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Cost Efficiency in UK and Irish Credit Institutions

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Abstract: This paper presents aggregated cost efficiency scores for a balanced panel of British and Irish credit institutions and relates these scores to loan loss reserves as a first step in investigating their usefulness as possible indicators of financial fragility. The efficiency scores are obtained using the two most popular methods of efficiency measurement – data envelopment analysis (DEA) and the stochastic frontiers approach.

I INTRODUCTION

Central bankers have traditionally endeavoured to better understand the roles that financial intermediaries and especially credit institutions play in the transmission mechanism of monetary policy. One aspect of this work involves the monitoring of forces such as deregulation, financial innovation, the impact of information technology and competition on the banking sector. An increasingly popular way of assessing the impact of these latent factors is to empirically identify cost efficiencies/inefficiencies of credit institutions.

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A second associated concern of central banks relates to financial stability, i.e., the absence of systemic crisis within the financial sector. An efficient and well-functioning financial system is a prerequisite to maintaining a stable financial environment. Given that credit institutions constitute a sizeable component of any particular financial system, the development of a robust set of efficiency measures may serve as an important input into indicators of banking fragility.

This paper seeks to address these two issues simultaneously by first generating a series of cost efficiency scores for a balanced panel data set (1996-2001) of 30 UK and Irish credit institutions with both parametric and non-parametric techniques. Subsequentially, these scores are used as explanatory variables in a second series of regressions, where the dependent variable is an indicator of the loan loss reserve of a particular credit institution. As such, the paper seeks to complement a comparatively new area of the banking efficiency literature, which explores the relationship between both the efficiency and the asset quality of a bank. To date, this work has mainly concentrated on US banks (see Berger and DeYoung (1997) for example). Therefore, our contribution is to extend this analysis to the UK and Irish banking sector in the context of both parametric and non-parametric efficiency scores. It should be thought of as a preliminary look at possible *ex ante* indicators of individual bank fragility and as a crosscheck on the efficiency scores.

In stressing the importance of bank level measurements of efficiency to policy makers in particular, Bauer *et al*. (1998) advance a set of consistency conditions, which they believe, efficiency measures from different approaches should meet in order to be of 'optimal use'. One of these conditions is that measured efficiencies, irrespective of the computational technique adopted, should be reasonably consistent with standard nonfrontier performance measures. Consequently, the objectives of an *ex-post* evaluation are twofold. First, the establishment of a relationship with non-frontier banking indicators provides a certain validation of the efficiency scores achieved and a potential ranking mechanism between alternative scores where significant differences occur between parametric and non-parametric methods of estimation/calculation. Simultaneously, however, the establishment of a relationship between efficiency scores and these indicators is significant, in itself, as useful information concerning the underlying performance of financial institutions can be inferred from these scores or models using these scores.

We select UK and Irish credit institutions as comparators because of the relatively similar structure of the UK and Irish financial systems. For example, both the UK and Ireland are the only English common law countries in the EU and both countries have a banking presence in each other's markets. Additionally, there is a substantial foreign (branch/subsidiary) bank presence in each country. A summary of the credit institutions included in the data set is presented in Table 1.

Table 1: *List of Credit Institutions Used in Sample (1996-2001)*

Barclays Bank PLC	Cheshire Building Society
Royal Bank of Scotland	Principality Building Society
Alliance and Leicester	Newcastle Building Society
Northern Rock PLC	Norwich and Peterborough Building Society
Bradford and Bingley PLC	Scarborough Building Society
Britannia Building Society	Bank of Scotland
Yorkshire Bank PLC	Halifax PLC
Yorkshire Building Society	*Bank of Ireland
Portman Building Society	*Allied Irish Bank PLC
Clydesdale Bank PLC	*Anglo-Irish Bank PLC
Co-Operative Bank PLC	*EBS Building Society
Leeds and Holbeck Building Society	*First Active PLC
West Bromwich Building Society	*Irish Nationwide Building Society
Northern Bank Limited	*ACC Bank PLC
Derbyshire Building Society	*National Irish Bank Limited

Note: *denotes an Irish credit institution.

The rest of the paper is laid out as follows: Section II introduces both parametric and non-parametric methods of efficiency measurement. Data and results of the initial empirical analysis are discussed in Section III, while Section IV reports the results of the *ex-post* empirical evaluation of the efficiency scores. Section V offers some concluding comments.

II COST EFFICIENCY ESTIMATES

In this section we present two of the most popular means of generating efficiency scores. We adopt the popular 'frontier' approach, where the efficiency of a bank is gauged relative to a frontier of best practice. In particular, we use both the parametric stochastic frontier model and the non-parametric data envelopment analysis (DEA) approaches to generate efficiency scores.

While some studies have examined purely the technical efficiency of credit institutions (such as Wheelock and Wilson (1999) and Drake (2001)), we specifically address the issue of cost efficiency (CE) i.e., given a bank's output levels and factor input prices, how far above the cost function does an individual bank operate? While the concept of cost efficiency can be separated into both Farrell (1957) concepts of allocative (AE) and technical efficiency

(TE), most parametric cost function applications assume full allocative efficiency resulting in CE being closely related to TE.[1] From the parametric perspective, we specify the following cost function for the sample of Irish and British credit institutions.

