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Efficiency in UK Building Society Branch Networks: A Comparative Analysis Using Parametric and Non-Parametric Distance Functions

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1 INTRODUCTION

While there have been many academic studies of the efficiency of financial institutions at the industry level (see Berger et al 1997a), there have been relatively few studies made of efficiency at the branch level. This is probably due to the difficulty in obtaining adequate branch level data, which is typically not publicly available. As Berger et al (1997b) point out, however, "…..information on branch efficiency may help improve our understanding of the underpinnings of efficiency at the bank level".

Aside from the paucity of branch level efficiency studies, those studies that have been carried out tend to be characterised by relatively small samples. Sherman and Gold (1985), for example, analysed the relative efficiency of a small sample of US savings bank branches using the non-parametric programming methodology, Data Envelopment Analysis (DEA). Similar studies have also been carried out by: Vassiloglou and Giokas (1990) in respect of bank branches located in the vicinity of Athens, Greece; Oral and Yolalan (1990) studied bank branches in Turkey; and Al-Faraj, Alidi and BuBshait (1993) studied bank branches in Saudi Arabia.

Efficiency studies which have used larger samples have tended to be cost function studies. Zarkoohi and Kolari (1994), for example, estimate a Translog cost function and examine branch level economies of scale and scope for a sample of 615 savings bank branches in Finland. Berger et al (1997b), however, specify and estimate the Fourier flexible form cost function in order to analyse the efficiency of a sample of over 760 US bank branches.

In respect of the UK, the only previous study into branch level efficiency was conducted by Drake and Howcroft (1994). This study calculated indices of technical efficiency for a sample of 190 UK bank branches. These indices were then decomposed into the constituent components - scale efficiency and technical efficiency. In common with most other studies which analyse technical efficiency at the branch level, Drake and Howcroft utilised the non-parametric approach, DEA. A potential problem with DEA, however, is that it is non-stochastic and cannot allow for random error. Hence, DEA may tend to overstate the true extent of technical inefficiency, as any deviation from the efficient frontier is associated with inefficiency. In contrast, the Stochastic Frontier Approach (SFA), which is typically applied in the context of cost functions, assumes a composite error term such that any deviation from the fitted (cost) frontier is assumed to be a combination of random error (as captured by a classical symmetric error term), and technical inefficiency (in the case of a production frontier) or X-inefficiency (in the case of a cost frontier). In the latter case, the X-inefficiency would be captured by a strictly one-sided, positive error term.

An associated potential weakness of DEA is that, as the efficient frontier must envelop all the units in the sample, some a-typical units may be self-identified as efficient simply by virtue of the fact that there are no similar units with which to compare them. This may be a particular problem for a-typically large or small units, as the variable returns to scale (production) frontier would be forced to pass through these observations.

For these reasons, it may be useful to contrast the results obtained from DEA, with those obtained from a parametric approach such as SFA. A potential difficulty here, however, is that, while physical data on inputs and outputs may be available at the branch level, accurate data on input prices is often not available, thereby precluding the estimation of a stochastic cost frontier. Furthermore, where cost frontiers can be specified and estimated, the deviations from the frontier will represent X-inefficiencies which are composed of both allocative and technical inefficiencies. In contrast, although DEA can be utilised to analyse allocative inefficiency, the basic DEA analysis usually reported typically focuses only on technical efficiency.

Hence, this paper extends the existing literature by contrasting the non-parametric technical efficiency results obtained using DEA with those from a directly comparable parametric approach which utilises the distance function in conjunction with SFA. Unlike DEA, which tends to produce a number of efficient decision making units (DMUs) with relative efficiency scores of unity, however, the distance function frontier approach typically tends to rank units between zero and unity, with no DMU ranked as 100% efficient. For completeness, DEA is also utilised to produce measures of scale efficiency in order to examine the nature of the size-efficiency relationship at the branch level.

