THE COST OF FUNDS AND BANK EFFICIENCY THROUGH TIME

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Abstract:

A super-efficiency model within Data Envelopment Analysis (DEA) was used to study the relative efficiency of New Zealand banks for the period 1996 to 2003. Evidence was found for improvement in efficiency, although it was found that this was significantly a consequence of the reduction in the general level of interest rates over the period, which reduced banks' apparent utilisation of resources.

Significant differences were found between banks in their relative efficiency.

Keywords:

Banking, New Zealand, Data Envelopment Analysis, super-efficiency model

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1 Introduction

A key choice to be made in modelling bank efficiency is in specifying the inputs and outputs of the production process: differences in the input and output variables chosen are commonly found to impact on the efficiency scores generated, while Wheelock & Wilson (1995) state that unreliable estimates of efficiency can be generated by models that omit key features of bank production. Tortosa-Ausina (2002) suggests that conclusions relative to the efficiency and potentially the competitive viability of firms in the industry could depend on the model chosen.

A further problem is that key inputs and outputs may be correlated with environmental factors, so that differences in efficiency scores may reflect differences in environmental factors rather than differences in efficiency. Obvious examples of inputs or outputs to be affected by environmental factors would be (total) interest expense or (total) interest income, or other measures that reflected these, such as total expenses or total income.

Tripe (2003) provided an example of a way in which this effect might occur, by showing for the New Zealand market how efficiency changes through time appeared to relate to movements in the general level of interest rates. Such a problem may not arise only in the context of interest rate changes through time, however, but also in terms of interest rate differentials between countries. This has been an area where Chaffai et al (2001) and Lozano-Vivas et al (2002) have criticised earlier cross-country studies of bank efficiency, arguing that they failed to properly take account of country-specific conditions or norms. This concern was also reflected in comments by Dietsch and Lozano-Vivas (2000) that previous approaches could misstate the relative efficiency of firms from different countries, because they did not account for cross-country differences in demographic, regulatory and economic conditions beyond the control of firm managers within their inputs and outputs.

This paper revisits the analysis of Tripe (2003), and looks to extend it. That earlier paper looked at individual banks separately, whereas the study reported in this paper looks at all the banks together in a grand panel, which allows the further benefit of letting us look at the banks' efficiency relative to each other. That earlier paper also applied OLS regression to constant returns to scale efficiency scores (as the response variable). Such an approach has a number of limitations, in that the efficiency scores used might not have been appropriately derived. This research uses a different technique to generate efficiency scores for the banks, the Slacks-Based Super-efficiency model (Tone, 2002), which has been argued as providing a more satisfactory basis for subsequent regression analysis.

The rest of the paper proceeds as follows. In the next section we outline relevant methods of efficiency measurement in more detail, to explain the background to the method used in this research. In Section 3 we briefly describe some features of the New Zealand banking market, including reporting on the set of banks used for this study. Section 4 outlines the approach followed and data used for this study. Section 5 of the paper looks at the results obtained, including the regression results, and discusses them. Section 6 looks at two separate approaches to measurement of banks' efficiency relative to each other, while Section 7 provides a summary and conclusion.

2 The measurement of efficiency

Berger & Humphrey (1997) reported 5 approaches to specification of an efficient frontier against which bank efficiency could be measured. Three of these are parametric and two nonparametric (although it is common to regard one of the nonparametric methods, the Free Disposal Hull approach, as a special case of the other, Data Envelopment Analysis (DEA)). This study uses DEA, as this exempts us from the requirement to have information on the prices of the inputs the banks use (although this means that we are unable to separately identify allocative efficiency from technical efficiency). DEA also relieves us from the requirement to specify a form for the production function which generates the efficient frontier: production relationships in banking are not subject to the same consensus as might apply to engineering relationships in other lines of business.