$$C_i = f(Y_i^*, P_i, \alpha)\, e^{(\kappa_i + \xi_i)} \tag{1}$$

where

C_i = bank level costs of production,
Y_i^* = optimum bank level outputs,
P_i = prices of bank level inputs X_i,
$f()$ = represents the cost function,
α = vector of parameters to be estimated,
κ = independent and identically distributed errors i.e., $\kappa_i \sim N(0, \sigma_\kappa^2)$ and
ξ_i = non-negative random variables which are assumed to account for the cost of inefficiency in production. These are usually assumed to be $\sim N|(0, \sigma_\xi^2)|$. ξ_i measures how far the individual bank operates above the cost function. The cost function measure of technical efficiency is defined in the following manner

$$\mathrm{CE} = E(C_i \mid \xi_i, P_i) \,/\, E(C_i \mid \xi_i = 0, X_i) \tag{2}$$

CE has a value of between one and infinity. (2) can be shown to be equivalent to[2]

$$\mathrm{CE} = \exp\,(\xi_i) \tag{3}$$

The unobservable ξ_i is obtained by deriving expressions of the conditional expectation of ξ_i, conditional on the observed value of $(\kappa_i + \xi_i)$. These expressions can be derived from equivalent expressions for the case of production function inefficiency measurements outlined in Battese and Coelli (1992) and Battese and Coelli (1993).

A specific functional form is assumed for the cost function specified in (1). Following other applications (Vander-Vennet (2002) and Bikker (2002) for example) we employ the translog cost function.[3] This is given by the following[4]

[1] For a full discussion of this point see Chapter 9 of Coelli *et al*. (1998).
[2] The exponent is taken as the *translog* cost function is specified.
[3] Standard likelihood ratio tests are performed to test the suitability of the more restrictive Cobb-Douglas functional form nested within the translog.
[4] Note that in the estimation we impose symmetry on the cross-products i.e.
$\alpha_{12} = \alpha_{21}$, $\alpha_{34} = \alpha_{43}$, α_{53} and $\alpha_{45} = \alpha_{54}$

$$\ln C_i = \alpha_0 + \sum_{j=1}^{2} \alpha_j \ln Y_j + \sum_{j=3}^{5} \alpha_j \ln P_j + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2} \alpha_{jk} \ln Y_j \ln Y_k$$
$$+ \frac{1}{2}\sum_{j=3}^{5}\sum_{k=3}^{5} \alpha_{jk} \ln P_j \ln P_k + \sum_{j=1}^{2}\sum_{k=3}^{5} \alpha_{jk} \ln Y_j \ln P_k + \kappa_i + \xi_i \quad (4)$$

The cost inefficiency model outlined in (1) and (4) estimates a *static* level of inefficiency for each bank for the specified time period. However, the availability of a panel data set enables the estimation of a time-varying model of inefficiency where inefficiency levels may increase or decrease through time. Battese and Coelli (1992) have modified (4) to allow for dynamic estimates of inefficiency

$$\ln C_{it} = \alpha_0 + \sum_{j=1}^{2} \alpha_j \ln Y_{jt} + \sum_{j=3}^{5} \alpha_j \ln P_{jt} + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2} \alpha_{jk} \ln Y_{jt} \ln Y_{kt}$$
$$+ \frac{1}{2}\sum_{j=3}^{5}\sum_{k=3}^{5} \alpha_{jk} \ln P_{jt} \ln P_{kt} + \sum_{j=1}^{2}\sum_{k=3}^{5} \alpha_{jk} \ln Y_{jt} \ln P_{kt} + \kappa_{it} + \xi_{it} \quad (5)$$

where the efficiency estimate ξ_{it} in (5) is now equal to $\xi_i \exp[-\phi(t-T)]$ – commonly referred to as the *time-varying decay* model.[5] The ξ_i's are now assumed to be i.i.d. as a generalised truncated-normal random variable of the $N(\mu, \sigma_\xi^2)$ distribution, t refers to the time period (t=1,…,T) and ϕ is an unknown parameter, which is estimated. The parameterisation of Battese and Corra (1977) is employed, where σ_κ^2 and σ_ξ^2 are replaced by $\sigma^2 = \sigma_\kappa^2 + \sigma_\xi^2$ and $\gamma = \sigma_\xi^2/(\sigma_\kappa^2 + \sigma_\xi^2)$. The parameter γ must lie between 0 and 1. The resulting log-likelihood function, expressed in terms of these variance parameters, can be observed in the appendix of Battese and Coelli (1992).

In the last period of the panel, the exponential function, $\xi_i \exp[-\phi(t-T)]$ has a value of 1, (t=T), so $\xi_{it} = \xi_i$. Therefore, if the parameter ϕ is positive, then $-\phi(t-T) \equiv \phi(T-t)$ = non-negative and $\exp[-\phi(t-T)]$is ≥ 1. As a result, $\xi_{it} \geq \xi_i$, thereby indicating a *decreasing* level of inefficiency over time. Conversely, a negative value of ϕ results in $\exp[-\phi(t-T)] \leq 0$ and $\xi_{it} \leq \xi_i$ with levels of inefficiency now *growing* over time.[6] As this specification restricts inefficiency

[5] Inefficiency levels either decay towards or increase to a base level.

[6] Note that a particular feature of the inefficiency model outlined in (5) is that the cost inefficiency effects of different credit institutions in a given year t is equal to an exponential function $\exp[-\phi(t-T)] \equiv \exp[-\phi(T-t)]$ of the corresponding institution-specific inefficiency effects for the last year of the panel (the ξ_i's). Therefore, this particular specification restricts the cost inefficiency ordering of the credit institutions to be constant through time.

movements across all credit institutions to move in a common direction for the time period, we also apply the time-invariant inefficiency model where ϕ is set equal to zero (i.e. (5) reduces to a panel application of (4)). This restriction is explicitly tested for in (5) above.