A further contribution of this paper is to analyse the relative efficiency of a sample of building society branches. Although there have been a number of studies examining scale and technical efficiency at the industry level (see, for example, Hardwick, 1989, 1990, Field, 1990, Drake, 1992, Drake and Weyman-Jones, 1992, 1996), to the author's knowledge, this is the first study to examine UK building society efficiency at the branch level.

Finally, it may be argued that an in-depth analysis of the efficiency of UK building society branches is both timely and important. There has been a significant increase in the level of competition within UK retail banking as a consequence of deregulation measures affecting both banks and building societies during the 1980s (see Drake, 1990). Indeed, a number of large building societies have opted to take advantage of the option provided in the 1986 Building Societies Act to convert from mutual to plc bank status. Furthermore, the advent of direct banking and other technology driven distribution channels, together with a trend towards mergers and rationalisation, has begun to focus increasing attention on the future role of branch networks in retail banking.

The remainder of the paper is accordingly structured as follows: Sections 2 and 3 outline the methodology and the data set, respectively. Section 4 provides details and analysis of the empirical results, and Section 5 provides a summary of the main conclusions of the paper.

2. Methodology

2.1. Non-Parametric Frontier Models

Data Envelopment Analysis (DEA)

Within the DEA framework it is possible to decompose relative efficiency performance into the categories initially suggested by Farrell (1957) and later elaborated by Banker, Charnes and Cooper (1984) and Fare, Grosskopf and Lovell (1985). The constructed relative efficiency frontiers are non-statistical or nonparametric in the sense that they are constructed through the envelopment of the DMUs with the "best practice" DMUs forming the non-parametric frontier. Farrell's categories are best illustrated, for the single output-two input case in the unit isoquant diagram, Figure 1, where the unit isoquant (yy) shows the various combinations of the two inputs (x_1, x_2) which can be used to produce 1 unit of the single output (y). The firm at E is productively (or overall) efficient in choosing the cost minimising production process given the relative input prices represented by the slope of WW'. A DMU at Q is allocatively inefficient in choosing an inappropriate input mix, while a DMU at R is both allocatively inefficient, (in the ratio OP/OQ), and technically inefficient, (in the ratio OQ/OR) because it requires an excessive amount of both inputs, x, compared with a firm at Q producing the same level of output, y.

INSERT FIGURE 1

The use of the unit isoquant implies the assumption of constant returns to scale. However a firm using more of both inputs than the combination represented by Q may experience either increasing or decreasing returns to scale so that, in general, the technical efficiency ratio OQ/OR may be further decomposed into scale efficiency, OQ/OS, and pure technical efficiency, OS/OR, with point Q in Figure 1 representing the case of constant returns to scale. The former arises because the firm is at an input-output combination that differs from the equivalent constant returns to scale situation. Only the latter pure technical efficiency represents the failure of the firm to extract the maximum output from its adopted input levels and hence may be thought of as measuring the unproductive use of resources. In summary,

productive efficiency =
allocative efficiency x scale efficiency x pure technical efficiency (1)

$$OP/OR = [OP/OQ] \times [OQ/OS] \times [OS/OR] \quad (2)$$

Hence, concentrating on overall technical efficiency, Farrell suggested constructing, for each observed DMU, a pessimistic piecewise linear approximation to the isoquant, using activity analysis applied to the observed sample of DMUs in the organisation/industry in question. This produces a relative rather than an absolute measure of efficiency since the DMUs on the piecewise linear isoquant constructed from the boundary of the set of observations are defined to be the efficient DMUs.

Subsequent developments have extended this mathematical linear programming approach. If there are n DMUs in the industry, all the observed inputs, and outputs are represented by the n-column matrices: X and Y. The input requirement set, or reference technology can then be represented by the free disposal convex hull of the observations, i.e., the smallest convex set containing the observations consistent with the assumption that having less of an input cannot increase output. We do this by choosing weighting vectors, ?, (one for each firm) to apply to the columns of X and Y in order to show that firm's efficiency performance in the best light.