The disadvantage of using DEA is that it does not allow for random error or other stochastic events that may influence the results obtained. We can, however, obtain some comfort relative to the impact of random error on efficiency scores (and particularly the cases where such error makes a firm appear unusually efficient) by use of the super-efficiency model. There is a rule of thumb which suggests that if a DMU's super-efficiency score is greater than 2 (see, for example, Hartmann et al, 2001), the DMU in question should be regarded as an outlier, and eliminated from subsequent analysis.[1]

DEA as we now know it was introduced by Charnes et al (1978) in a constant returns to scale (CCR)[2] model. Banker et al (1984) then introduced a variable returns to scale (BCC)[3] model. Use of these two models together allows estimation of scale efficiency, in that technical efficiency (from the CCR model) is the product of pure technical efficiency (from the BCC model) and scale efficiency. Care needs to be exercised in use of the BCC model, however, in that it envelopes the data more tightly than does the CCR model, and DMUs may thus be identified as scale inefficient just because there are relatively few of them relative to a particular section of the efficient frontier (Dyson et al, 2001). Avkiran (1999) has thus suggested that researchers should run both CRS and VRS models, and "if the majority of DMUs are assessed as having the same efficiency under both methods, one can work with CRS without being concerned about scale efficiency confounding the measure of technical efficiency".

One of the issues that arises with DEA is with the pattern of efficiency scores, which are both highly skewed and censored at one under both the CCR and BCC models, which raises questions as to their suitability for use in subsequent regression analysis. Ferrier & Hirschberg (1997) have noted that the distribution of efficiency scores is neither known nor specified, while they will also be dependent on each other. This means that, if one wishes to regress efficiency scores against environmental factors, one should use a logit

[1] Common sense can also play a role in screening variables, and we will see below that some cases have been omitted from our analysis because we can otherwise identify them as exceptions.
[2] The abbreviation CCR is based on the names Charnes, Cooper & Rhodes, who were the authors of the 1978 paper.
[3] The abbreviation BCC is based on the names Banker, Charnes & Cooper, who were the authors of the 1984 paper.

or preferably tobit regression (Coelli et al, 1998, pp 170-171). OLS regression is not appropriate (Grosskopf, 1996), although it has been often-enough used in previous research.

One approach suggested to overcoming this problem is through use of scores from the super-efficiency model as response variables for subsequent regression analysis (Lovell et al, 1994).[4] The super-efficiency scores are calculated by omitting the DMU under consideration from the reference set of the set of DMUs being analysed, and the scores are thus no longer bounded at one (Andersen & Peterson, 1993).

The next section of the paper provides further background on the New Zealand banking system, which is the sample set within which this research has been undertaken.

3 The New Zealand banking system and its data

Deregulation of an extensive range of aspects of the New Zealand economy occurred mainly following the replacement of the previous (conservative) National Party regime by a reform-minded Labour government in 1984. The financial sector was not immune to this process, and there were significant changes in both the banking market and in the approach followed to monetary policy.

Monetary policy had previously been directed at a range of objectives, and was conducted largely in response to the government's (often political) instructions. The deregulated environment saw a switch to a focus on a single objective, price stability. With interest rates now allowed to vary, the Reserve Bank of New Zealand's campaign against inflation was largely effected by much higher short term interest rates, with the 90-day bank bill rate (the key indicator) sometimes exceeding 20%, and not settling below 10% until the middle of 1991, by which time inflation had reduced substantially. These rates and the volatility in them gradually reduced through the 1990s, although rates

[4] Use of this approach is highlighted again by Lovell & Rouse (2003).

and significant volatility in them remained relatively high, as the Reserve Bank responded to perceived inflationary pressures, reflected in factors such as residential property prices and movements in the exchange rate. Since the adoption of a new instrument for monetary policy in 1999, the extent of movement in interest rates has generally eased, and peaks in the interest rate cycle are generally lower than in earlier times. Interest rate volatility has nonetheless led to significant volatility in both banks' cost of funds and gross interest revenues.

The focus of this research is on the six banks operating in New Zealand with extensive branch networks and a significant focus on retail banking: ANZ Banking Group (New Zealand) Limited (ANZ), ASB Bank Limited (ASB), Bank of New Zealand (BNZ), the National Bank of New Zealand Limited (NBNZ), TSB Bank Limited (TSB) and the New Zealand Branch of Westpac Banking Corporation (Westpac). Although the New Zealand Government has established Kiwibank as a retail bank through New Zealand Post, it only commenced business in early 2002, and its relatively short period of operation and its failure to earn consistent profits during the period of the study would make it unfair to include it in the study, despite its extensive branch network.[5] Superbank, which commenced business only in February 2003, and which uses New World supermarkets and other Foodstuffs outlets as its public face, has been omitted from the study for similar reasons.

TSB is much smaller than any of the other banks in the study, with assets at 31 December 2003 of $2.03 billion, compared to the next smallest bank, ASB, at $30.40 billion. It is therefore plausible that, if there are scale inefficiencies for New Zealand banks, they might be observed in TSB's case.

