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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.

1 Introduction

Central bankers have traditionally endeavoured to better understand the roles that financial intermediaries and especially banks[1] 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 banks.

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 banks 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.

A wide and varied literature exists on both the causes of financial instability and bank-level crises and on the development of models seeking to forecast such crises. These latter models are of significant interest to policy-makers who wish, per-emptively, to avoid, or mitigate, these effects. As noted by Bell and Pain (2000), this type of work can be roughly divided into two main areas: macro and micro causes of financial system instability. An example of macroeconomic/financial instability could be the stress exerted on the financial system by, say, the collapse of a housing price bubble, whereas, an example of micro instability could be the failure of an individual credit institution. Obviously, a relationship exists between both. The collapse of one institution may lead to 'knock-on' or systemic effects across the banking system. The present paper concentrates on this latter micro area by firstly drawing on the empirical inefficiency literature. Estimated inefficiency scores are then used as explanatory variables in a second series of regressions, where the dependant variable is an indicator of the loan loss reserve of a particular bank. As such, the paper seeks to complement a comparatively new area of the banking efficiency literature, which explores the relationship between both the efficiency

[1]We refer to 'banks' as a generic term for all credit institutions such as banks and building societies.

and the asset quality of a bank. To date, this work has mainly concentrated on US banks (see Berger and DeYoung (1997) for example). 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, Berger and Humphrey (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 such an *ex-post* evaluation are twofold. Firstly, 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.

Initially, therefore, this paper provides a series of cost efficiency scores for a balanced panel data set of 30 Irish and UK banks (8 Irish and 22 UK) over the sample period 1996-2001. We select UK banks as comparators because of the relatively similar structure of the UK financial system to the Irish retail banking market. For example, both UK and Ireland are the only English common law countries in the EU and both countries have a banking presence in each others markets. Additionally, there is a substantial foreign (branch/subsidiary) bank presence in each country. A summary of the banks included in the balanced panel data set is presented in Table 1 (insert Table 1 here).

The rest of the paper is laid out as follows; section 2 presents a brief discourse on the concept of efficiency, while section 3 introduces both parametric and non-parametric methods of efficiency measurement. Data and results of the initial empirical analysis are discussed in section 4, while section 5 reports the results of the *ex-post* empirical evaluation of the efficiency scores. Section 6 offers some concluding comments.

2 Efficiency Measurements Concepts

Following the landmark contribution of Farrell (1957), the efficiency of a firm or individual unit can be decomposed into two components - *technical efficiency* (TE), which provides an indication of the firms ability to achieve a maximum level of output from a given set of inputs and *allocative efficiency* (AE), which illustrates whether or not a firm is using the optimal level of factor inputs, given the respective input prices and the underlying production technology of the firm.

Figure 1 (insert Figure 1 here) relates these two concepts graphically under a number of different production scenarios. Say a firm produces one output (y) with two factor inputs (x_1, x_2) under the assumption of constant returns to scale. For all firms in the market, the fully efficient unit isoquant is identified as II'. If the factor inputs of a particular firm are such as to locate the firm at point B, then the technical inefficiency of the firm is given by the range CB. This is the amount by which the firm could achieve a proportionate reduction in inputs, while keeping output constant. This can be presented in percentage terms as the ratio CB/0B. The technical efficiency (TE) of a firm is most commonly reported as one minus this ratio = 0C/0B. Given information on the prices of the factor inputs enables the addition of the isocost TT'. Allocative efficiency can then be shown to be the ratio 0A/0C, as the distance AC denotes the reduction in production costs which would occur if production were to occur at the allocatively (and technically) efficient point C', and not the technically efficient, but allocatively inefficient point C. Combined, these two aspects of efficency provides a measurement of total *economic efficiency* (EE)

$$\mathrm{EE} = \mathrm{TE} * \mathrm{AE} = \frac{0\mathrm{C}}{0\mathrm{B}} * \frac{0\mathrm{A}}{0\mathrm{C}} = \frac{0\mathrm{A}}{0\mathrm{B}} \tag{1}$$

These indicators of efficiency are mainly generated through use of the *frontier* approach. Under this approach, a frontier denoting the best practice for an individual unit is contrasted with the actual performance of a sample of units or firms and efficiency indicators are measured relative to this frontier. The two principal methods of estimating these frontiers are

(1) data envelopment analysis (DEA) and,

(2) stochastic frontier analysis (SFA).