For each DMU in turn, using x and y, to represent its particular observed inputs and outputs, pure technical efficiency is calculated by solving the problem of finding the lowest multiplicative factor, ?? which must be applied to the firm’s use of inputs, x, to ensure it is still a member of the input requirements set or reference technology. That is choose

??⁇? to : min ? such that: ?x ? ?’X

y ? ?’Y

?i ? 0, ??i = 1, i = 1,..., n

(3)

To determine scale efficiency, we solve the technical efficiency problem (3) without the constraint that the input requirements set be convex., i.e. we drop the constraint ??i = 1. This permits scaled up or down input combinations to be part of the DMUs production possibility set. Figure 2 illustrates this for the case of a single input and a single output.

In Figure 2, the production possibility set under constant returns to scale is the region to the right of the ray, OC, through the leftmost input-output observation. Any scaled up or down versions of the observations are also in the production possibility set under this assumption of constant returns to scale.

Imposing the convexity constraint, ??i = 1, ensures the production possibility set is the area to the right of the piecewise linear frontier VV’, which does not assume constant returns to scale, but allows for the possibility of increasing returns to scale at low output levels and decreasing returns at high output levels. The resulting overall technical and pure technical efficiency ratios, AQ/AR, and AS/AR are illustrated for one of the observations. Scale efficiency is the ratio of the two results.

INSERT FIGURE 2

In the case of programme (3), the efficiency ratios with and without the convexity constraint may be labelled ?p and ???and scale efficiency, ?s is then ??/?p. In the subsequent results we refer to overall technical efficiency as OE, pure technical efficiency as PTE and scale efficiency as SE. As explained above, it follows that :

OE = PTE x SE, and SE = OE / PTE (4)

Although the scale efficiency measure (SE) will provide information concerning the degree of inefficiency resulting from the failure to operate with constant returns to scale, ie, at the minimum efficient scale (MES), it does not provide information as to whether a DMU is operating above or below the MES. Hence, in order to establish whether scale inefficient branches exhibit increasing or decreasing returns to scale, we simply solve the technical efficiency problem (3) under the assumption of non-increasing returns to scale rather than variable returns to scale. If these two measures of PTE differ, this indicates that the branch is operating in the region of increasing returns to scale. Conversely, if the two measures coincide then the branch is operating in the region of decreasing returns to scale.

2.2 Parametric Frontier Models

The Stochastic Frontier Approach (SFA)

An alternative approach to the non-parametric frontier methodology is that of stochastic frontier models suggested by Aigner, Lovell and Schmidt (1977, henceforth ALS). This typically involves the specification of a stochastic production or cost frontier. In the context of the latter, for example, we might write the cost function as follows:

$$\ln C_{it} \; ? \; \ln C ? y_{it}, w_{it} ?? \; ?_{it} \qquad (5)$$

Where C represents total costs, y is a vector of outputs, w is a vector of input prices and ? is a composed error term that reflects both statistical noise and the X inefficiency of the firms in the sample.

$$?_{i} \; ? \; ?_{i} ?? _{i} \qquad\qquad ?_{i} \; ? \; 0 \qquad (6)$$

The component $?_{i}$ is assumed to be symmetrically distributed around a zero mean but $?_{i}$ is assumed to be non-negative (non-positive in the case of a stochastic production frontier). Hence, $?_i$ represents the deviations above the minimum cost frontier (X-inefficiency) associated with either technical inefficiency (excessive use of inputs in the production of outputs) or allocative inefficiency (the failure to utilise the cost minimising input bundle given input prices and the level of outputs). Estimation of such models has largely followed ALS (1977). By specifying particular density functions for the composed error terms, maximum likelihood estimation can be used (see Bauer, 1990, for details of the likelihood functions).

The Distance Function Approach

Although both stochastic production functions and stochastic cost functions have been widely used in empirical research, both have drawbacks with respect to measuring the relative efficiency of building society branches. The stochastic production frontier approach has the disadvantage that, as output is the dependent variable, only a single output production process can be modeled. This is clearly not appropriate as building society branches typically produce a range of outputs or services. Furthermore, it would be very difficult to construct an appropriate composite output measure.