Because of the relatively small number of full-service banks in New Zealand, analysis of individual quarters' data would be problematic, with artificially high efficiency scores generated. The analysis has therefore been undertaken on a panel of quarterly observations for the 6 banks. This would normally entail an assumption that there was no

[5] This approach can be justified in terms of previous research – see DeYoung & Hasan (1998).

technical change occurring through the period of the data window (Asmild et al, 2004), although our approach does not require this, in that we are happy to accept that changes in technical efficiency might reflect technical change.[6]

Although the time period is generally from the June quarter 1996 through to the December quarter 2003, some minor adjustments were required for some banks. The June quarter 1996 figures for Westpac were distorted by its acquisition of Trust Bank during the quarter, while for the December quarter 2003 figures for both ANZ and NBNZ were distorted by the ANZ's acquisition of NBNZ. Observations for these banks for these quarters have therefore been omitted. Data have been obtained from banks' income statements reported as part of their quarterly disclosures (which provide the basis for the prudential supervision of New Zealand banks). Summary descriptive statistics for the data used in this research are reported in Table 1.

Table 1: Summary descriptive statistics for the input and output variables used, across all banks.

$M	Minimum	Maximum	Mean	Standard deviation
Interest expense	8.94	485.9	275.56	139.86
Non-interest expense	4.01	207.1	114.86	58.72
Net interest income	6.04	267	10.4	74.7
Non-interest income	1.09	149	74.56	43.3

Our approach to the use of this data and the detail of the method used are described in the next section.

4 Data and Method

The study commences with running standard CCR and BCC models for our all-bank data set, and then goes on to use of an all-bank slacks-based super-efficiency model. Following the approach used by Lovell et al (1994), the natural logs of the super-

[6] This is thus consistent with the approaches to studying efficiency through time, using panel data, discussed by Tulkens & Vanden Eeckaut (1995). This technique has also been relatively little utilised in previous research, although a notable example of its use was by Bhattacharyya et al (1997).

efficiency scores are then regressed against the average 90-day bank bill rate,[7] bank total assets (which could reflect the benefits of increased scale), and a time trend variable (which might reflect the impact of technological change).

A further set of regression results is then generated incorporating individual bank dummy variables, which allows us to identify differences in bank efficiency. These differences are then compared with the differences in bank relative efficiency ascertained from use of the non-parametric Mann-Whitney test.[8]

DEA models are run with an input orientation, reflecting common practice in previous research looking at banks relative to each other, and which also reflects the emphasis by bank managements on reducing costs (and thus, by implication, inputs). It also recognises that banks collectively have only limited scope to change their outputs, other than at the expense of some other bank.

A correlation matrix with the full range of inputs and outputs is shown in Table 2. The levels of the correlation coefficients do not suggest that there is anything inappropriate about the input and output variables selected. This is further confirmed by the maximum score from the super-efficiency model being 1.07, which is considerably lower than the guideline figure for potential concern as to the presence of outliers, of 2.

Table 2: Correlations between inputs and outputs for all banks

	Non-Interest expense	*Net interest income*	*Non-interest income*
Interest expense	0.912	0.883	0.848
Non-interest expense		0.908	0.926
Net interest income			0.887

[7] We use the 90-day bank bill rate as it is the most important indicator interest rate in practice in the New Zealand market, and the most liquid maturity.

[8] The Mann-Whitney test is commonly used to test for differences in scores from DEA models because of the non-normality of DEA efficiency scores, particularly from CCR and BCC scores (Cooper et al, 2000; Casu & Molyneux, 2003).

Analysis of bank efficiency is undertaken using the software DEA-Solver, as described by Cooper et al (2000). The results from this analysis are reported and discussed in the next section.