DEA analysis involves the use of linear programming methods to construct a non-parametric piece-wise frontier over the data, while stochastic frontiers involves parametric techniques to econometrically estimate the frontier. There are advantages and disadvantages associated with both approaches. For instance, the DEA approach assumes that any deviation from the best practice frontier is a function of inefficiency exclusively whereas, the stochastic frontier approach allows for random disturbances to be an additional cause of deviation. Both techniques, separately, have been used to gauge the efficiency of different banking markets (see Berger and Humphrey (1997) for an international survey). However, certain studies have sought to cross-check efficiency scores achieved under both approaches. We follow this avenue of approach as a means of improving the informativeness of the scores established.

Cost efficiency is just one efficiency indicator, that may be used to gauge the performance of the banking sector. For instance, standard profit efficiency establishes how close a bank is to achieving the maximum possible profit given a particular set of input and output prices. In such a case, the profit dependent variable enables the possibility of revenues to be generated through the varying of outputs as well as inputs. Inefficiencies in this case are in terms of the choice of outputs, when responding to a *given* set of output prices.

A separate but related issue is the notion of banking performance and welfare analysis within the banking market itself. Estimates of cost efficiencies may provide information, which can be used subsequently in an analysis of market structure (see Vander-Vennet (2002) for example), however, these efficiency scores, in themselves, do not convey any direct information concerning the behaviour of banks in a particular market and the associated welfare implications.

The next section provides an introduction to both efficiency measurement methods.

3 Estimates of Efficiency

3.1 Stochastic Frontiers

Econometric or parametric estimations of efficiency have proven particularly popular in the estimation of bank level efficiency in recent years. Examples of the approach can be observed in Berger and Mester (1997), Clark and Siems (2002), Vander-Vennet (2002) and Bikker (2002). Stochastic frontier efficiency scores are achieved in one of the two following approaches

(1) primal models and,

(2) dual models.

The former involves the estimation of a production function while the latter involves specifying a profit or cost function. Most bank level studies involve the dual option and thus, follow the advice in Berger and Mester (1997), which suggests dual models as the most appropriate form for financial institutions because "they are based on economic optimization in reaction to market prices and competition, rather than being based solely on the use of technology."[2]

The chief efficiency indicator associated with the cost function approach is the notion of *cost efficiency* (CE). This provides a measurement of how far above the cost frontier an individual firm is, given the output level and factor input prices of the firm. Cost efficiency under certain conditions can be decomposed into both Farrell concepts of AE and TE. However, owing to empirical restrictions necessitated in such a decomposition, most cost function applications assume full allocative efficiency, resulting in CE being closely related to TE.[3] The following cost function is specified for the sample of Irish and British banks

$$C_i = f\left(Y_i^*, P_i, \alpha\right) e^{(\kappa_i + \xi_i)} \tag{2}$$

[2]As noted by Bos and Kool (2001), the use of cost functions to parametrically determine stochastic frontiers is the most traditional approach in the literature. In an European context, examples include Altunbas and Chakravarty (1998), Battese, Heshmati and Hjalmarsson (1998) and Bikker (2002).

[3]For a full discussion of this point see Chapter 9 of Coelli, Prasada-Rao and Battese (1998).

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. $\kappa \sim N(0, \sigma_\kappa^2)$ 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

$$\text{CE} = E\left(C_i|\xi_i, P_i\right)/E\left(C_i|\xi_i = 0, X_i\right) \tag{3}$$

CE has a value of between one and infinity. (3) can be shown to be equivalent to[4]

$$\text{CE} = exp\left(\xi_i\right) \tag{4}$$

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 (2). Following other applications (Vander-Vennet (2002) and Bikker (2002) for example) we employ the translog cost function.[5] This is given by the following[6]

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[4]The exponent is taken as the *translog* cost function is specified.

[5]Standard likelihood ratio tests are performed to test the suitability of the more restrictive Cobb-Douglas functional form nested within the translog.