The usual solution to this problem in empirical applications is to make use of the duality between cost and production functions and to specify and estimate a stochastic cost frontier. This permits the modeling of a multi-input, multi-output production process. A particular drawback in utilizing a cost function specification in this case, however, is that full and accurate branch level cost data is often not available. In particular, the required data on all input prices is typically problematic. For example, in respect of capital inputs, an important element will be the branch premises themselves. In retail branch banking, however, these premises will often be a mix of owned and rented premises. Furthermore, some branches may be high cost or high rent branches simply by historical accident or by virtue of their location. Both of these factors are outside the current control of the branch, but may nevertheless cause such a branch to appear inefficient.

A further potential drawback of the stochastic cost frontier approach is that any non-random deviations above the cost frontier will be associated with both allocative and technical efficiency. In contrast, the relative efficiency measures derived from non-parametric methodologies such as DEA typically relate only to technical efficiency. Hence, the relative efficiency measures derived from parametric and non-parametric approaches are often not directly comparable even though, in principle, DEA can be adapted to analyse allocative as well as technical efficiency.

A potential solution to these problems, but one which has not been widely used empirically, it to use employ a parametric approach but to specify and estimate a stochastic distance frontier rather than a stochastic cost or production frontier. The distance function specification has the advantages of permitting the modeling of a multi-input, multi-output production process, and being a function only of outputs and inputs. Hence, the distance function does not require data on input prices. Furthermore, as it is a function of outputs and inputs, the stochastic distance frontier produces a relative efficiency measure that is directly comparable to the measure of technical efficiency produced by DEA.

Input Based Distance Function

The input oriented distance function can be interpreted as the greatest radial contraction of the input vector, with the output vector held fixed, such that the input vector still remains in the input requirement set V(y).

$$D_I(x, y) = \max\{\rho : (x/\rho) \in V(y)\} \qquad (7)$$

The distance function $D_I(x, y)$ will take a value which is greater than or equal to unity if the input vector, *x*, is an element of the feasible input set, and will take a value of unity if x is located on the inner boundary of the input requirement set.

In order to be consistent with the DEA analysis, we employ the input orientated distance function. As this produces a measure which is the inverse of the Farrell (DEA) efficiency measure, however, we report the reciprocal of the input distance function measure in order that the results are directly comparable with the DEA measures.

In this paper we employ the popular Translog flexible functional form, and the Translog output distance function with 4 outputs and 3 inputs can be expressed as:

$$\ln D_{Ii} = const + \sum_{i=1}^{4} ?_i \ln y_i + \tfrac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4} ?_{ij} \ln y_i \ln y_j + \sum_{m=1}^{3} ?_m \ln x_m$$

$$+ \tfrac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3} ?_{mn} \ln x_m \ln x_n + \tfrac{1}{2}\sum_{i=1}^{4}\sum_{m=1}^{3} ?_{im} \ln y_i \ln x_m + \ln ?_i \qquad (8)$$

Young's theorem requires that the second order parameters of the cost function must be symmetric, that is, $?_{ij} = ?_{ji}$ for all i, j, and $?_{mn} = ?_{nm}$ for all m, n. A convenient method of imposing homogeneity upon the Translog distance function is to follow Lovell et al (1994) and observe that homogeneity implies that:

$$D_I(? x, y) = ? D_I(x, y) \text{ for any } ? > 0 \qquad (9)$$

Hence, if we arbitrarily choose the Mth input, and set ? = 1/*x*M then, using TL(.) to
represent the Translog function, we can express the input distance function as:

$$\ln(D_{Ii}/xM_i) = TL(y_i, x_i/xM_i, const, ?, ?, ?, ?) \qquad i = 1,2,...,N \qquad (10)$$

or $$\ln D_{Ii} - \ln(xM_i) = TL(y_i, x_i/xM_i, const, ?, ?, ?, ?) \qquad i = 1,2,...,N \qquad (11)$$

