An investigation into the efficiency of a bank's branch network using Data Envelopment Analysis

Darrel Thomas

David Tripe*

Centre for Banking Studies

Massey University

Palmerston North

New Zealand

* Corresponding author. Postal address, Private Bag 11-222, Palmerston North, New Zealand; E-mail D.W.Tripe@massey.ac.nz; Phone +64 6 350-5799 ext 2337; Fax +64 6 350-5651.

An investigation into the efficiency of a bank's branch network using Data Envelopment Analysis

Abstract:

This paper applies the non-parametric frontier analysis technique, Data Envelopment Analysis (DEA) to investigate the relative efficiency of part of a New Zealand bank's branch network.

Inputs and outputs were chosen on the basis of what the bank regarded as key indicators of branch performance: inputs were salary expense, brokerage expense and interest expense, with outputs asset growth, liability growth, non-interest income and a measure of customer satisfaction.

Consistent with the concerns identified by Dyson et al, 2001 (European Journal of Operational Research) about use of quantified qualitative data, problems were found with use of customer satisfaction as an output, as the projections shown required branches to improve performance to unachievable levels. Attempts to resolve this problem by use of variable returns to scale models were unsuccessful, as the model then lacked discriminatory power.

A number of methodological changes are proposed to improve future research.

Keywords: Bank branches, efficiency, data envelopment analysis, bank customer satisfaction

JEL Codes: D200, G200, L200

1. Introduction

Following the work of Berger & Humphrey (1991), it is widely accepted that banks are often not as efficient as they might be, with the source of inefficiency more commonly arising from X-inefficiency, rather than from scale. If we are to focus on X-inefficiency, alternatively described as management inefficiency, the existence of which recognises that banks do not always manage to produce maximum relative quantities of outputs at minimum costs, we need to understand where within a large and complex banking organisation it might arise. Where a bank has an extensive branch network it is not unreasonable to expect that some of the inefficiency might arise from within that network. Berger et al (1997) noted the relative dearth of studies of the efficiency of bank branches, with Berger & Humphrey (1997) reporting only 13 such studies among the 130 bank efficiency studies that they reviewed. Even though the number of studies reported has increased since that time, studies of bank branches remain very much a minority.

This paper looks at part of the branch network of a New Zealand bank, and attempts to measure the relative efficiency of a subset of the network, comprising a total of 67 branches. One of the original objectives of the study was to try and establish some criteria for measurement of the performance of branch managers, as an alternative to the previously used ratio analysis.

The research findings pose a number of challenges, which will provide useful opportunities for further research in the future. Despite these, however, the research findings provide some useful outputs for bank management, in terms of identifying sources of inefficiency, particularly for branches failing to achieve satisfactory levels of output, having regard to the resources they have been utilising. The research should allow the bank’s management to focus on issues that will let them improve the bank’s overall performance in the future.

The rest of the paper is structured as follows. The next section provides some background to the general concepts of efficiency and its measurement. Section 3 describes the bank and the operation of the New Zealand banking market more generally. Section 4 looks at previous approaches to the measurement of relative efficiency of bank branches, while section 5 looks at the method that used in this research, and describes the data that are used. Section 6 reports the results, describes the attempts to enhance the rigour of these, and discusses the findings. Section 7 concludes, with some outline provided of the sorts of issues that ought to be subject to further exploration in the future.

2. What is efficiency, and how can it be measured?

In general terms, a financial institution or a bank branch (referred to as decision-making unit or DMU) can be said to be efficient if it cannot produce more output without a corresponding relative increase in inputs, or if it cannot reduce its inputs without a corresponding relative decrease in output. Popular approaches to measurement of efficiency are inclined to focus on simple ratios, although ratios have a number of deficiencies. DeYoung (1998) suggests that blind pursuit of accounting-based benchmarks might reduce a bank's cost efficiency by cutting back on those expenditures necessary to run the bank properly. More generally, Berger et al (1993) note that financial ratios may be misleading because they do not control for product mix or input prices.

X-efficiencies are measured relative to an efficient frontier, which defines the maximum levels of outputs that can be obtained with any specified usage of inputs, or the minimum levels of inputs that can be used to obtain a specified level of output. There are five approaches to determining the position of this efficient frontier, three parametric and two non-parametric. A major challenge for both sets of approaches is in distinguishing random error, arising from accounting practice or some other source, from inefficiency. Each of the parametric approaches has different ways of dealing with random error, whereas the non-parametric approaches generally ignore it.

This study uses Data Envelopment Analysis (DEA), a non-parametric technique originally developed by Charnes Cooper & Rhodes (1978). This was developed on a basis of constant returns to scale (referred to as CCR after the authors of the original article), but subsequently extended by Banker Charnes & Cooper (1984) into a model providing for variable returns to scale (referred to as BCC). DEA is a linear programming technique where the frontier is assembled on a piecewise basis from the best practice observations (classified as 100% efficient). It does not specify any functional form for the data, allowing this (reflected in the weights for the inputs and outputs) to be determined by the data.