[6]Note, that in the estimation we impose symmetry on the cross-products i.e. $\alpha_{12} = \alpha_{21}$, $\alpha_{34} = \alpha_{43}$, $\alpha_{35} = \alpha_{53}$ and $\alpha_{45} = \alpha_{54}$.

$$lnC_i = \alpha_0 + \sum_{j=1}^{2} \alpha_j lnY_j + \sum_{j=3}^{5} \alpha_j lnP_j + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2} \alpha_{jk}\ lnY_j\ lnY_k$$
$$+\frac{1}{2}\sum_{j=3}^{5}\sum_{k=3}^{5} \alpha_{jk}\ lnP_j\ lnP_k + \sum_{j=1}^{2}\sum_{k=3}^{5} \alpha_{jk} lnY_j\ lnP_k + \kappa_i + \xi_i \qquad (5)$$

The cost inefficiency model outlined in (2) and (5) 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 (5) to allow for dynamic estimates of inefficiency

$$lnC_{it} = \alpha_0 + \sum_{j=1}^{2} \alpha_i lnY_{jt} + \sum_{j=3}^{5} \alpha_j lnP_{jt} + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2} \alpha_{jk}\ lnY_{jt}\ lnY_{kt}$$
$$+\frac{1}{2}\sum_{j=3}^{5}\sum_{k=3}^{5} \alpha_{jk}\ lnP_{jt}\ lnP_{kt} + \sum_{j=1}^{2}\sum_{k=3}^{5} \alpha_{jk} lnY_{jt}\ lnP_{kt}$$
$$+\kappa_{it} + \xi_{it} \qquad (6)$$

where the efficiency estimate ξ_{it} in (6) is now equal to ξ_i exp$[-\phi$(t-T)] - commonly referred to as the *time-varying decay* model.[7] 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, $\exp[-\phi(t-T)]$ 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, $\xi_{it} \geq \xi_i$,

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

thereby indicating a *decreasing* level of inefficiency over time. Conversely, a negative value of ϕ results in $\exp[-\phi(\text{t-T})] \leq 0$ and $\xi_{it} \leq \xi_i$ with levels of inefficiency now *growing* over time.[8] As this specification restricts inefficiency movements across all banks 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. (6) reduces to a panel application of (5)). This restriction is explicitly tested for in (6) above.

3.2 DEA Analysis

The second popular method of generating bank efficiency scores vis-à-vis frontiers of best practice is through non-parametric linear programming techniques. The expression Data Envelopment Analysis (DEA) was originally used by Charnes, Cooper and Rhodes (1978). Non-parametric frontiers are constructed by *enveloping* a sample of individual units (banks) with a frontier constructed by the banks 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, Cooper, Lewin and Seiford (1995) and Seiford (1996) while Coelli, Prasada-Rao and Battese (1998) present an overview of the different programming options available.[9]

Under DEA, a non-parametric envelopment frontier over the data points is constructed with all observed data points residing on or below the production frontier.[10] Conceptually, in the case of a single output, 2 input firm, this may be envisaged as a series of intersecting planes generating a tight-fitting cover over a scatter of various points in three-dimensional space. Technical efficiency is estimated by solving the following problem for each firm, i = 1,2,. . .,S in each year of the sample

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

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

[10] On or above in the cost function case.

$$
\begin{aligned}
\text{TE }(y_i, x_i) = \text{Min}_{\theta,\lambda}\ \theta \\
\textit{subject to}: \quad & Y\lambda \geq y_i \\
& X\lambda \leq \theta x_i \\
& \lambda \geq 0
\end{aligned} \tag{7}
$$

where θ is a scalar and 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. The value of the scalar θ satisfies the constraint $\leq$ 1 and is the technical efficiency score for the firm/bank in question. A score of 1 indicates a point on the frontier and hence a technically efficient bank as defined by Farrell (1957). The linear programming problem is solved N times for each bank in the sample with a corresponding bank specific score for θ obtained.

The score is achieved by taking the input vector x_i of a particular bank and radially contracting it as much as possible while remaining within the feasible input set (as defined by the isoquant II' in Figure 1). The inner boundary of this set is given by a piece-wise linear version of II'. The radial contraction of x_i results in a projected point $(X\lambda, Y\lambda)$ on the surface of this technology. This point is a linear combination of the observed data points and the constraints associated with (7) ensure that the point does not lie outside the feasible set of the bank.