It follows that we can re-write this Translog distance function as:

$$? \ln ? xM_i ? ? \; TL ? y_i, x_i / xM_i, ?, ?, ?, ? ? ? \ln ? D_{Ii} ? \quad i = 1,2,...,N \tag{12}$$

Hence, if we append a symmetric error term, $?_i$ to account for statistical noise, and re-write $\ln ? D_{Ii} ?$ as $?_i$, we can obtain the stochastic input distance function, with the usual composite error term, $?_i \; ? ?_i \; ? ?_i$.

$$? \ln(xM_i) \; ? \; TL ? y_i, x_i / xM_i, ?, ?, ?, ? ? ? ?_i \; ? ?_i \qquad i = 1,2,...,N \tag{13}$$

We make the standard assumptions that the $?_i$ are normally distributed random variables while the $?_i$ are assumed to have a truncated normal distribution. As is usual in the stochastic frontier approach, however, the predicted value of the input distance function for the ith firm, $D_{Ii} \; ? \; \exp ? ? ?_i ?$, is not directly observable, but must be derived from the composed error term, $?_i$. Hence, predictions for D_{Ii} are obtained using Coelli's Frontier 4.1 programme, based on the conditional expectation:

$$D_{Ii} \; ? \; E ? ? ? ?_i ? ?_i ? \tag{13}$$

3. Data

The sample consists of data from the first half year of 1996 for 220 of the branches of a top 10 national UK building society. Following consultations with the senior management of the building society, it was decided that four outputs (Y) and three inputs (X) best characterised the operations of the branches. These are detailed below:

Y1: No of new and further loan advances.

Y2: No of new deposit accounts.

Y3: No of transactions.

Y4: No of insurance sales.

X1: FTE senior staff.

X2: FTE clerical staff.

X3: Total no of existing loan and deposit accounts

Y1 and Y2 reflect the traditional business of building societies. Specifically, raising funds from depositors to intermediate into loans (predominantly mortgage loans). What is important from a branch performance perspective, however, is not the historical level of business, but the new business generated within the period. Similarly, whereas the volume of deposit inflows will reflect factors outside the control of branches, such as the relative competitiveness of the societies' deposit rates, branches will typically be targeted with expanding the number of new deposit (and loan) accounts.

The output, Y3 reflects the fact that building society branches need to service their loan and deposit accounts via, for example, taking deposits, granting withdrawals, creating standing orders, etc. Finally, the output Y4 reflects the fact that both banks and building societies are diversifying, at the margin, away from traditional intermediation business, and into "off-balance sheet business". In the case of this particular building society, this reflects the sales of various types of insurance products, such as property insurance and payment protection policies. As with the other outputs, we elect to specify the number, rather than value of sales, in order to avoid any bias associated with the use of monetary values. It would be expected, for example, that both average mortgage loan values and any associated insurance premiums would be higher in London and the South-East than elsewhere, simply by virtue of higher average property prices.

Turning now to the inputs, X1 reflects the full time equivalent (FTE) number of senior staff working in the branch, while X2 reflects the FTE number of clerical staff in the branch. In practice, this distinction was made on the basis of staff seniority grade rather than job description, ie, manager, cashier, etc.

The final input, X3, is the total number of existing loan and deposit accounts held by the branch. This measure was included as no direct measure of branch size (such as branch area) was available. Furthermore, no suitable proxy was available for “other non-labour resource usage”. Following extensive discussion with the senior management of the building society, however, it was felt that X3 would prove to be a particularly relevant input. As well as providing some sort of proxy for branch size and non-labour resource utilisation, the specification of X3 also recognises that branches with large existing customer bases should be better placed to cross-sell products/outputs to their existing customers. For example, insurance products and consumer loans could be marketed to existing mortgage borrowers. Similarly, attempts could be made to market mortgage loans and insurance to non-borrowing depositors. While it could legitimately be argued that branches with larger customer bases will typically encounter correspondingly greater account servicing demands, this should be taken into account on the output side by Y3, the number of branch level transactions.