The basic (multiplier form of the) DEA problem,[1] in the constant returns to scale version, can be expressed as a requirement to maximise efficiency, for output weights u and input weights v, for i inputs x and j outputs y (with bold to indicate vectors). If we set the weighted sum of inputs as 1, in mathematical notation this gives us a requirement to

$$\max_{uv} (\mathbf{u} y_j)$$

$$\text{st} \quad \mathbf{v} x_i = 1$$

$$\mathbf{u} y_j - \mathbf{v} x_i \leq 0$$

$$u, v > 0$$

Because DEA assesses efficiency by comparing a financial institution's efficiency with those of others, each inefficient financial institution will have a group of efficient institutions against which its performance is identified as inefficient. This group of efficient institutions is then described as being the reference set for that inefficient institution. This is a basis for arguing that DEA provides an operational approach to measurement of efficiency, in that it more directly identifies ways in which inefficiency can be reduced.

DEA can be used to derive measures of scale efficiency by using the variable returns to scale, BCC model alongside the CCR model. Coelli et al (1998) note that variable returns to scale models have been most commonly used since the beginning of the 1990s. Caution must be exercised in use of BCC models, however, particularly where cross

[1] For a more extensive discussion of DEA mathematics, refer to Coelli et al (1998), Cooper et al (2000), Zhu (2003), and Avkiran (2006), including the further references they provide.

sections are small, and where there is diversity in size among the institutions being studied. As Dyson et al (2001) note, if a BCC model is used, small and large units will tend to be over-rated in the efficiency assessment. This means that scale inefficiencies identified for such institutions may be spurious, with the actual cause of inefficiency being X-inefficiency. If a CCR model shows a DMU as inefficient, it may be difficult to ascertain whether the source of that inefficiency is scale or X-inefficiency.

A DEA model can be constructed either to minimise inputs or to maximise outputs. An input orientation aims at minimising the input amounts while keeping at least the present output levels, while an output orientation aims at maximising output levels without increasing use of inputs (Cooper et al, 2000).

3. The New Zealand banking environment

Since the acquisition of the National Bank of New Zealand by the ANZ Banking Group (NZ) Ltd in 2003, the New Zealand banking market has been dominated by just four banks, which together accounted for 86.4% of the assets of the New Zealand banking system as at 31 December 2004. Each of these banks has an extensive nationwide branch network, with a total of 797 branches between them as at the end of 2004. Despite the small number of banks (the total number of registered banks in 2005 was 16), and major banks with a relatively large combined market share, the New Zealand market appears to be reasonably competitive.

During the 1990s, and particularly between 1995 and 1999, the major banks undertook severe reductions in their branch networks in an attempt to drive down costs. This scaling down of branch numbers was accompanied by more assiduous efforts by most of the banks to charge account-keeping and transaction fees to their customers, at more economic levels. The combined effect of these changes was to contribute to a general perception that the quality of banks' customer service had deteriorated. This has been reflected in publicity given to surveys of bank customer satisfaction undertaken by the Consumer magazine and the University of Auckland. [2]

Since 2000, banks have making more strenuous efforts to try and improve perceptions of the service they offer, although customers have shown a continuing trend over a longer period of time to make less use of branch channels for service delivery. This has been reflected in increased use of electronic banking, initially through IVR-based telephony, but more recently using the internet. Customer transaction patterns have shown a switch from cheques to card-based payments, with substantial increases in both (pin-based) debit and credit card transactions. Branches have also become less important for the initiation of housing lending, with approximately 25% of residential mortgage lending now initiated through independent mortgage brokers.

Residential mortgage lending has become an increasingly important part of banks' asset portfolios, with mortgage secured lending accounting for 46.4% of assets by 31 December 2005. This has in turn been reflected in strong rates of asset growth, the funding of which has been inclined to pose something of a challenge for the banks. Although significant amounts of funds have been sourced for non-residents, there is still strong competition for funds for the domestic market, with branch networks being perceived as having a strong role in promoting deposit activity.

This study focuses on part of one of the major banks' branch networks, its branches in and around Auckland, which is New Zealand's largest city. This is considered to comprise a relatively homogeneous set of branches, to which a common frontier could realistically be expected to apply. Data were made available to the researchers on the understanding that the identity of the bank would not be disclosed, and for similar reasons, individual branches (DMUs) are identified only as numbers.

[2] These adverse reactions to branch closures provided a basis for New Zealand Post, with government backing, to establish a new bank, Kiwibank, which commenced business in 2002. This has an extensive branch network through New Zealand Post's post shops, which are additional to the 797 branches of the major banks reported above as operating at the end of 2004.