(7) imposes constant returns to scale. However, this specification can be expanded to allow for variable returns to scale by the addition of the convexity constraint $N1'\lambda = 1$ to yield

$$
\begin{aligned}
\text{Min}_{\theta,\lambda}\ \theta \\
\textit{subject to}: \quad & Y\lambda \geq y_i \\
& X\lambda \leq \theta x_i \\
& N1'\lambda = 1 \\
& \lambda \geq 0
\end{aligned} \tag{8}
$$

where $N1$ is a N * 1 vector of ones. 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, the minimisation problem becomes

$$\begin{aligned} &\mathrm{Min}_{\lambda, x_i^*}\ p_i^{'} x_i^* \\ &\qquad\qquad subject\ to: \quad Y\lambda \geq y_i \\ &\qquad\qquad\qquad\qquad\quad X\lambda \leq x_i^* \\ &\qquad\qquad\qquad\qquad\quad N1'\lambda = 1 \\ &\qquad\qquad\qquad\qquad\quad \lambda \geq 0 \end{aligned} \tag{9}$$

p_i[11] 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 the bank is obtained via the ratio of minimum cost to actual, observed cost

$$\mathrm{CE} = p_i^{'} x_i^* / p_i^{'} x_i \tag{10}$$

This estimate of cost efficiency can then be checked against the estimate obtained under the stochastic cost function approach in (4). Given (1) and the fact that (TE) is obtainable from (7) means that an estimate of allocative efficiency can be retrieved from the following

$$\mathrm{AE} = \mathrm{CE}/\mathrm{TE} \tag{11}$$

4 Data and Empirical Results

In an Irish context, there have 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

[11] Superscript $'$ denotes transpose.

and scope economies were explicitly examined. Lucey (1993) generated efficiency estimates for 17 Irish banks over the 1988-1991 time period. The results suggest that Irish banks 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) conceeds, the results are significantly conditioned by the relative lack of information on individual banks and the short time period involved in the empirical investigation.

Studies of the efficiency of the UK banking sector have also 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 banks 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 banks over the 1995-2001 period. Their scores are also derived from non-parametric techniques.

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.[12] Consolidation and ownership issues (UK of Irish and vice versa) necessarily limits the number of banks that we could include in our sample and we also exclude branches and subsidiaries of foreign credit institutions.

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.[13] In particular, we treat the balance sheet level of total loans as a bank output (Y_1). 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 personel expenses / number of employees), the price of physical capital (P_4 = non-interest expenses - personel expenses/ corrected fixed assets) and the price of financial capital (P_5 = total inter-

[12]Produced by Bureau Van Dijk (BVD).

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

est expenses/ total deposits). In 'correcting' the fixed assets figure, we follow the approaches of both Resti (1997) and Bikker (2002) and use the fitted values from the following regression

$$\begin{aligned} lnFA_{it} = \beta_0 + \beta_1 lnC_{it} + \beta_2 lnTA_{it} + \beta_3 (lnC_{it})^2 + \beta_4 (lnTA_{it})^2 \\ + \beta_5 lnC_{it}\, lnTA_{it} + \psi_{it} \qquad \left(\mathrm{R}^2 = 0.89\right) \end{aligned} \tag{12}$$

where FA = fixed assets, C is as in (2), (5) and (6) and TA = total assets.[14] The aim of this correction is to minimise the influence of so-called 'book-keeping tricks' and to consequently bring the book-keeping values of fixed assets more in line with the size of the bank approximated by the total assets and costs of the bank.

In addition, we include total non-interest revenue as a bank output (Y_2). Non-interest income has become increasingly important for banks. For instance, in some countries, (such as Finland), non-interest income can account for over 50 per cent of total operating income. Rogers (1998), in examining the non-traditional activities of U.S. 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.[15] To minimise the effects of potential large scale differentials amongst the banks in the sample, we normalise all cost and output data by total assets. Table 2, (insert Table 2 here), presents a summary of all cost and output data used for the banks in the sample.

The parameter estimates of the time-varying decay translog cost function (6) are summarised in Table 3 (insert Table 3 here).[16] 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,

[14] Full regression results from the estimation are available from the authors upon request.

[15] 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.

[16] 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

a question arises as to the suitability of the translog in this particular application.[17] It may well be, for instance, that the translog model is *over parameterised* in this case.