5 Results and discussion

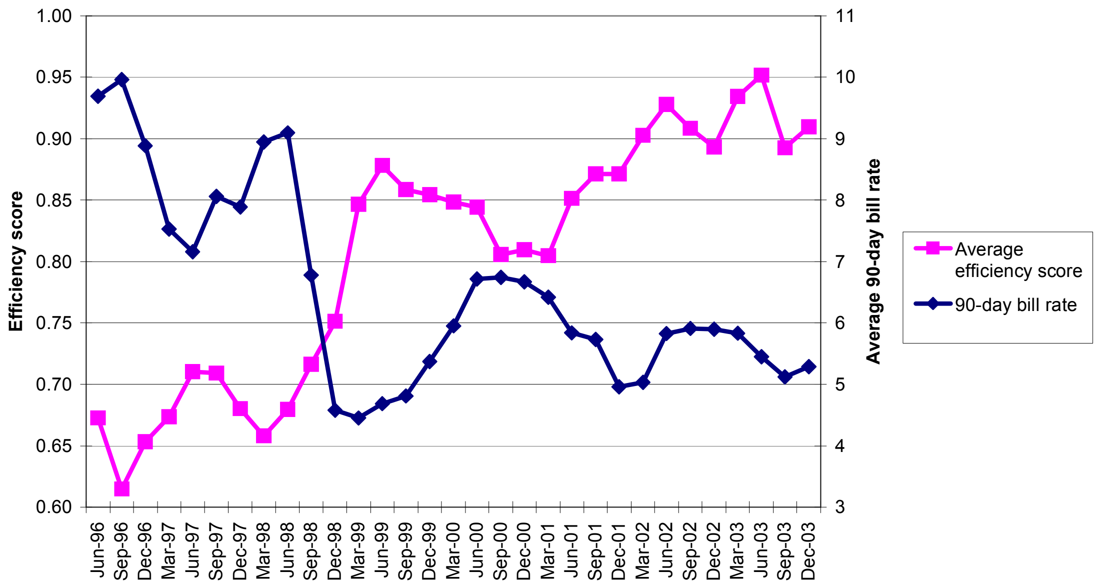
The results from the CCR model are shown in Table 3.

Table 3: Efficiency scores for all banks studied together (Constant returns to scale)

	ANZ	*ASB*	*BNZ*	*NBNZ*	*TSB*	*Westpac*
Jun-96	0.75359	0.635131	0.692881	0.479643	0.801753	-
Sep-96	0.698677	0.584392	0.622696	0.507753	0.748256	0.526789
Dec-96	0.697283	0.615231	0.699943	0.561069	0.762945	0.583355
Mar-97	0.815385	0.680281	0.711036	0.597747	0.633346	0.602869
Jun-97	0.859383	0.654936	0.727437	0.623481	0.722212	0.674483
Sep-97	0.906674	0.62125	0.703146	0.554091	0.755125	0.713539
Dec-97	0.643482	0.643593	0.715577	0.574051	0.784433	0.720012
Mar-98	0.654012	0.622167	0.652413	0.602601	0.740875	0.67586
Jun-98	0.673315	0.585728	0.696876	0.600676	0.787898	0.731825
Sep-98	0.874077	0.613077	0.617923	0.62091	0.776591	0.794026
Dec-98	0.808677	0.694692	0.759743	0.684862	0.778435	0.781105
Mar-99	0.876419	0.756864	0.819643	0.863246	0.825896	0.937397
Jun-99	1	0.770507	0.895526	0.784483	0.932037	0.885769
Sep-99	0.995345	0.744746	0.707112	0.815447	0.937413	0.950467
Dec-99	0.915601	0.731678	0.790497	0.784342	1	0.903372
Mar-00	0.859665	0.760024	0.814855	0.843518	0.955661	0.856628
Jun-00	0.82892	0.708413	0.802792	0.888002	0.978316	0.857175
Sep-00	0.756516	0.70173	0.788709	0.773791	0.961529	0.851366
Dec-00	0.841819	0.670243	0.818635	0.770599	0.947688	0.807501
Mar-01	0.901196	0.673157	0.820049	0.841603	0.793216	0.798869
Jun-01	0.912936	0.768572	0.761078	0.870035	0.954455	0.840167
Sep-01	1	0.721699	0.764446	0.865851	0.899936	0.974962
Dec-01	0.969568	0.787359	0.82207	0.753459	1	0.895811
Mar-02	0.980859	0.791316	0.878759	0.939308	0.985601	0.840076
Jun-02	0.981324	0.795133	0.901702	0.938272	1	0.949175
Sep-02	0.93837	0.771885	0.832754	0.906428	1	1
Dec-02	0.920677	0.781454	0.865483	0.851337	0.947372	0.992518
Mar-03	0.944952	0.793762	1	0.953754	0.914103	1
Jun-03	0.936812	0.792143	1	1	0.983625	0.997888
Sep-03	0.966757	0.788452	0.831068	0.895089	0.979169	0.894004
Dec-03	-	0.810002	0.882722	-	0.967436	0.97822
Average	0.863743	0.711923	0.787018	0.758182	0.879204	0.833841

These results suggest that there has been an improvement in bank efficiency through time, and also that there are some significant differences in efficiency between banks over the period of the study. The trend in efficiency through time is more evident in Figure 1, which also shows the trend in the 90-day bill rate, generally in the opposite direction.[9] A potential explanation for this effect is provided in the next paragraph.