4. Previous research on the efficiency of bank branches

Although the number of prior studies of bank branches is not large, there have been a number of useful contributions in the field. Sherman & Gold (1985), for example, was one of the first reported studies that used data envelopment analysis (DEA) for a banking study, and looked at the relative efficiency of branches of a savings bank in the United States. Other earlier studies have included Oral & Yolalan (1990), Al-Faraj et al (1992), and Sherman & Ladino (1995), although a number of these studies were rather less useful than they might have been because of the relatively small number of branches included, which reduced the discriminatory power of the models used to identify inefficient branches. This last point was highlighted by Berger et al (1997) and influenced their choice of parametric methods, rather than DEA as used for those previously listed, to look at 761 and 769 branches of a large US commercial bank.[3]

More recent studies have included Athanassopoulos (1997), Schaffnit et al (1997), Soteriou & Stavrinides (1997), Avkiran (1999), Golany & Storbeck (1999), Zenios et al (1999), Soteriou & Zenios (1999), Athanassopoulos & Giokas (2000), and Athanassopoulos (2000). There has been one previous New Zealand study, Murray & Tripe (2004), although that looked at the branches of a non-bank financial institution. These studies have all used DEA, which has offered the advantage, in a number of cases, of allowing use of non-monetary quantities as inputs and outputs. An important variable in this respect, used in a number of studies, has been a measure of customer satisfaction.

Avkiran (1999) used number of teller windows and staff and staff conduct to represent the level of customer service delivery for an Australian bank whereas Mukherjee et al. (2002) used the measures of non-interest-income and interest spread as a proxy for customer service. Neither of these approaches may provide wholly satisfactory measures of service quality and customer satisfaction because they are indirect. For example a branch may have many teller windows but the service delivery from the staff behind

[3] For a discussion of the distinctions between parametric and non-parametric methods of estimating the position of the efficient frontier, against which X-efficiency can be measured, and of the strengths and weaknesses of the different approaches, see Berger & Humphrey (1997).

those windows may be poor. Non-interest income and interest spread would also be expected to be affected by many more factors than customer satisfaction.

Soteriou and Stavrinides (1999) used an internal survey of service quality as a measure of customer service quality and satisfaction combined with an external survey that was administered directly to the bank's customers. Golany and Storbeck (1999) also used a quarterly survey of a bank's customers to get an indication of service quality.

Another factor common to many of these previous studies has been use of the production approach to modelling the financial services firm. Under the production approach, banks are seen as using labour and capital to produce deposits and loans, with both inputs and outputs typically measured as physical magnitudes, rather than in dollars, whereas the intermediation approach (based on Sealey & Lindley, 1977) sees deposits and other funds being transformed into loans. The production approach has generally been regarded as more suitable for bank branch studies as customer level transactions are carried out at branch level, whereas branch managers often have little control over decisions regarding the bank's funding or investment decisions.

In practice, the importance of the taxonomic distinctions may be overstated. A key factor that will determine what input and output variables are used will be what can be measured. A more important issue is one highlighted by Dyson et al (2001), particularly where using DEA, that the input/output set should cover the full range of resources used and outputs created. At the same time, the researcher will also want to be mindful of degrees of freedom constraints, and will want to avoid using these up by using input or output variables which don't contribute to the identification of bank efficiency. Common sense and expert judgement can play a role in this. It is important to include key resources as inputs and to include in outputs those objectives regarded as key to the DMU's success (Avkiran, 1999).

5. The method and data used for this study

Inputs and outputs used for this study were not, in the end based specifically on either the production or intermediation approach, but rather on what the bank's management specified as important outputs, and on the inputs to generate these. The bank's targets for outputs at branch level were asset and liability growth, non-interest income and customer satisfaction (which the bank measures on a regular basis using customer surveys). The inputs identified as contributing these to outputs, and which were important to the bank, were salary expense, brokerage paid (in respect of loan acquisition, and which might thus be regarded as promotional expense), and interest expense.

Some of these inputs and outputs have been quite commonly used in previous research (e.g. salary expense, interest expense and non-interest income), but others are less common. For example it would be more usual to look at absolute levels of assets and liabilities rather than just at their growth, but it is possible to use these outputs in this case because of the rapid rate at which the bank has been growing (with all branches achieving growth). However, if larger branches are not achieving relative growth as fast as smaller ones, there will be a bias towards decreasing returns to scale for these larger branches. Some of the side effects of using these variables are evident in our results.

Some of the inputs and outputs reflect peculiarities of the way in which the bank operates, and the discretions given to branch managers in trying to achieve their targets. Most previous approaches to measurement of branch efficiency have treated interest expense as a given (consistent with the production approach), but in this case, branch managers have some discretion, which they can use to win deposits, thus boosting liability growth. Branch managers also have some discretion with respect to whether they collect the fees that comprise non-interest income at branch level.

