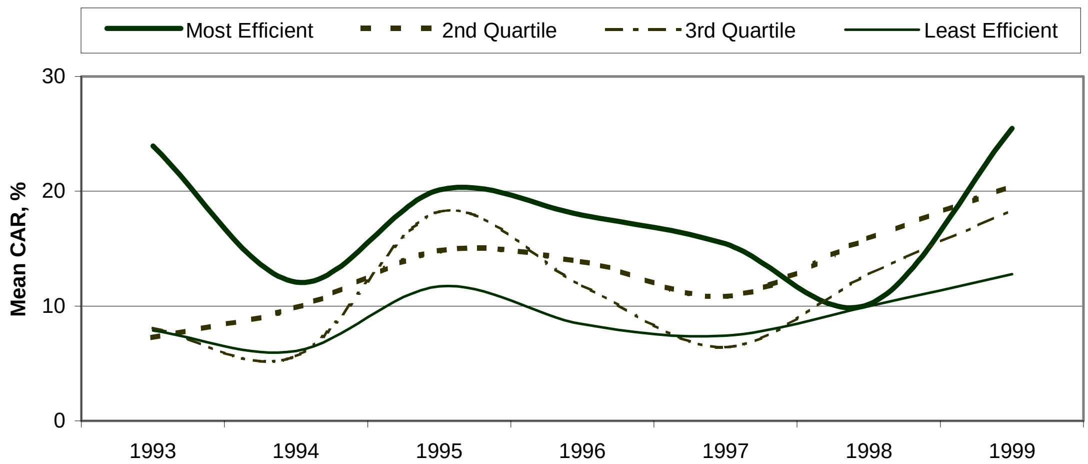

Figure 7. Risk Weighted Assets By Efficiency Quartile.

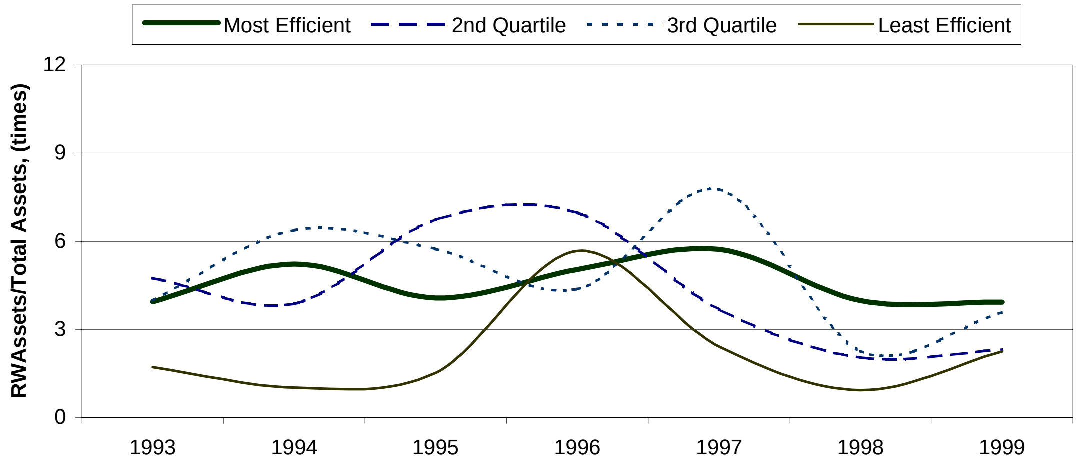

Figure 8. Mean Adjusted Deposits By Efficiency Quartile.