The second popular method of generating bank efficiency scores *vis-à-vis* frontiers of best practice is through non-parametric linear programming techniques. Non-parametric frontiers are constructed by *enveloping* a sample of individual units (credit institutions) with a frontier constructed by the credit institutions of best practice within the sample. Frain (1990) presents a neat exposition on the use of such techniques. Comprehensive reviews of the approach are also contained in Lovell (1993), Charnes *et al.* (1995) and Seiford (1996) while Coelli *et. al.* (1998) present an overview of the different programming options available.[7]

Under DEA, a non-parametric envelopment frontier over the data points is constructed with all observed data points residing on or above the cost frontier. Adopting the cost minimisation behavioural postulate enables the derivation of both estimates of cost efficiency and allocative efficiency (the quantity of inputs to produce a given level of outputs at minimum cost). For a cost minimising bank, under variable returns to scale, cost efficiency is obtained by solving the following minimisation problem for each bank, i = 1,2,…,S in each year of the sample

$$\begin{aligned} &\mathrm{Min}_{\lambda, x_i^*}\, p_i' x_i^* \\ &\quad \textit{subject to: } Y\lambda \geq y_i \\ &\quad\quad X\lambda \leq x_i^* \\ &\quad\quad N1'\lambda = 1 \\ &\quad\quad \lambda \geq 0 \end{aligned} \tag{6}$$

where λ is a N * 1 vector of constants. Y is an N * S output matrix and X is an M * S input matrix, with y_i and x_i being the corresponding N * 1 and M * 1 vectors of the ith bank. p_i[8] is an N * 1 vector of bank input prices and x_i^* is the cost-minimising vector of input quantities for the ith bank given factor input prices p_i and output level y_i. In this case, the cost efficiency (CE) of each bank in the sample is obtained via the ratio of minimum cost to actual, observed cost

$$\mathrm{CE} = p_i' x_i^* \,/\, p_i' x_i \tag{7}$$

[7] In a recent contribution Wheelock and Wilson (2003), following work by Cazals *et al.* (2002), adopt the non-parametric order-*m* frontier, which measures the performance of credit institutions relative to *expected* maximum output among *m* institutions using no more of each input than the given institution.

[8] Superscript ' denotes transpose.

with a score of 1 indicating a point on the frontier and hence a perfectly cost efficient bank. This estimate of cost efficiency can then be checked against the estimate obtained under the stochastic cost function approach in (3).

III DATA AND EMPIRICAL RESULTS

Studies of the efficiency of the UK banking sector have been relatively scarce. Drake (2001), for instance, comments that "to date, however, no such analysis has been conducted for the UK banking sector as a whole". Using DEA, Drake (2001) generates efficiency scores for 9 UK credit institutions over the sample period 1984-1995. Drake and Simper (2003) provide a breakdown of efficiency scores into pure technical, scale and overall efficiency for 20 UK credit institutions over the 1995-2001 period. Their scores are also derived from non-parametric techniques. To our knowledge, no study, to date, presents parametrically generated cost efficiency scores for UK credit institutions (unless within a broader sample of the euro wide area) and, certainly, no study compares parametric and non-parametric scores for the UK financial system.

In an Irish context, there also has been relatively few empirical investigations of bank level performance. McKillop and Glass (1991) looked at the internal workings of Allied Irish Bank from 1972 to 1988 while Glass and McKillop (1992) examined the performance within Bank of Ireland between 1972 and 1990. In both cases, scale and scope economies were explicitly examined. Lucey (1993) generated efficiency estimates for 17 Irish credit institutions over the 1988-1991 time period. The results suggest that Irish credit institutions over the period displayed a severe degree of inefficiency and that a level of inefficiency equal to a considerable portion of actual profits was lost due to various inefficiencies. However, as Lucey (1993) concedes, the results are significantly conditioned by the relative lack of information on individual credit institutions and the short time period involved in the empirical investigation.

We include both banks and building societies in our sample. At the level of input and output aggregation and given the balance sheet structure of the different institutions, the sample used constitutes a relatively similar group of credit institutions. This is particularly the case when compared to other similar studies. The balance sheet data used are all sourced from Bankscope. Bankscope is a commercial database provided by Bureau Van Dijk (see www.bvdep.com for more details). It contains published consolidated and unconsolidated accounts for several thousand credit institutions worldwide. It is the standard source of information for applied research in the area, given the absence of harmonised publicly available regulatory data for European banks. The data were checked to ensure that any institutions with implausible (i.e., total loans greater than total assets) or missing values were excluded. Consolidation and ownership issues (UK of Irish and vice versa) necessarily limits the number of credit institutions that we could include in our sample and we also exclude branches and subsidiaries of foreign credit institutions. This resulted in a balanced panel of 30 banks for 6 years.