Figure 1: Average (CCR) Efficiency score relative to average 90-day bill rate



Suppose as a simplifying assumption that net interest income is constant over time, and that we look at two separate time periods, one of which is characterised by high interest rates and the other by low interest rates. All other aspects of bank cost and efficiency (i.e. non-interest expense and income) are unchanged. Let us pick some numbers as examples – an aggregate average cost of funds of 8% in the high interest case and a cost of funds of 4% in the low interest rate case, with a net interest income of 2% in each case. We thus have, in the high interest case, interest expense of 8% being used to generate net interest income of 2%, and in the low interest environment, interest expense of 4% being used to generate net interest income of 2%. The ratio of the output price to input price is thus higher (and the bank will therefore appear to be more efficient) when interest rates are lower.

[9] The apparent slight lag in response of efficiency scores to changes in the general level of interest rates might be attributed to the lag between changes in the 90-day bill rate and these being reflected in banks' cost of funds.

We then checked for other explanations for this effect, the most obvious of which would be expected to be scale. The same data were therefore run through a BCC model, but significant scale efficiency could be identified only for TSB (at the 1% level),[10] with the effect more marked during the earlier part of the period studied, while the bank was smaller.[11]

Table 4: Super-efficiency scores for all banks studied together

	ANZ	*ASB*	*BNZ*	*NBNZ*	*TSB*	*Westpac*
Jun-96	0.715224	0.607392	0.662938	0.448671	0.800524	-
Sep-96	0.678666	0.564568	0.597016	0.453211	0.743	0.504262
Dec-96	0.671309	0.581931	0.661805	0.496391	0.749982	0.557337
Mar-97	0.784948	0.646065	0.679889	0.56687	0.629791	0.570922
Jun-97	0.815397	0.625538	0.698857	0.590945	0.715515	0.648635
Sep-97	0.868547	0.588902	0.668168	0.534331	0.75156	0.68737
Dec-97	0.630193	0.615426	0.682463	0.551868	0.779106	0.700059
Mar-98	0.652934	0.599483	0.620142	0.57588	0.740322	0.659838
Jun-98	0.640547	0.57064	0.656193	0.57359	0.766895	0.693803
Sep-98	0.779928	0.586267	0.586896	0.589581	0.759709	0.754484
Dec-98	0.794575	0.661969	0.736216	0.649116	0.778324	0.768136
Mar-99	0.875283	0.733691	0.797258	0.831371	0.818899	0.919188
Jun-99	1.020177	0.747312	0.89276	0.759808	0.930968	0.869094
Sep-99	0.993541	0.723754	0.63756	0.786223	0.906388	0.937499
Dec-99	0.88836	0.711535	0.74654	0.750576	1.041706	0.899921
Mar-00	0.850823	0.721028	0.744919	0.811158	0.95452	0.85355
Jun-00	0.805412	0.671378	0.771141	0.866077	0.978168	0.836273
Sep-00	0.736822	0.673999	0.770296	0.752553	0.940652	0.822529
Dec-00	0.804563	0.628384	0.744084	0.730816	0.884545	0.777845
Mar-01	0.846801	0.651507	0.752434	0.820295	0.788725	0.769277
Jun-01	0.878946	0.745231	0.727485	0.844845	0.88373	0.80614
Sep-01	1.069853	0.695223	0.740784	0.839238	0.855809	0.964558
Dec-01	0.965499	0.752444	0.789784	0.733077	1.003224	0.889559
Mar-02	0.977602	0.754678	0.84634	0.923231	0.985422	0.80416
Jun-02	0.979146	0.765589	0.871877	0.925632	1.0173	0.928343
Sep-02	0.929628	0.748995	0.807392	0.891129	1.008706	1.058255
Dec-02	0.902691	0.759803	0.823512	0.824621	0.945979	0.989412
Mar-03	0.926235	0.77416	1.003034	0.949174	0.913927	1.002071
Jun-03	0.910513	0.769035	1.008981	1.042162	0.953484	0.996532
Sep-03	0.951461	0.768475	0.801346	0.880364	0.975946	0.854985
Dec-03	-	0.792115	0.861728	-	0.96591	0.968776
Average	0.844854	0.685049	0.754511	0.733093	0.869959	0.816427