Brokerage is another unusual input into an efficiency study. It is paid to mortgage brokers responsible for submitting successful loan applications to the bank, and is charged to the branch on whose books the broker-originated loan is carried. There should thus be a direct relationship between brokerage expense and asset growth, although it is arguable that brokerage expense is not altogether under branch manager control: if the loan comes through a broker, payment of the brokerage once the loan has been advanced is automatic. On the other hand, branch managers who manage to achieve growth in the branch loan portfolio without reliance on the broker channel should be identified as superior performers.

The use of a customer satisfaction score would have been particularly challenging for a parametric model, but an inability to readily distinguish input and output prices from quantities provided a further rationale for use of DEA. The customer satisfaction scores are on a 0 to 5 rating. The figures actually used in this study are an average of 24 monthly scores for each branch, which reduces the impact of rogue results from individual monthly surveys.

Initial exploration of the data was undertaken using standard CCR and BCC models, and a range of further models were then used for subsequent exploration of the data.[4] The models were generally run with an output orientation, reflecting the fact that the outputs were regarded as being under management control. DEA software packages used were DEA-Solver, as per Cooper et al (2000), and DEA Excel Solver, as per Zhu (2003).

The bank that is the subject of the study provided applicable proprietary data. An initial check of the data was undertaken using a super-efficiency model (which, after correction of errors, did not identify any exceptional cases) and by looking at the correlations between the inputs and outputs. To eliminate some of the sources of random error, which are a recognised limitation of DEA, the data for each branch were taken as an average of two years' figures. The correlation matrix is shown in Table 1.

[4] Space precludes a detailed exposition of the DEA models used. For more detail, on this refer to a standard work such as Coelli et al (1998), Cooper et al (2000), Zhu (2003), or Avkiran (2006).

Table 1: Correlations between inputs and outputs

	Brokerage	Interest Expense	Asset Growth	Liability Growth	Non-Interest Income	Customer Satisfaction
Salary	0.67	0.67	0.80	0.75	0.88	-0.15
Brokerage		0.48	0.85	0.59	0.62	-0.21
Interest Expense			0.63	0.82	0.68	-0.24
Asset Growth				0.74	0.75	-0.17
Liability Growth					0.78	-0.19
Non-interest income						-0.18

We can see from the above that there are acceptable correlation coefficients between the inputs, the outputs, and between the inputs and outputs, with the exception of those between the customer satisfaction measure and the input variables: increased utilisation of the inputs does not appear to lead to increased levels of customer satisfaction. The negative correlation coefficients between the non-interest income and customer satisfaction is not an inherent problem, as it would suggest that there was a trade-off between the two - if a branch is collecting more in the way of fees from its customers, customers might regard it less favourably (although even then, a more satisfied customer might be happy to pay more in the way of fees). As will be seen below, however, this is not the only problem with the customer satisfaction variable.

Descriptive statistics for the data set are shown in Table 2.

Table 2: Descriptive Statistics

$000	*Salary expense*	*Brokerage expense*	*Interest expense*	*Asset growth*	*Liability growth*	*Non-interest income*	*Customer satisfaction score*
Minimum	346.8	0	1399.7	4221.2	2276.7	767.2	2.78
Maximum	2427.1	1820.4	25199.2	128181.8	69194.2	6286.5	4.67
Mean	1021.9	206.7	9318.0	35013.5	22136.1	2681.1	3.70
Standard deviation	485.1	328.7	5717.1	28343.5	14646.6	1254.7	0.43

6. Results

6.1 The basic CCR and BCC models

We commence by reporting the results from basic CCR and BCC models, with the results, including initial estimates of scale efficiency, reported in Table 3. Mean efficiency from the CCR model was 0.912, mean efficiency from the BCC model was 0.979, and mean scale efficiency was 0.931. Median efficiency from the CCR model was 0.9457, and from the BCC model 1: according to the Mann-Whitney test this difference, and thus scale inefficiency, is significant at the 1% level.

The obvious inference from these results is that there is not a great deal of difference between the efficiencies of individual branches, and that the main source of inefficiency is scale (rather than X-inefficiency).[5] If we look at the returns to scale status as reported by DEA-Solver, we find that there were only two branches showing increasing returns to scale, as opposed to 32 showing constant returns to scale, and 33 showing decreasing returns to scale. This would suggest that branches were more likely to suffer from being too large, rather than too small, and we note that the two branches facing increasing returns to scale were among the smaller branches in the network (with less than the mean level of interest expense).