Table 4, (insert Table 4 here), 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 banks deviate from a frontier of best practice on the basis of random error alone, is not supported by the data.[18] 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 banks have declined over the period. Table 4 also contains the results of a likelihood ratio 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 (insert Table 5 here). 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 one per cent level and the estimates for γ and ϕ are quite similar to those achieved with the translog (T) approach i.e. ($\gamma = 0.727$ (T) versus 0.794 and $\phi = 0.074$ (T) versus 0.048). Therefore, a stochastic specification is again supported by the data,[19] while the significance of the ϕ parameter suggests that inefficiency is

[17]Note the exact same model was estimated with Stata 8.1 for windows with similar parameter estimates obtained. These results are available from the authors upon request.

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

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

declining across the sample for all banks.[20]

Table 6, (insert Table 6 here), 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 banks into either a 'big' or 'small' category. 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 banks for 1996, *then* for 1997 etc. up until 2001. Programming scores in 2001, for example, are not affected by bank scores in, say, 1998.

In general, all approaches reveal cost inefficiencies in the sample of UK and Irish banks. 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 banks, 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 banks, are the more efficient. As such, the finding tallies with those of Eisenbeis, Ferrier and Kwan (1999) for U.S. 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.

Based on our parameter estimates, we examine the issue of scale economies within the sample of banks. We follow Hughes, Mester and Moon (2000) and explicitly measure scale economies by calculating the inverse of the cost elasticity

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

of output

$$\text{scale economies} = \frac{1}{\sum_{i=1}^{2} \frac{\partial lnC}{\partial lnY_i}} \tag{13}$$

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. We highlight this finding as a possible avenue for further exploration.

Both parametric approaches suggest that UK banks are more efficient than Irish banks. 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 banks under the Cobb Douglas approach. We empirically test the apparent differences in the mean efficiency scores (i) between big and small banks and (ii) between UK and Irish banks. 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.[21]

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 banks relative to the general sample. This is motivated by the clear differential in average efficiency scores between Irish and UK banks and the apparent greater efficiency of larger banks. Accordingly, the Cobb-Douglas model is re-estimated with two dummies included for Irish banks (D_1) and for the 'big' banks category (D_2). The results are presented in Table 7 (insert Table 7 here). On average, Irish banks would appear to have statistically significantly higher costs relative to their UK counterparts, while larger banks, as suggested by their efficiency scores, have a significantly lower cost base.[22]

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

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

[22]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.

results from both Eisenbeis, Ferrier and Kwan (1999) and Berger and Humphrey (1997) who both found, in comparisons of parametric and non-parametric inefficiency scores for US banks, that non-parametric approaches yielded larger levels of inefficiency. Indeed, Eisenbeis, Ferrier and Kwan (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 banks achieving efficiency scores of 1, that is, perfect cost efficiency. The average scores for UK and Irish banks are remarkably similar to those of the translog approach with a 7 per cent difference in inefficiency between the two sets of banks.

In conclusion, therefore, 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 banks 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.

5 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. Firstly, banks 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 bank 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 bank's balance sheet may arise due to adverse macroeconomic conditions or some other exogenous shock to the bank. 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, bank 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 preceeded by an increase in cost efficiency scores - Barr, Seiford and Siems (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 I-I accord, a parallel literature has attempted to ascertain how bank's credit risk management varies across countries and economic circumstance. 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.

The following equation is estimated

$$LLR_{it} = \mu_0 + \mu_1 LOAN_{it} + \mu_2 LOAN_{it-1} + \mu_3 CE_{it} + \mu_4 EQY_{it-1} + \mu_5 D + \epsilon_{it} \quad (14)$$

where LLR is the ratio of a bank'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 periods 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 banks are expected to have lower expected losses. Finally, we include a dummy variable D which denotes whether or not a bank is a building society or not ($D = 1$ if the bank is not a building society, otherwise $D = 0$).[23]

[23] Given the trend component within the time-decay model i.e. $\exp[-\phi(\text{t-T})]$, we also included a time trend in our specification of (14), however it wasn't significant in any of the regressions.

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 hetroscedastic 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 are common across banks and that any heterogenous variation shows up in the error term ϵ_{it}. Consequently, the error term is assumed to be non-iid. Specifically, we allow cross bank hetroscedasticity and assume that these disturbances are contemporaneously correlated and we also assume a common autocorrelation parameter over time for all banks. 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.[24]

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 (insert Table 8 here). 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 banks amongst the sample have significantly higher loan loss reserves.