[10] Tests were undertaken using the Mann-Whitney test, looking for differences between the CCR and BCC efficiencies for each bank.
[11] This contrasts with the results obtained by Tripe (2003), where significant scale effects were found for all banks. The difference is likely to arise from the use of the larger all-bank data set, which means that there are relatively fewer observations at extreme values, likely to be treated as scale inefficient just because of that condition. See Dyson et al (2001) and the discussion above.

To test for the causes of the apparent improvement in efficiency, we therefore first obtained a set of slack-based super-efficiency scores for all the banks. The results are reported in Table 4. Note that these scores differ from those shown in Table 3 in that the efficiency scores are no longer censored at 1, and that the scores of the inefficient DMUs are inclined to be lower (reflecting the way in which the slack-based model also identifies mix efficiencies, with the result that inefficiencies can be lower than under the CCR model. This is reflected in lower mean efficiency scores for each bank).

Table 5: Regression results – logs of efficiency scores from super-efficiency model for all banks.

A: Interest rate as explanatory variable					
Constant	Interest rate	R^2	F-statistic		
0.237*** (5.39)	-0.0766*** (-11.59)	42.6%	134.29***		
B: Interest rate and time trend as explanatory variables					
Constant	Interest rate	Time Trend	R^2	F-statistic	
-0.157** (-2.25)	-0.0392*** (-4.87)	0.00957*** (6.83)	54.4%	107.36***	
C: Interest rate and total assets as explanatory variables					
Constant	Interest rate	Total assets	R^2	F-statistic	
0.263*** (4.88)	-0.0780*** (-11.41)	-0.000001 (-0.84)	42.8%	67.38***	
D: Time trend as explanatory variable					
Constant	Time Trend	R^2	F-statistic		
-0.486*** (-24.46)	0.0142 (13.02)	48.4%	169.64***		
E: Total assets as explanatory variable					
Constant	Total assets	R^2	F-statistic		
-0.301*** (-10.62)	0.000002 (1.65)	1.5%	2.71		
F: Interest rate, time trend and total assets as explanatory variables					
Constant	Interest rate	Time trend	Total Assets	R^2	F-statistic
-0.121* (-1.73)	-0.0395*** (-5.01)	0.0107*** (7.50)	-0.000002*** (-2.94)	56.5%	77.5***

*** indicates significance at the 1% level
** indicates significance at the 5% level
* indicates significance at the 10% level
t-statistics are given in brackets beneath the relevant estimated coefficient

We then regressed the natural logs of these super-efficiency scores against the general level of interest rates, time and total assets for the bank at the end of the relevant quarter. The results are reported in Table 5.

We tested for multicollinearity by reviewing variance inflation factors, but no evidence was found of any problems in this regard.[12] The results show interest rate (with the expected negative coefficient) and time trend (with a positive coefficient which would be consistent with technical progress)[13] to be the most important explanatory variables, with very little impact from total assets, which suggests that there is not likely to be any major benefit from asset growth in terms of achieving economies of scale. It is also noted that there is no consistency to the sign applying to total assets.

6 Differences in efficiency between banks

We extended the regressions reported in the previous section by undertaking a further regression with no intercept, but with individual dummy variables for each bank, the coefficients for which will relate to the banks' relative efficiency. The relevant coefficient estimates, standard errors and t-statistics are reported in Table 6.

The ranking of banks' relative efficiency can be ascertained from the ranking of the coefficients in this model, with the significance of the differences between individual banks' efficiency being able to be ascertained by the significance of the difference between the coefficients applying to individual banks. Thus, although TSB shows with a higher value for its coefficient than does ANZ, the t-statistic applying to the difference between the two coefficients is only (0.0474-0.0724)/0.05309, or -0.47: the difference is

[12] Significant Durbin-Watson statistics were found, but these reflected the way the data were organised, rather than providing definitive evidence for serial correlation.