A peculiar feature of the results from the CCR model becomes evident when we look at the projections (to the efficient frontier) for customer satisfaction: in 27 out of 67 cases, the projected customer satisfaction score exceeds the maximum of 5. Moreover, shortages in the customer satisfaction output appear to be a major source of inefficiency for those firms that are not on the efficient frontier. By contrast, for the BCC model, none of the projected figures for customer satisfaction exceed 5 (and none exceed 4.67 which was the actual maximum score in the original data set). The tighter envelopment of the data under the BCC model prevents infeasibly high projected figures arising, but at the

[5] With the product of the numbers of inputs and outputs being 12, relative to a total of 67 DMUs, we would not expect the size of the data set to be the cause of the relatively high efficiency scores.

same time, we seem to have our scale efficiency estimates unduly dependent on the BCC frontier enveloping the customer satisfaction points more tightly. Because customer satisfaction scores cannot increase as other scale related variables increase, larger branches are likely to show as being scale inefficient accordingly.

This finding is consistent with pitfalls identified by Dyson et al (2001), in terms of mixing indices and volume measures, and in use of percentages and other normalised data. A solution to this could be found in scaling the customer satisfaction data by, for example, the number of customers associated with each branch, so that we had a measure that reflected the numbers of customers that enjoyed that level of satisfaction. Unfortunately, however, our data set does not provide either customer numbers or any other suitable data to use as a satisfactory basis for scaling, such as staff numbers, or branch assets or liabilities (and even then, such an adjustment would be prone to distortion for the sorts of reasons identified by Berger et al, 1997, where customers of one branch might undertake their transactions at another branch).

To get around this problem, in trying to assess the extent of scale efficiency across the bank's branch network, we therefore test alternative models, without the customer satisfaction output.

6.2 Models without the customer satisfaction output

We report the results from these alternative CCR and BCC models, including initial estimates of scale efficiency, in Table 4. Mean efficiency from the CCR model was 0.901, mean efficiency from the BCC model was 0.958, and mean scale efficiency was 0.941. Median efficiency from the CCR model was 0.9120, and from the BCC model 1: according to the Mann-Whitney test this difference, and thus scale inefficiency, is significant at the 5% level.

With the reduction in the numbers of inputs and outputs, the number of inefficient units in the BCC models has increased from 20 to 25. The number of branches operating at increasing returns to scale is now 11, with 25 branches at constant returns to scale, and 31 at decreasing returns to scale. Because the number of variables is one fewer in this second analysis, the efficiency scores must be not greater than those from the original models (which included the service quality score as an output).

We have compared the two sets of technical efficiency scores, derived from the BCC models, by looking at the correlations between them, and by looking at the spread ratios, as described by Schaffnit et al (1997). The spread ratio is defined as the efficiency score from the model without customer service divided by the efficiency score from the model with the customer service measure included, and it may thus be argued as reflecting the improvement in efficiency arising from inclusion of the customer service variable. There were 6 branches with spread ratios less than 0.9: these were generally branches with high customer satisfaction ratings, but sometimes with significant other sources of inefficiency (such as high brokerage).

The Pearson correlation between the two sets of efficiency scores was 0.829, while the Spearman correlation was 0.867, both significant at the 1% level. This indicates a reasonable degree of consistency between the efficiency scores generated by the two different models, although the large numbers of branches with efficiency scores of 1 undermines the usefulness of the comparison. It is therefore regarded as more appropriate to compare efficiency scores and branches' relative rankings generated from super-efficiency models, which are not truncated at 1, as we report below.

Because of infeasibility problems with the standard Super-efficiency model (on a variable returns to scale basis), we were obliged to use the slacks-based Super-efficiency model (as per Tone, 2002). The Pearson correlation between the two sets of efficiency scores was 0.884, while the Spearman correlation was 0.911, both significant at the 1% level. This gives us a stronger indication of consistency between the efficiency scores generated by the two different models.

Running the slacks-based Super-efficiency models highlighted some particularly low slacks-based efficiency scores for a small number of branches. This suggests quite low levels of mix-efficiency, which we confirmed using an ordinary slacks-based model (on a variable returns to scale basis). A very high proportion of branches continued to show as fully efficient, but we found 11 branches from each model with mix efficiency of less than 0.9, although not exactly the same list in both cases. Major sources of inefficiency, in terms of shortfall from projected targets, would appear to be in the areas of asset and liability growth, two variables with which we had anticipated problems (see above).

The branches with low levels of mix efficiency should be the subject of further investigation, but we lack access to detailed information on the bank's branch network to allow us to investigate them further.

Table 5 shows the results of running the basic BCC model, together with the results from the model without the customer service measure, from the slacks-based model. All models are run on a variable returns to scale, output-oriented basis. Table 5 shows a remarkable degree of uniformity in identification of inefficient branches. Both Pearson and Spearman rank correlation coefficients are high and significant at less than 1%, as shown in Table 6.