In order to try to provide further insight into the determinants of branch level relative efficiency, the technical efficiency scores will be regressed against potential efficiency correlates in a second stage analysis. These efficiency correlates include: loan quality, as proxied by the number of loans more than two months in arrears (ARREARS); a merger dummy, reflecting whether a particular branch had been affected by the previous merger activity of the building society (MERGER); branch location, a percentage score relative to the prime location for the town in which the branch is located (LOCATION); staff quality, as measured by the ratio of senior to clerical staff (RATIO); branch size, proxied by the total number of staff (STAFF), and finally, appearance, as proxied by an internal index (1,2,or 3, reflecting poor, average or good) developed by the building society to reflect the attractiveness of the branch and its merchandising (APPEAR).

In order to take account of the fact that the relative efficiency score is a bounded variable taking a value ranging from zero to unity, we utilise Tobit regression rather than OLS.

4. Results

In the interests of brevity, the full set of efficiency measures are provided in Table 1, together with some summary statistics. As the initial analysis will concentrate on the parametric and non-parametric distance function measures of technical efficiency, under the assumption of variable returns, column 1 contains the stochastic distance function results (SDF), while column 2 details the DEA pure technical efficiency results (PTE). These alternative measures are combined in column 3, and this is discussed in more detail below. The remaining columns provide details of the DEA measures of overall and scale efficiency, OE and SE respectively, together with an indication of whether a branch exhibits increasing (I), decreasing (D), or constant returns to scale (C).

Technical Efficiency

It is clear from a casual inspection of the results in Table 1 that there is, in general, a good correspondence between the SDF scores and the DEA PTE results. Branches units 132 and 119, for example, are the least efficient units according to DEA, with efficiency scores of 0.45 and 0.48 respectively. Their corresponding distance function scores are 0.71 and 0.72 respectively, relative to the minimum score of 0.70. Similarly, the lowest ranked branches according to the distance function estimates are branches 166 and 165 with scores of 0.696 and 0.699 respectively. In contrast, these branches record DEA scores of 0.56 and 0.53 respectively.

At the other end of the spectrum, the most efficient branch according to the distance function estimate is branch 37 with a score of 0.963. Not surprisingly, this branch is ranked as efficient by DEA. Furthermore, it is clear from Table 1 that the mean levels of efficiency are also similar as between the distance function and DEA, at 0.89 and 0.84 respectively. It is clear from the minimum scores, however, that the non-parametric nature of DEA may tend to overstate the true level of inefficiency. Whereas the minimum technical efficiency score recorded by the stochastic distance function is 0.70, it is 0.45 according to DEA.

While the generally good correspondence between the two sets of efficiency results does suggest that both methods are credible techniques for measuring relative efficiency, a more formal analysis suggests that it would be unwise to rely on just one of these techniques as there can be considerable variation across the two measures. The correlation coefficient, for example, is 0.64. Hence, while this supports the notion of a statistically significant positive correlation between the two sets of distance function measures, it is indicative of the possibility that a particular branch could be given quite different efficiency scores and rankings by the two techniques. This is confirmed by the scatter plot of the two sets of efficiency scores provided in Figure 3. In respect of those units ranked as efficient by DEA, for example, the distance function scores range from 0.96 to 0.79. Similarly, a branch with a relatively high distance function score of 0.95 (relative to the maximum score of 0.96) can have a DEA efficiency score as low as 0.75. It is quite clear, therefore, that in order to guard against erroneous conclusions, the two alternative distance function measures should be used in parallel rather than as alternative techniques.