To check the robustness of our results, we also estimate (14) 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 bank'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

[24] The estimation was carried out using Stata 8.0.

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. The results are reported in the final 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' coeffficients 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 and the loan loss reserves within the sample of institutions.

There are several promising avenues for further research in this area. These can be separated in terms of the two-step approach employed here. Firstly, the current approach of estimating cost efficiencies can be extended to a larger sample of banks and to different size classes of banks. Other frontier estimates such as profit efficiency can be estimated, which would allow for banks adjusting their revenue side of the balance sheet and take into account differences in product quality. The second-stage of the approach can be extended by examining the dynamics of the relationship between the various variables using panel data methods suitable for panels with relatively small time horizons and large numbers of banks. Additional work could also look at the dynamic interaction of efficiency, loan loss reserves and capitalisation of institutions using such methods as two stage least squares.

6 Concluding Comments

This paper generates a series of efficiency scores for a sample of Irish and British banks 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 banks' 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 banks 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 big banks are more efficient than smaller banks 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 banks are at least 4 per cent greater than that of Irish banks. This result is reinforced by additional cost function estimates, which reveal, on average, higher significant costs for Irish banks 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 banking 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. DEA generated scores, on the other hand, under the same hypothesis, have a counter-intuitive effect.

Increasingly, in these second stage models, individual efficiency scores are not only used to characterise the performance of the bank 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 bank performance and market structure.

It is hoped, therefore, that by providing an example of the methodologies applied to this question, this paper will characterise the first output in a series of research to be conducted in this area.

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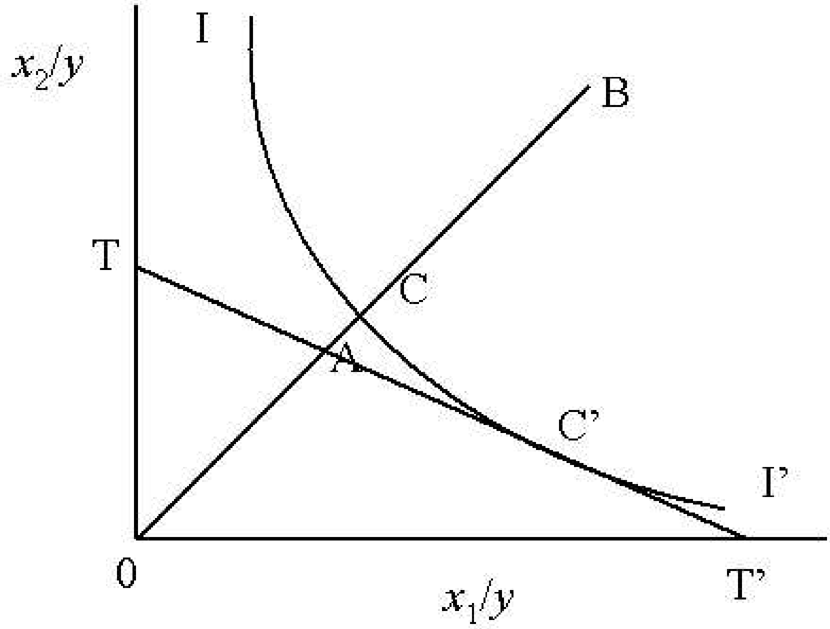

Figure 1: Technical and Allocative Efficiencies

Table 1: List of Banks Used in Sample (1996-2001)

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

Note: * denotes an Irish bank and B.S. = building society.

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

Variable	Notation	Mean	Std. Deviation
Cost:	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_4, P_5 and P_3 are prices per unit.

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 Function		259.001	

Note: **N** = 180 i.e. 30 banks 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.

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	Non-Interest Income	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		0.794	14.218
μ		0.182	4.325
ϕ		0.048	3.714

Note: **N** = 180 i.e. 30 banks and 6 time-periods.

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.

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	Non-Interest Income	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 banks and 6 time-periods. D_1 is the dummy for Irish banks and D_2 is the dummy for the 10 largest banks.

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

		Prais-Winsten		Random-Effects		IV
Parameter	Variable	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.