In specifying the inputs and outputs of a bank for both parametric and non-parametric approaches, we follow the classification used in a non-exhaustive list of the more recent literature.[9] In particular, we treat the balance sheet level of total loans as a bank output (Y_i). This involves the aggregation of commercial, consumer and other loans. Costs (C) consist of interest and non-interest expenses. Input prices are the price of labour (P_3 = total personnel expenses/number of employees), the price of physical capital (P_4 = non-interest expenses – personnel expenses/corrected fixed assets) and the price of financial capital (P_5 = total interest expenses/ total deposits). In 'correcting' the fixed assets figure, we follow the approaches of both Resti (1997) and Bikker (2002) in order to minimise the influence of so-called 'book-keeping tricks' on credit institutions' reported fixed asset levels.[10]

Table 2: *Summary of Cost and Output Data Used in Empirical Analysis: 1996-2001*

Variable	*Notation*	*Mean*	*Std. Deviation*
Costs:	C	0.061	0.010
Outputs:			
Loans	Y_1	0.734	0.094
N.I. Income	Y_2	0.009	0.006
Prices:			
Labour	P_3	32.129	9.641
Physical Capital	P_4	0.850	0.504
Financial Capital	P_5	0.054	0.014

Note: N.I. = non-interest. All variables are in ratio form, C, Y_1, Y_2 are normalised by total assets while P_3, P_4 and P_5 are prices per unit.

[9] Examples include Berger and Mester (1997); Cummins and Weiss (1998); Vander-Vennet (2002); Carbo *et al*. (2003); Bikker (2002) and Clark and Siems (2002). Additionally, Frain (1990) provides a summary of some of the pre-1990 literature.

[10] For fixed assets, we use the fitted values from a quadratic regression of fixed assets on total costs and total assets. Full regression results from the estimation are available from the authors upon request.

In addition, we include total non-interest revenue as a bank output (Y_2). Non-interest income has become increasingly important for credit institutions. For instance, in some countries, (such as Finland[11]), non-interest income can account for over 50 per cent of total operating income. Rogers (1998), in examining the non-traditional activities of US commercial banks, argues that the omission of such non-traditional banking activities from a bank's behavioural postulate can result in an understating of measured efficiency scores.[12] To minimise the effects of potential large-scale differentials amongst the credit institutions in the sample, we normalise all cost and output data by total assets. Table 2 presents a summary of all cost and output data used for the institutions in the sample.

The parameter estimates of the time-varying decay translog cost function (6) are summarised in Table 3.[13] From the table it is evident that very few of the parameter estimates are significant at even the 10 per cent level. In total, two of the 26 parameters of the cost function are significant at the 5 per cent level and only one additional parameter is significant at the 10 per cent level. Thus, a question arises as to the suitability of the translog in this particular application.[14] It may well be, for instance, that the translog model is *over parameterised* in this case.

Table 4 presents the results of the variance parameters associated with (6). Of particular interest in Table 4 are the results for the γ and ϕ parameters. Recall that γ must lie between 0 and 1. A score of 0.727 suggests that the majority of the total residual variation is due to the inefficiency effect i.e. a significant estimate of γ means that the ξ_i expression is warranted in the cost function and that a deterministic function, where credit institutions deviate from a frontier of best practice on the basis of random error alone, is not supported by the data.[15] The ϕ parameter conveys information concerning any movements in inefficiency levels for the time period in question. A significant and positive value for ϕ denotes a *declining* level of bank inefficiency for the period. While a positive estimate for ϕ is obtained, the parameter is not significant at the 10 per cent level. Thus, we are unable to conclude, with certainty, whether inefficiency levels for the sample of credit institutions have declined over the period. Table 4 also contains the results of a likelihood ratio

[11] *Source:* OECD Bank profitability data 2002.

[12] An additional reason for the inclusion of non-interest income as an output is to enable the comparison of our results with similar type research.

[13] Estimates are obtained using the computer program FRONTIER Version 4.1, which is available on the Centre for Efficiency and Productivity Analysis (CEPA) web-site at www.uq.edu.au/economics/cepa/frontier.htm and Stata 8.0.

[14] Note the exact same model was estimated with Stata 8.0 for windows with similar parameter estimates obtained. These results are available from the authors upon request.

[15] Furthermore, the null hypothesis of a one-sided error is also rejected by a likelihood ratio test.

Table 3: *Translog Stochastic Cost Function Estimates*

Parameter	*Variable*	*Estimate*	*T-Ratio*
α_0	Constant	–2.178	–2.314
α_1	Loans	2.471	2.467
α_2	N.I.	0.303	0.807
α_3	Labour	–0.069	–0.107
α_4	P. Capital	–0.035	–0.043
α_5	F. Capital	–1.101	–1.266
α_{11}	Loans^2	–0.333	–0.354
α_{12}	Loans * N.I.	0.143	0.225
α_{22}	N.I.^{2}	0.013	0.884
α_{33}	Labour^2	0.021	0.108
α_{34}	Labour * P. Capital	0.019	0.109
α_{35}	Labour * F. Capital	0.056	0.271
α_{44}	P. Capital^2	–0.098	–1.787
α_{45}	P. Capital * F. Capital	–0.158	–1.345
α_{55}	F. Capital^2	–0.236	–1.229
α_{13}	Loans * Labour	–0.416	–0.631
α_{14}	Loans * P. Capital	0.326	0.655
α_{15}	Loans * F. Capital	0.205	0.392
α_{23}	N.I. * Labour	0.002	0.022
α_{24}	N.I. * P. Capital	0.105	1.419
α_{25}	N.I. * F. Capital	0.005	0.066
Log-Likelihood		259.001	

Note: N = 180 i.e. 30 credit institutions and 6 time periods. N.I. refers to non-interest income, P. = physical and F. = financial.

Table 4: *Hypothesis Test and Variance Parameter Translog Estimates*

Variance Parameters	*Estimate*	*T-Ratio*
σ^2	0.006	1.418
γ	0.727	1.959
μ	0.099	2.232
ϕ	0.074	1.476
Hypothesis Test	τ	Decision
H_0: $\alpha_{ii,i=1,\ldots,5} = 0$	24.47	?