A very simple way of combining the two sets of efficiency estimates is to take the mean of the parametric and non-parametric scores, as in column 3 of Table 1. This combined measure ranges from 0.98 to 0.58 and has a mean efficiency level of 0.86. Furthermore, this measure tends to preserve the rank ordering at both ends of the spectrum while "smoothing out" any serious outliers. Branch 132, for example, has the lowest combined score of 0.58 and this is a combination of the lowest DEA score (0.45) and the third lowest distance function score (0.712). Similarly, branch 37 has the highest combined score of 0.982 which is composed of a DEA score of 1.0 and the highest distance function score of 0.963.

Technical Efficiency Correlates

In order to identify possible influences on the technical efficiency scores reported above, Table 2 reports the results of a Tobit regression of the mean (combined) efficiency scores from Table 2 (column 3) against the potential efficiency correlates discussed in Section 3. It is clear from Table 3 that there is no significant relationship between branch size and technical efficiency, when branch size is proxied by the total number of branch staff. Very similar results were also obtained when branch size was proxied by the total number of accounts. Hence, although there is evidence in the literature that larger banks are more efficient than smaller banks (see Berger et al, 1997), this correlation does not seem to apply at the branch level, at least for building societies. It is also interesting to note that there appears to be no significant relationship between technical efficiency and the ratio of senior to clerical staff.

Turning now to what we might refer to as marketing variables, an interesting result is that branch appearance appears to have a significant positive impact upon branch level technical efficiency. A possible explanation for this may be that the resources or inputs of a branch are often determined centrally on the basis of factors such as the physical size of the branch and the number of accounts held at the branch (which are historically determined). The success of a branch in terms of generating new business, however, may well be influenced by the attractiveness of the branch and its merchandising, as measured by APPEAR. Hence, branches which score highly in terms of this variable seem to be relatively successful in generating new business given the resources/inputs available. In contrast, the variable LOCATION, although positively signed, does not appear to have a significant impact on branch level efficiency. This is an interesting result in the sense that branch location is a variable which, a-priori, is usually considered to have an important impact on branch level performance. Considerable attention is typically given to the location of new branches, for example, with prime locations generally considered to be in the proximity of key shopping centres or financial centres. The results in Table 2, however, suggest that, of the 2 marketing variables considered, the attractiveness of the branch and its merchandising is much more important than its location in terms influencing technical efficiency.

The merger dummy has a negative sign. This is in accordance with our a-priori expectations, as it would be expected that branches affected by previous mergers would experience some disruption that might adversely affect branch level performance. It is clear form Table 2, however, that branch level efficiency does not seem to be significantly affected by prior merger activity.

Finally, the inclusion of the variable, arrears, is designed to capture the possible influence of risk and lending quality on branch level efficiency. The a-priori expectation is that this variable would be negatively signed, either because of the resources necessary to monitor problem loans, or simply due to the fact that relatively inefficient branches might also be expected to be relatively inefficient at assessing risks in respect of the lending function. It is interesting to note from Table 2, therefore, that arrears is not only negative signed but is also highly significant in a statistical sense. As intimated above, however, the explanation for this significant negative relationship between risk/loan quality and technical efficiency is at the centre of a controversy in the literature. Specifically, whether risk should be controlled for in the analysis of the efficiency of financial firms. If the negative impact of risk on efficiency is endogenous and due to poor management, then there is no rationale for controlling for this impact. If, however, the impact is due to exogenous factors outside the institutions or branches control, then it may be appropriate to control for this negative impact. As Berger et al (1997) point out:

"If problem loans are generally caused by 'bad luck' events exogenous to the bank, such as regional specific downturns, then measured cost efficiency may be artificially low because of the expenses of dealing with these loans (e.g., extra monitoring, negotiating workout arrangements, etc)." (P. 194).

It may be, therefore, that the significant negative coefficient on arrears reflects the impact of regional mortgage/housing market variations on arrears levels, and the consequent impact of these problem loans on branch level resources and hence efficiency. Equally, it may also reflect the general level of efficiency and staff quality at particular branches. Hence, it is impossible with the current data set to determine whether the impact of risk/lending quality is endogenous or exogenous. What is clear, however, is that arrears are one of the most important discernable influences on branch level technical efficiency in UK building societies.