Table 6: Correlations between results from different models.

Pearson correlations			**Spearman (rank) correlations**		
	Model without customer service measure	*Slacks-based model*		*Model without customer service measure*	*Slacks-based model*
Basic model	0.829	0.891	**Basic model**	0.867	0.948
Model without customer service measure		0.729	**Model without customer service measure**		0.856

7. Summary and conclusion

This paper has reported on an investigation of the efficiency of part of a New Zealand bank's branch network, using criteria as defined by the bank's management. This entailed looking at asset and liability growth, non-interest income and customer satisfaction as goals for branch managers to maximise, subject to the resources utilised of salary expense, interest expense and brokerage. This might be regarded as a somewhat unusual list of inputs and outputs, in that they might be likely to generate decreasing returns to scale for larger branches, but this effect was countered to a significant extent by use of variable returns to scale DEA models. There is an implication from this, however, that a different input/output set might lead to different conclusions with regard to scale efficiency and returns to scale.

In all cases, and despite a sample size that ought to have been large enough to provide adequate discriminatory power, a high proportion of the branches studied were found to be efficient. Moreover, with each of the models used, there was a very high degree of consistency between the branches found to both efficient and inefficient, and in the extent of inefficiency estimated. This gives us some confidence in the robustness of our results, although it also raises questions as to the appropriateness of our input/output set.

It is also notable that, except where the slacks-based model was used, the extent of inefficiency found was relatively small, with high average efficiency scores. Note, however, that although this may mean that the bank's branches are highly efficient, we cannot substantiate that conclusion. All we know is that there is not much difference between branches' relative efficiency, and it may be that there is significant scope for all branches to improve their performance.

In terms of management action to improve branch performance, it would be valuable to focus particularly on those branches identified as inefficient by the slacks-based model. Initial review of the detailed results suggests that the problems may arise through shortfalls relative to estimated targets in asset and liability growth, which may be a consequence of the particular input/output set used.

This suggests a number of angles for fruitful further research. It would be useful to do some additional work with the existing variables, in particular by adjusting the customer service score by some measure to take account of the scale of each branch's business, such as number of customers. We also suspect that it might be useful to use absolute levels of assets and liabilities per branch, rather than their growth, so as to obtain a better assessment of optimal branch size. The implication from this research that larger branches are scale inefficient might not be the correct conclusion to be drawn. Use of total assets and liabilities, rather than their changes, might also cause greater attention to be given to margins (which drive profits).

This research was intended to focus on practical business performance improvement. It has used a number of the techniques of Data Envelopment Analysis to pursue this, and it has identified a number of areas where management could link with academic researchers to improve performance. The additional revenues that could be generated, and costs that could be saved, even based on existing models, are likely to be enough to justify the effort.

References:

Al-Faraj, T. N.; Alidi, A. S. & Bu Bshait, K. A. (1992). Evaluation of bank branches by means of Data Envelopment Analysis. *Journal of Operations and Production Management.* 13 (9). 45-52.

Athanassopoulos, A. D. (1997). Service quality and operating efficiency synergies for management control in the provision of financial services: evidence from Greek bank branches. *European Journal of Operational Research.* 98. 300-313.

Athanassopoulos, A. D. (2000). An optimisation framework of the triad: service capabilities, customer satisfaction and performance. Chapter 9 in Harker, P. T, & Zenios, S. A., *Performance of Financial Institutions – Efficiency, Innovation and Regulation.* (pp 312-335). Cambridge University Press.

Athanassopoulos, A. D. & Giokas, D. (2000). The use of Data Envelopment Analysis in banking institutions: evidence from the Commercial Bank of Greece. *Interfaces.* 30 (2). 81-95.

Avkiran, N K. (1999). An application reference for data envelopment analysis in branch banking: helping the novice researcher. *International Journal of Bank Marketing.* 17 (5). 206-220.

Avkiran, N. K. (2006). *Productivity Analysis in the Service Sector with Data Envelopment Analysis.* (Third Edition). Camira, Queensland: N K Avkiran.

Banker, R. D.; Charnes, A. W. & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in Data Envelopment Analysis. *Management Science.* 30 (9) 1078-1092.

Berger, A. N. & 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. & Humphrey, D. B. (1997). Efficiency of financial institutions: international survey and directions for future research. *European Journal of Operational Research.* 98. 175-212.

Berger, A. N.; Hunter, W. C. & 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.

Berger, A. N.; Leusner, J. & Mingo, J. (1997). The efficiency of bank branches. *Journal of Monetary Economics.* 40 (1). 141-162.

Charnes, A.: Cooper, W. W. & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research.* 2. 429-444.

Coelli, T.; Prasada Rao, D. S. & Battese, G. E. (1998). *An Introduction to Efficiency and Productivity Analysis.* Boston: Kluwer Academic Publishers.