Note: τ is a likelihood ratio statistic calculated as –2[log(likelihood(H_0)) – log(likelihood(H_1))]. It has an approximate chi-squared distribution with degrees of freedom equal to the number of independent constraints under the H_0 hypothesis. The test is at the 5 per cent level. The null of this test is that the use of a more restrictive Cobb-Douglas functional form does not reduce the explanatory power significantly.

test between the more restrictive Cobb-Douglas specification and that of the translog. At the 1 per cent level, we are unable to reject the null of the Cobb-Douglas, while at the 5 per cent level we obtain a test statistic of 24.47 versus a critical value of 25. Given this result and the relatively small number of significant parameters with the translog approach, we elect to estimate the same model with the Cobb-Douglas specification.

Both the parameter estimates of the cost function as well as the variance estimates associated with the Cobb-Douglas model are presented in Table 5. Nearly all parameter estimates are significant at the 1 per cent level. The variance parameters are somewhat reassuring, in that, all estimates are significant at the 1 per cent level and the estimates for γ and ϕ are quite similar to those achieved with the translog (T) approach i.e. (γ = 0.727 (T) versus 0.794 and ϕ = 0.074 (T) versus 0.048). Therefore, a stochastic specification is again supported by the data,[16] while the significance of the parameter suggests that inefficiency is declining across the sample for all credit institutions.[17]

Table 5: *Cobb-Douglas Stochastic Cost Function Estimates*

Parameter	*Variable*	*Estimate*	*T-Ratio*
α_0	Constant	–1.227	–9.240
α_1	Loans	0.0581	1.749
α_2	N.I.	0.041	3.096
α_3	Labour	0.062	2.038
α_4	P. Capital	0.179	7.783
α_5	F. Capital	0.584	21.737
Log-Likelihood		246.763	
Variance Parameters			
σ^2		0.010	3.345
γ		0.791	14.218
μ		0.182	4.325
ϕ		0.048	3.714

Note: N = 180 i.e. 30 credit institutions and 6 time-periods.

Table 6, presents a statistical summary of cost inefficiency scores under both parametric and non-parametric approaches. We present results for both parametric approaches and for the DEA model. Results are presented by splitting the sample of credit institutions into either a ‘big’ or ‘small’ category.

[16] The null hypothesis of a one-sided error is again rejected with a likelihood ratio test.

[17] However, we also estimate the *time-invariant* panel model (ϕ = 0) for both the translog and Cobb-Douglas model.

This is determined by the average value of a bank's total assets over the sample period. One significant difference in the estimation/calculation of the inefficiency scores should be noted at this point. Stochastic estimates of bank scores are obtained from a panel data set for 1996-2001, whereas scores under the programming approach are achieved on a multi-annual basis i.e. scores are determined for relevant credit institutions for 1996, *then* for 1997 etc. up until 2001. Programming scores in 2001, for example, are not affected by bank scores in, say, 1998.

Table 6: *Parametric and Non-Parametric Cost Inefficiency Estimates (Time-varying Decay): Statistical Summary*

Cobb-Douglas	*Big*	*Small*	*Irish*	*UK*
Average	0.162	0.216	0.223	0.177
Range	0.33	0.158		
St. Deviation	0.098	0.036		
Skewness	0.859	–1.320		
C. of Variation*	0.601	0.167		
N	90	90	8	22
Translog				
Average	0.089	0.174	0.188	0.111
Range	0.254	0.187		
St. Deviation	0.085	0.050		
Skewness	1.289	-0.454		
C. of Variation*	0.96	0.288		
N	90	90	8	22
DEA				
Average	0.095	0.169	0.190	0.116
Range	0.241	0.299		
St. Deviation	0.093	0.076		
Skewness	0.419	-0.523		
C. of Variation*	0.973	0.451		
N	90	90	8	22

Note: *C. = Coefficient of Variation = Standard Deviation/Mean. Irish and UK refers to the average value for the credit institutions in both countries for the different approach used. Range is between the maximum and minimum values for each quartile. For the DEA approach, variable returns to scale are assumed.

In general, all approaches reveal cost inefficiencies in the sample of UK and Irish credit institutions. Depending on the method used, the average degree of inefficiency can be as great as 22 per cent (Cobb-Douglas) or 17 per cent for both the translog and DEA method. Contrasting the scores from both parametric approaches first, it would appear that the degree of inefficiency is greater under the Cobb-Douglas approach with big credit institutions, in particular, being over 7 per cent more *efficient* with the translog approach. However, the translog scores would appear to be more volatile as suggested by the coefficient of variation. Both sets of results suggest that larger credit institutions, are the more efficient. As such, the finding tallies with those of Eisenbeis *et al.* (1999) for US banks who find that, on average, smaller banks tend to deviate more than larger banks from their respective cost frontiers. Furthermore, in an evaluation of the performance of UK banks, Drake (2001) found tentative evidence to suggest that very large UK banks were less inefficient than their smaller competitors. Using a similar timeframe as the present study, Drake and Simper (2003) estimate that overall efficiency for UK retail banks increased from 85 per cent in 1995 to 90 per cent in 2001.