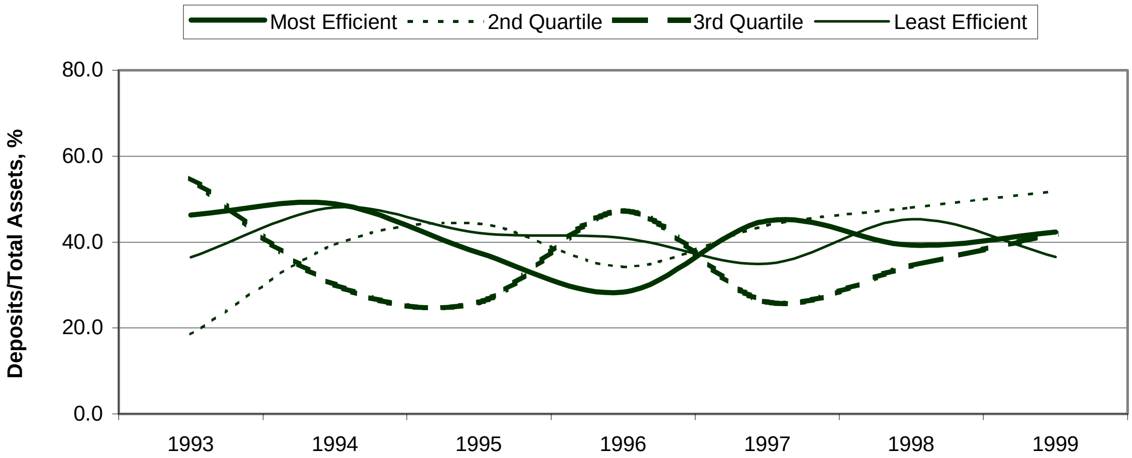

Figure 9. Mean Adjusted Fixed Assets By Efficiency Quartile

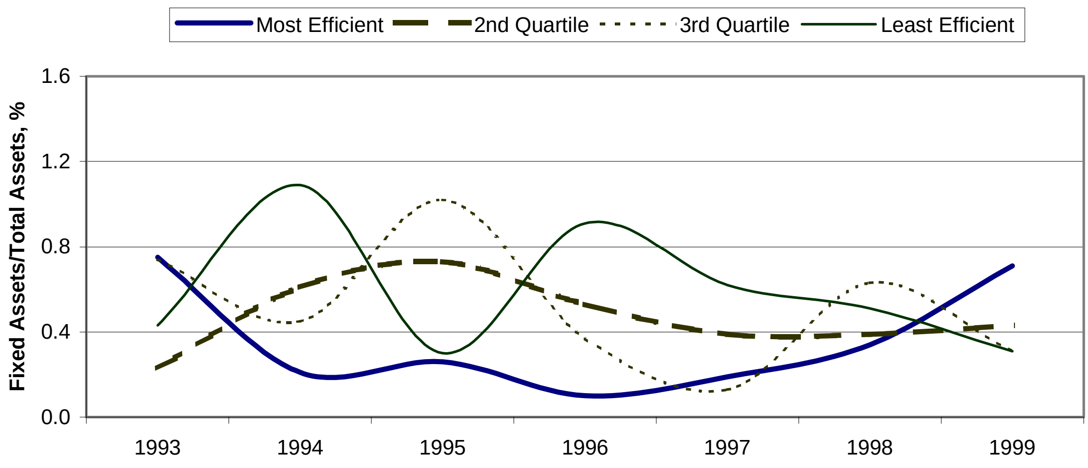

Table 1. Models A and B – VRS DEA variants.

MODEL B (2 inputs, 2 outputs)		MODEL A (2 inputs, 1 output)	
Inputs	Outputs	Inputs	Outputs
Interest Expenses	Interest Income	Deposits	Loans
Operating Expenses	Other Income	Fixed Assets	
Data Years Available: 1998, 1999		Data Years Available: 1993-1999	

Table 2. Model C (2 x 1 DEA – VRS)

Inputs	Outputs
Deposits	Risk Weighted Assets
Fixed 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 B**	**Model A**
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 B	Model A
Model C (2x1)	1.00	-	-
Model B (2x2)	- 0.69	1.00	-
Model A (2x1)	0.28	- 0.34	1.00

Notes:

1. Models A 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 B – 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. Relative Efficiency Scores Pre- And Post-Merger – Model C Scores.

	Merged Institution	Year	Constituent A	Constituent B
Case 1	*Keppel Tatlee Bank*		*Keppel Bank*	*Tat Lee Bank*
		1993	*0.25 (Rank: 32/32)*	*1.00 (Rank: 7/32)*
		1994	*0.81 (Rank:6/33)*	*0.17 (Rank: 30/33)*
	0.21 (Rank: 28/31)	*1997*		
	0.08 (Rank: 15/30)	*1998*		
	1.00 (Rank: 4/30)	*1999*		
Case 2	*Bank of Tokyo-Mitsubishi*		*Bank of Tokyo*	*Mitsubishi Bank*
		1993	*0.52 (Rank: 18/32)*	*0.27 (Rank: 30/32)*
		1994	*0.85 (Rank: 5/33)*	*0.20 (Rank 26/33)*
	0.77 (Rank: 9/28)	*1996*		
	0.24 (Rank: 26/31)	*1997*		
	0.05 (Rank: 19/30)	*1998*		
	0.39 (Rank: 16/30)	*1999*		

Footnote 1.

A CAMELS rating is a confidential six-part composite rating and the outcome of an on-site examination of a bank by the US Federal Reserve. The overall rating is divulged to the management of the bank, but component ratings are withheld by regulators. The CAR is an integral component of the rating.

Footnote 2.

This was largely due to outliers in the data. While we had removed the extreme observations from the sample, the variation in mean RWA/total assets between observations remained large.