Cooper, W. W.; Seiford, L. M. & Tone, K. (2000). *Data Envelopment Analysis.* Boston: Kluwer Academic Publishers.

DeYoung, R. (1998). Management quality and X-efficiency in national banks. *Journal of Financial Services Research.* 13 (1). 5-22.

Dyson, R. G.; Allen, R.; Camanho, A. S.; Podinovski, V. V.; Sarrico, C. S. & Shale, E. A. (2001). Pitfalls and protocols in DEA. *European Journal of Operational Research.* 132. 245-259.

Golany, B. & Storbeck, J. E. (1999). A Data Envelopment Analysis of the Operational Efficiency of Bank Branches. *Interfaces.* 29 (3). 14-26.

Mukherjee, A.; Nath, P. & Pal, M. N. (2002). Performance benchmarking and strategic homogeneity of Indian banks. *International Journal of Bank Marketing.* 20(3). 122-139.

Murray, D. & Tripe, D. (2004, July). *The cost of inefficiency: an empirical study into the relative efficiency of a financial institution's branches.* Paper presented at the Asia Pacific Productivity Conference, Brisbane.

Oral, M. & Yololan, R. (1990). An empirical study on measuring operating efficiency and profitability of branches. *European Journal of Operational Research.* 46 (3). 282-294.

Schaffnit, C.; Rosen, D. & Paradi, J. C. (1997). Best practice analysis of bank branches: an application of DEA in a large Canadian bank. *European Journal of Operational Research.* 98. 269-289.

Sealey, C. W. & Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *Journal of Finance.* 32 (4). 1251-1266.

Sherman, H. D, & Gold, F. (1985). Bank branch operating efficiency: evaluation with data envelopment analysis. *Journal of Banking and Finance.* 9. 297-315.

Sherman, H. D. & Ladino, G. (1995). Managing bank productivity using Data Envelopment Analysis (DEA). *Interfaces.* 25 (2). 60-73.

Soteriou, A. C. & Stavrinides, Y. (1997). An internal customer service quality data envelopment analysis model for bank branches. *International Journal of Operations and Production Management.* 17 (8). 780-789.

Soteriou, A. C. & Zenios, S. A. (1999). Operations, quality and profitability in the provision of banking services. *Management Science.* 45 (9). 1221-1239.

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research.* 143. 32-41.

Zenios, C. V.; Zenios, S. A.; Agathocleous, K & Soteriou, A. C. (1999). Benchmarks of the efficiency of bank branches. *Interfaces.* 29 (3). 37-51.

Zhu, J. (2003). *Quantitative models for performance evaluation and benchmarking.* Kluwer Academic Publishers: Boston.

Table 3: Results from basic CCR and BCC models

Branch number	Efficiency Score - CCR	Efficiency Score - BCC	Scale Efficiency
1	0.715	0.975	0.733
2	0.742	0.896	0.828
3	0.842	1.000	0.842
4	0.805	1.000	0.805
5	0.982	1.000	0.982
6	0.830	1.000	0.830
7	0.840	0.965	0.871
8	1.000	1.000	1.000
9	0.897	1.000	0.897
10	1.000	1.000	1.000
11	0.792	0.839	0.943
12	1.000	1.000	1.000
13	1.000	1.000	1.000
14	0.675	1.000	0.675
15	0.977	1.000	0.977
16	1.000	1.000	1.000
17	0.903	0.996	0.906
18	1.000	1.000	1.000
19	0.774	0.971	0.797
20	0.987	1.000	0.987
21	0.761	0.906	0.841
22	1.000	1.000	1.000
23	0.886	0.978	0.907
24	0.706	1.000	0.706
25	0.862	1.000	0.862
26	0.837	1.000	0.837
27	0.912	1.000	0.912
28	0.898	1.000	0.898
29	0.846	1.000	0.846
30	0.759	0.948	0.801
31	0.979	1.000	0.979
32	1.000	1.000	1.000
33	1.000	1.000	1.000
34	0.804	0.805	0.998
35	1.000	1.000	1.000
36	1.000	1.000	1.000
37	0.818	0.980	0.834
38	1.000	1.000	1.000
39	1.000	1.000	1.000
40	0.926	0.937	0.989
41	0.877	1.000	0.877
42	1.000	1.000	1.000
43	0.792	0.874	0.906
44	0.657	0.886	0.742
45	1.000	1.000	1.000
46	0.883	0.886	0.996
47	0.906	1.000	0.906
48	0.794	1.000	0.794
49	1.000	1.000	1.000
50	1.000	1.000	1.000
51	1.000	1.000	1.000
52	1.000	1.000	1.000
53	1.000	1.000	1.000
54	1.000	1.000	1.000
55	1.000	1.000	1.000
56	1.000	1.000	1.000
57	1.000	1.000	1.000
58	0.944	0.992	0.952
59	1.000	1.000	1.000
60	1.000	1.000	1.000
61	0.824	0.911	0.904
62	1.000	1.000	1.000
63	0.840	0.910	0.923
64	0.946	0.989	0.956
65	0.960	1.000	0.960
66	0.924	0.937	0.987
67	1.000	1.000	1.000