Both parametric approaches suggest that UK credit institutions are more efficient than their Irish counterparts. The relative difference in inefficiency is greater, however, for the translog approach at approximately 7 per cent. This contrasts with a difference of 4 per cent between both sets of credit institutions under the Cobb Douglas approach. We empirically test the apparent differences in the mean efficiency scores (i) between big and small credit institutions and (ii) between UK and Irish credit institutions. A t-test of no significant difference between the two sets of mean efficiency levels is rejected for all models at the 1 per cent level.[18]

In order to further explore some of the results from the econometric application, we conduct some additional estimation. In particular, we explicitly examine the relative cost structure of both Irish and larger credit institutions relative to the general sample. This is motivated by the clear differential in average efficiency scores between Irish and UK credit institutions and the apparent greater efficiency of larger credit institutions. Accordingly, the Cobb-Douglas model is re-estimated with two dummies included for Irish credit institutions (D_1) and for the 'big' credit institution category (D_2). The results are presented in Table 7. On average, Irish credit institutions would appear to have statistically significantly higher costs relative to their UK counterparts, while larger credit institutions, as suggested by their efficiency scores, have a significantly lower cost base.[19]

The results for the non-parametric scores are quite similar in magnitude to those of the parametric applications, in particular, the translog model. This contrasts with results from both Eisenbeis *et al.* (1999) and Berger and Humphrey (1997) who both found in comparisons of parametric and non-

[18] The test statistic tests for differences between the means of two groups X and Y where the null hypothesis is H_0: $\mu_X = \mu_Y$ and $\sigma_X{}^2$ and $\sigma_Y{}^2$ are unknown but $\sigma_X{}^2 \neq \sigma_Y{}^2$.

[19] We also estimate the *time-invariant* cost function for both parametric applications, however, we find little difference between the results and those of the time-varying model. The results are available from the authors upon request.

Table 7: *Cobb-Douglas Stochastic Cost Function Estimates with Dummies Included*

Parameter	*Variable*	*Estimate*	*T-Ratio*
α_0	Constant	–1.052	–10.964
α_1	Loans	–0.086	–1.579
α_2	N.I.	0.061	4.912
α_3	Labour	0.054	2.169
α_4	P. Capital	0.179	9.149
α_5	F. Capital	0.579	22.680
α_6	D_1	0.053	3.489
α_7	D_2	–1.159	–6.384
Log-Likelihood		260.907	
Variance Parameters			
σ^2		0.005	5.543
γ		0.579	9.308
μ		0.107	2.262
ϕ		0.084	2.225

Note: N = 180 i.e. 30 credit institutions and 6 time-periods. D_1 is the dummy for Irish credit institutions and D_2 is the dummy for the 10 largest institutions.

parametric inefficiency scores for US banks, that non-parametric approaches yielded larger levels of inefficiency. Indeed, Eisenbeis *et al.* (1999) actually found that DEA inefficiency scores were over twice the level of the corresponding stochastic cost function estimates. The smaller non-parametric efficiency scores in our case, may be explained by the relatively smaller sample employed with the DEA averages being influenced by those credit institutions achieving efficiency scores of 1, that is, perfect cost efficiency. The average scores for UK and Irish credit institutions are remarkably similar to those of the translog approach with a 7 per cent difference in inefficiency between the two sets of credit institutions.

Based on our parameter estimates, we also examine the issue of scale economies within the sample of credit institutions. We follow Hughes *et al.* (2000) and explicitly measure scale economies by calculating the inverse of the cost elasticity of output

$$\text{scale economies} = \frac{1}{\sum_{i=1}^{2} \frac{\partial \ln C}{\partial \ln Y_i}} \tag{8}$$

where scale economies > 1 implies increasing returns to scale. Based on our Cobb-Douglas estimates, we obtain a value of 10.09. Thus, economies of scale would appear to pertain within the sample. While we highlight this finding as a possible avenue for further exploration, the comments of Berger and Mester (1997), who found evidence of scale economies for a sample of US banks, are somewhat applicable in our case:

> (1) First, scale economies may exist because of the relatively low interest rate environment of the sample (1996-2001). Given that 'traditional' intermediation is still the most important function of the institutions in our sample, it is unsurprising that interest expenses are the largest expense item. On average, these interest expenses are larger for big credit institutions than small credit institutions because a larger proportion of large credit institutions' liabilities tend to be market-sensitive.
>
> (2) Improvements in technology and applied finance may have cut costs more for larger credit institutions than smaller institutions. Improvements in Information Technology (IT) have reduced costs in back office (payments processing) and as well as at the retail end (i.e., credit scoring). This may have reduced the costs of extending loans, credit cards etc., more for larger credit institutions.

In conclusion, a comparison of the results under both the parametric and non-parametric methodologies reveals both differences and similarities, a conclusion also reached in an international survey of efficiency scores by Berger and Humphrey (1997). While the results from the translog model and the DEA approach are similar, the Cobb-Douglas functional form would appear to offer a better characterisation of the production technology of credit institutions in the sample. Furthermore, in comparisons with other work, the results from the Cobb-Douglas form and the DEA scores are quite similar. In the next section, we explore the informativeness of the inefficiency scores in terms of their potential relationships with nonfrontier indicators of banking performance.

IV EFFICIENCY SCORES AND NONFRONTIER BANK INDICATORS

Several areas of the bank efficiency and financial stability literature have identified links between credit risk and efficiency in credit institutions. Berger and DeYoung (1997) provide a useful taxonomy of the possible relationships. First, credit institutions with poor cost control may also suffer from poor credit risk assessment leading to a positive relationship between cost inefficiency and credit risk. A senior management which fails to control the cost structure of a particular credit institution may be more likely to have poor evaluation skills in relation to (i) individual loan credit scoring, (ii) appraising the level of collateral offered against loans and (iii) monitoring the behaviour of borrowers once loans are issued. This, Berger and DeYoung (1997) label, the 'bad management' hypothesis. Alternatively, bank loans on a credit institution's balance sheet may arise due to adverse macroeconomic conditions or some other exogenous shock to the institution. This is known as the 'bad luck' hypothesis. In this case, the increased costs associated with dealing with these problem loans gives the appearance of increased inefficiency, even though the increase in problem loans is outside of the control of the institution. Credit institutions that do not devote adequate resources to credit risk assessment appear to be cost efficient in the short run, but, over time, as the level of problem loans grows, the measured cost efficiency is a symptom of inadequate resources devoted to credit risk assessment.