[13] It could also indicate catch-up. The relative merits of the two causes might be disentangled using the Malmquist Index, although its application in this context might be distorted by the small cross-section of banks. Despite this difficulty, Tripe (2004) has explored New Zealand bank performance through time, using the Malmquist Index, and found that technical change generally had a positive effect, while catch-up was negative for most banks (the exceptions were the NBNZ and Westpac, which showed significant improvements in total factor productivity: these two banks also appear to show the greatest efficiency improvement in this study). Note, however, that Tripe (2004) used total interest-bearing liabilities (but not including subordinated debt) as an input, rather than gross interest cost as used in this study.

not significant at the 5% level. The t-statistics applying to the difference in efficiency between the banks, and their significance is reported in Table 7.

Table 6: Regression results – logs of efficiency scores from super-efficiency model for all banks, with individual bank dummies.

	Coefficient	Standard Error	t-statistic
Interest rate	-0.0390***	0.005875	-6.64
Time trend	0.00958***	0.001023	9.36
ANZ	-0.0724	0.05309	-1.36
ASB	-0.284***	0.05319	-5.34
BNZ	-0.191***	0.05319	-3.59
NBNZ	-0.229***	0.05309	-4.32
TSB	-0.0474	0.05319	-0.89
Westpac	-0.128**	0.05310	-2.41

*** indicates significance at the 1% level
** indicates significance at the 5% level

Our efficiency ranking from the results reported in Table 6 is that TSB is most efficient, followed by ANZ, Westpac, BNZ, NBNZ and ASB, although as can be seen, not all the efficiency differences are significant.

Table 7: t-statistics for difference in efficiency between banks, based on regression results (of super-efficiency scores)

	ASB	BNZ	NBNZ	TSB	Westpac
ANZ	3.98***	2.22**	2.95***	-0.47	1.04
ASB		-1.75*	-1.13	-4.47***	-2.93***
BNZ			0.73	-2.69**	-1.18
NBNZ				-3.42***	-1.91*
TSB					1.52

*** indicates significance at the 1% level
** indicates significance at the 5% level
* indicates significance at the 10% level

We can compare these results with those generated by applying the Mann-Whitney test to the banks' super-efficiency scores (as reported in Table 4). Table 8 shows the median efficiency score for each bank, and also provides a cross-reference table of the significance of the differences in efficiency scores between the banks.

Table 8: Difference in efficiency between banks, as per Mann-Whitney test

	ANZ	ASB	BNZ	NBNZ	TSB	Westpac
Median	.8597	.6952	.7449	.7562	.8845	.8294
ANZ		.0000***	.0035***	.0070***	.4402	.5298
ASB			.0100**	.1317	.0000***	.0001***
BNZ				.8569	.0003***	.0398**
NBNZ					.0013***	.0501*
TSB						.1774

*** indicates significance at the 1% level
** indicates significance at the 5% level
* indicates significance at the 10% level

The patterns of difference in efficiency between the banks are broadly similar, but we should not expect exactly identical results, in that the efficiency comparisons generated by the regression model have already been adjusted for the effects of interest rates and the passage of time. This may also account for the apparently greater significance of the differences reported by the Mann-Whitney test.

7 Summary and conclusion

This paper has sought to demonstrate the way in which environmental variables, and the general level of interest rates in particular, can impact on estimates of bank efficiency, if the input and output variables are related to those environmental variables. We have looked at the particular example of the general level of interest rates and its relationship to interest expense, but the same might be observed in other areas. It tells us that we should be cautious in using interest expense as an input in efficiency studies, particularly if banks are operating in different interest rate environments (as will often be the case in cross-border studies).

The technique used for this research has entailed OLS regression of the logs of super-efficiency scores. This approach has been very little used in previous research, since it was first reported by Lovell et al (1994), but this may be a reflection of the relatively limited discussion and utilisation of the super-efficiency technique in previous empirical literature.

We have also looked at banks' efficiency relative to each other, and have found a reasonable degree of consistency in the rankings. Even though one of the sets of results was adjusted for the effects of interest rates and time (as a proxy for technical progress), no significant change was evident, which would support a view that the general level of interest rates and technical progress affected all banks more or less equally.

This research could be extended by use of an interest cost variable that adjusted for changes in the general level of interest rates, or by the addition of further input and output variables. There would also be value in further utilisation of the slacks-based model (Tone, 2001) to generate measures of mix-inefficiency.

Once we have greater confidence in the reliability of the DEA models that we use, and in the consistency of the results they generate, we can use them for more extensive studies of bank efficiency.

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