Table 4: Results from CCR and BCC models, with service quality output omitted

Branch number	Efficiency Score - CCR	Efficiency Score - BCC	Scale Efficiency
1	0.715	0.950	0.753
2	0.730	0.731	0.999
3	0.842	0.960	0.876
4	0.805	0.978	0.824
5	0.982	1.000	0.982
6	0.830	1.000	0.830
7	0.840	0.965	0.871
8	1.000	1.000	1.000
9	0.897	1.000	0.897
10	1.000	1.000	1.000
11	0.792	0.801	0.988
12	1.000	1.000	1.000
13	1.000	1.000	1.000
14	0.675	1.000	0.675
15	0.976	1.000	0.976
16	1.000	1.000	1.000
17	0.903	0.980	0.921
18	1.000	1.000	1.000
19	0.774	0.862	0.898
20	0.987	1.000	0.987
21	0.761	0.906	0.841
22	0.982	1.000	0.982
23	0.886	0.895	0.990
24	0.706	1.000	0.706
25	0.862	1.000	0.862
26	0.837	0.848	0.987
27	0.912	1.000	0.912
28	0.867	0.896	0.967
29	0.846	1.000	0.846
30	0.759	0.816	0.930
31	0.979	1.000	0.979
32	1.000	1.000	1.000
33	1.000	1.000	1.000
34	0.769	0.803	0.958
35	1.000	1.000	1.000
36	1.000	1.000	1.000
37	0.818	0.922	0.887
38	1.000	1.000	1.000
39	1.000	1.000	1.000
40	0.917	0.917	1.000
41	0.877	0.939	0.935
42	1.000	1.000	1.000
43	0.792	0.834	0.950
44	0.657	0.711	0.925
45	1.000	1.000	1.000
46	0.874	0.878	0.995
47	0.906	1.000	0.906
48	0.718	1.000	0.718
49	1.000	1.000	1.000
50	1.000	1.000	1.000
51	1.000	1.000	1.000
52	0.864	1.000	0.864
53	1.000	1.000	1.000
54	1.000	1.000	1.000
55	1.000	1.000	1.000
56	0.956	1.000	0.956
57	0.960	1.000	0.960
58	0.893	0.992	0.901
59	0.927	1.000	0.927
60	1.000	1.000	1.000
61	0.824	0.911	0.904
62	1.000	1.000	1.000
63	0.839	0.858	0.978
64	0.946	0.989	0.956
65	0.910	1.000	0.910
66	0.796	0.858	0.928
67	1.000	1.000	1.000

Table 5: Results from different variable returns to scale models

Branch number	Basic model	Customer service omitted	Slacks-based model
1	0.975	0.950	0.902
2	0.896	0.731	0.775
3	1	0.960	1
4	1	0.978	1
5	1	1	1
6	1	1	1
7	0.965	0.965	0.936
8	1	1	1
9	1	1	1
10	1	1	1
11	0.839	0.801	0.648
12	1	1	1
13	1	1	1
14	1	1	1
15	1	1	1
16	1	1	1
17	0.996	0.980	0.885
18	1	1	1
19	0.971	0.862	0.924
20	1	1	1
21	0.906	0.906	0.727
22	1	1	1
23	0.978	0.895	0.931
24	1	1	1
25	1	1	1
26	1	0.848	1
27	1	1	1
28	1	0.896	1
29	1	1	1
30	0.948	0.816	0.844
31	1	1	1
32	1	1	1
33	1	1	1
34	0.805	0.803	0.613
35	1	1	1
36	1	1	1
37	0.980	0.922	0.876
38	1	1	1
39	1	1	1
40	0.937	0.917	0.925
41	1	0.939	1
42	1	1	1
43	0.874	0.834	0.747
44	0.886	0.711	0.627
45	1	1	1
46	0.886	0.878	0.409
47	1	1	1
48	1	1	1
49	1	1	1
50	1	1	1
51	1	1	1
52	1	1	1
53	1	1	1
54	1	1	1
55	1	1	1
56	1	1	1
57	1	1	1
58	0.992	0.992	0.936
59	1	1	1
60	1	1	1
61	0.911	0.911	0.511
62	1	1	1
63	0.910	0.858	0.830
64	0.989	0.989	0.915
65	1	1	1
66	0.937	0.858	0.879
67	1	1	1