Using Granger causality tests and time-series data, Berger and DeYoung (1997) find evidence to support these (non-mutually exclusive) hypotheses. Related work tries to explain variations in the efficiency score using various measures of idiosyncratic risk such as equity price volatility, credit institution loan loss provisions, and capitalisation. The intuition here is that institutions may try to compensate for inefficiency by altering their risk-taking behaviour. Kwan and Eisenbeis (1996) present evidence for US credit institutions that inefficient banks exhibit higher stock return variances, greater idiosyncratic risk in their stock returns, lower capital ratios and higher levels of problem loans.

A separate part of the literature incorporates efficiency scores as explanatory variables in early warning models. These are statistical models that classify institutions into (usually) two groups: failure and non-failure. Two relevant findings are that (*ex post*) failed institutions are cost inefficient (Wheelock and Wilson, 1995) and that an increase in bad loans is usually preceded by an increase in cost efficiency scores – Barr *et al.* (1994).

A more recent addition to this area is trying to include the credit risk and other macroeconomic/environmental variables directly in the estimation of the cost efficiency scores. The advantage of this method is that it has the potential to decompose the bad luck component from the bad management component. Pastor (2002) proposes a three-stage method to accomplish this. Drake (2001) also attempts to incorporate risk variables (loan loss provisions) directly into the calculation of the efficiency score. However, both papers rely exclusively on the DEA method of calculating efficiency scores, which may mean that the relatively promising results obtained are dependent on the method used.

Finally, given the discussions surrounding the implementation of the Basel II accord, a parallel literature has attempted to ascertain how credit institution's credit risk management varies across countries and with the business cycle. One area of this literature is explaining the factors that influence credit institutions provisioning for losses on their loan portfolio. For recent examples, see Hasan and Wall (2003), Pain (2003), and Laven and Majnoni (2002).

We contribute to the literature in this area by considering whether there is any statistical relationship between the loan loss reserve and cost efficiency scores controlling for other variables such as loan growth and capitalisation. We do this as an *ex post* check on the possible informativeness of efficiency scores for financial stability purposes and as a starting point for further work to be undertaken in this area. Provisions appear in credit institutions accounts as a flow variable in the profit and loss account and as a stock variable in the balance sheet. We concentrate on the stock (reserves) measure here, because the reserve measure reflects the accumulated net provisioning that, on the whole, should reflect the institutions expected loan losses.[20]

The following equation is estimated

$$LLR_{it} = \mu_0 + \mu_1\, LOAN_{it} + \mu_2\, LOAN_{t-1} + \mu_3\, CE_{it} + \mu_4\, EQY_{it-1} + \mu_5\, D + \varepsilon_{it} \qquad (9)$$

where *LLR* is the ratio of a credit institution's loan loss reserves to its total assets. *LOAN* is the ratio of loans to total assets and is included as a control for loan growth – we expect a positive value for this variable's coefficient. In line with other studies, we include a further control variable – *EQY*, which is the ratio of the previous period's equity to total assets. The previous period's equity level is used to avoid any simultaneity issues as the present period equity and loan loss reserve are impacted by current loan loss provisions. *CE* is the relevant cost efficiency score from both parametric methods and the DEA approach. We expect a negative sign on the *CE* coefficient, as more efficient credit institutions are expected to have lower expected losses. Finally, we include a dummy variable *D* which denotes whether or not a credit institution is a building society or not ($D = 1$ if the credit institution is not a building society, otherwise $D = 0$).[21]

As a first step, we utilise a pooled cross section time series estimations for several reasons. The data are based on a sample of UK and Irish institutions over time and we observe cross section variation, so the data are likely to be heteroscedastic and autocorrelated. Under these conditions, ordinary pooled OLS will produce inefficient estimates and unreliable standard errors. Here, we assume that the (systematic) influences on the ratio of loan loss reserves

[20] A second reason was that the flow of provisions was not available for all banks in the sample.
[21] Given the trend component within the time-decay model $\exp[-\phi(t - T)]$ i.e., we also included a time trend in our specification of (9), however it was not significant in any of the regressions.

are common across credit institutions and that any heterogeneous variation shows up in the error term ε_{it}. Consequently, the error term is assumed to be non-iid. Specifically, we allow cross credit institution heteroscedasticity and assume that these disturbances are contemporaneously correlated and we also assume a common autocorrelation parameter over time for all institutions. The Prais-Winsten transformation (see Prais and Winsten (1954) for more details) is used to mitigate the effects of autocorrelation, before standard errors adjusted for heteroscedasticity are calculated.[22]

Estimation results are reported for the Cobb Douglas cost efficiency estimates and the DEA scores. The results are presented in columns 3 and 4 of Table 8. From the results, it would appear that the parametric approaches yield cost efficiency scores, which are compatible with the Berger and DeYoung (1997) 'bad management' hypothesis i.e. an increase in cost efficiency reduces the credit institution's levels of loan loss reserves relative to its total assets. The Cobb Douglas set of cost efficiency score coefficients are significant at the 1 per cent level. With the DEA generated score, however, the level of cost efficiency appears to be *positively* related to the level of loan loss reserves. We also find, across both models, that the non-building society credit institutions amongst the sample have significantly higher loan loss reserves.

To check the robustness of our results, we also estimate (9) as a random effects model. These results are reported in Table 8 (columns 5 and 6). We find broadly similar results for both the CD and DEA cost efficiency scores. Namely, the coefficient on the CD CE variable is negatively signed and significant at the 1 per cent level, while the DEA CE variable's coefficient is positively signed and insignificant at the 5 per cent level. Finally, as our CE variables are only *estimates* of individual credit institution's cost efficiency, we seek to control for the ensuing 'errors in variables' issue. Accordingly, we instrument for the CD CE variables. The instrumental variable model adopted is the error components two stage least squares (EC2SLS) model proposed by Baltagi (1981). As an instrument we choose the ratio of total employees to total assets on the basis that an increase in employee numbers, *ceterus paribus*, would lead to a reduction in cost efficiency. An examination of the cost scores achieved suggested a relatively strong correlation between the scores and the total employees ratio (of approximately 74 per cent).[23] We also explored the use of both the ratio of financial and physical capital to total assets and lagged values of CE as alternative instruments, however, the initial first-stage regressions suggested that the ratio of total employees appeared to be a stronger instrument. The results of this estimation are reported in the final

[22] The estimation was carried out using Stata 8.0.
[23] We are obviously assuming that the total employees ratio is uncorrelated with ε_{it}.

Table 8: *Second Stage Estimates of Non-Frontier Indicators and Efficiency Scores*

Parameter	*Variable*	*Prais-Winsten*		*Random-Effects*		*IV*
		CD	DEA	CD	DEA	CD
μ_0	Constant	0.022	0.004	0.009	–0.005	0.008
		(0.000)	(0.352)	(0.074)	(0.148)	(0.231)
μ_1	$LOAN_t$	0.004	0.003	0.007	0.007	0.010
		(0.340)	(0.541)	(0.032)	(0.055)	(0.008)
μ_2	$LOAN_{t-1}$	–0.006	–0.008	–0.002	–0.002	–0.004
		(0.093)	(0.051)	(0.526)	(0.461)	(0.252)
μ_3	CE_t	–0.021	0.003	–0.013	0.003	–0.015
		(0.001)	(0.102)	(0.007)	(0.059)	(0.044)
μ_4	EQY_{t-1}	–0.005	0.012	0.013	0.018	0.040
		(0.803)	(0.529)	(0.467)	(0.303)	(0.013)
μ_5	D	0.006	0.005	0.007	0.006	0.007
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2		0.59	0.52	0.52	0.39	0.50
Obs.		162	162	162	162	162

Note: CD = Cobb Douglas, IV = instrumental variable and p-values are in parentheses. The IV model is the EC2SLS model proposed by Baltagi (1981) and the instrument chosen is the ratio of total employees to total assets.

column of Table 8. It is evident that the IV results are quite similar to the random effects model estimated with the CD's cost efficiency variable (column 5 of Table 8). The respective CE variables' coefficients differ in magnitude only marginally and the cost efficiency variable is still significant (at the 5 per cent level) under the two-stage model. Overall, therefore, in the case of the parametric efficiency score, there would appear to be some evidence of a negative relationship between cost efficiency levels and the loan loss provision levels within the sample of institutions.

V CONCLUDING COMMENTS

This paper generates a series of efficiency scores for a sample of Irish and British credit institutions over the 1996-2001 time period. Efficiency scores are estimated/calculated with parametric and non-parametric methods and the results are then compared with nonfrontier indicators of banking performance. Results suggest that the sample exhibit inefficiencies in production costs – although the degree of inefficiency is at the lower bound of international results reviewed by Berger and Humphrey (1997). Parametric scores give an indication of the ranking of credit institutions' average efficiency over the period, as well as an indication of whether that average efficiency is improving, or disimproving over time. Our econometric results suggest that the degree of inefficiency has been falling over the period. As such, these results are somewhat in agreement with non-parametric results for UK credit institutions in studies by Drake (2001) and Drake and Simper (2003) for similar time periods. Unlike other studies, however, non-parametric inefficiency scores are closely aligned, in magnitude, to those of the econometric estimation. Both sets of scores suggest that large credit institutions are more efficient than smaller institutions in the sample. We also find evidence of increasing returns to scale within the sample. Irrespective of the method used, we find that average efficiency levels for UK credit institutions are at least 4 per cent greater than that of Irish institutions. This result is reinforced by additional cost function estimates, which reveal, on average, higher significant costs for Irish credit institutions *vis-à-vis* their UK counterparts.

The second exercise of relating inefficiency scores to other indicators is an increasing feature of studies examining the efficiency of the credit institution sector. We find, that parametric estimates of cost efficiency are negatively related to the level of loan loss reserves. This result holds for different panel data estimators and as such, we believe, this link could be further explored in future research. DEA generated scores, on the other hand, under the same hypothesis, have a counter-intuitive effect. However, this result is tempered somewhat by the size of the sample used in the non-parametric approach.

Increasingly, in these second stage models, individual efficiency scores are not only used to characterise the performance of the credit institution itself, but are also used to reveal information pertaining to the overall structure of the market within which financial institutions operate. Vander-Vennet (2002) for instance, uses stochastically generated efficiency scores as a determining variable within the structure-conduct-performance (SCP) paradigm, in examining credit institution performance and market structure. Future work could explore this issue in greater detail.

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