Scale Efficiency

The analysis so far has focused on technical efficiency, or more correctly, pure technical efficiency, as all the efficiency scores have been derived under the assumption of variable returns to scale technology. It is potentially informative, however, to analyse scale efficiency in order to examine the extent to which building society branches deviate from the minimum efficient scale. Hence, in this section we calculate the DEA efficiency scores under the assumption of constant returns to scale technology. As detailed in Section 2, this allows us to decompose overall technical efficiency into the constituent components, scale efficiency and pure technical efficiency.

As mentioned above, the full set of DEA results are presented in Table 1, together with some descriptive statistics. The mean level of overall branch efficiency is 0.78, which is considerably lower than the mean level for UK bank branches of 0.921 established by Drake and Howcroft (1994). This is an interesting result as building societies are often argued to be more efficient than banks at the industry level, based on data such as comparative cost income ratios (see Drake, 1990). With respect to the decomposition of overall technical efficiency, the results suggest that pure technical inefficiency (PTE) is a more serious source of inefficiency than is scale inefficiency (SE). Whereas the mean level of the latter is 0.93, the corresponding value for PTE is 0.84. These figures contrast with the figures of 0.937 for PTE and 0.982 for SE found by Drake and Howcroft (1994).

It is clear from the variation in SE levels, however, that scale inefficiency is a serious problem for many building society branches. Table 1 reveals, for example, that the minimum SE score is 0.57, and that only 14.16% of the sample exhibit constant returns to scale. In contrast, 41.1% of the sample exhibit increasing returns while 44.75% exhibit decreasing returns to scale.

Hence, in order to gain a clearer picture of the size - scale efficiency relationship operating in building society branches, the data set has been subdivided into size bands according to the total number of accounts. These size bands are as follows:

Band 1	Above 20000
Band 2	10000 – 20000
Band 3	7500 – 10000
Band 4	5000 – 7500
Band 5	4000 – 5000
Band 6	2500 – 4000
Band 7	0 - 2500

Table 3 shows the mean SE levels for these size bands together with the mean number of accounts and also the mean number of total FTE staff. The latter is included to provide a further perspective on the size-scale efficiency relationship.

It is quite clear from Table 3 that a powerful size efficiency relationship is operating across building society branches with the largest Band 1 branches exhibiting a mean SE score of only 0.668. Not surprisingly, all the branches in this size band were found to be operating with decreasing returns to scale. Hence, all these very large branches appear to be operating well above the minimum efficient scale (MES) of operation. As branch size falls, however, mean SE levels clearly rise, which is consistent with a movement closer to MES. In fact, the mean SE levels increase smoothly and continuously until we reach Band 5, with a mean SE score of 0.97. The branches in this size band clearly seem to be operating closest the MES as the corresponding mean SE levels for the adjacent Band 4 and 6 branches are 0.935 and 0.949 respectively. Finally, the smallest branches (Band 7) exhibit a mean SE figure of 0.924 with the majority exhibiting increasing returns to scale.

An interesting aspect of the results presented in Table 3 is that the MES for a building society branch appears to be at a relatively small size scale, with the implication that a large number of branches are much too large to be scale efficient. This result is consistent with the findings of Drake and Howcroft (1994), however, who found that the MES in bank branches was associated with a mean total staff number of around nine, in contrast to a mean of 17.20 for the largest branches. As can be seen from Table 3, the MES appears to be even lower in this study with the Band 5 branches having a mean total staff number of around 6, in contrast to the mean of 29 for the largest branches. Hence, based on staff figures alone, these results suggest that some of the largest branches are almost five times the optimal size.

Furthermore, the results suggest a considerable asymmetry in the size – efficiency relationship. Specifically, the efficiency consequences of being above the MES appear to be much greater than those of being below the MES. The mean SE figure of 0.924 for the smallest branches, for example, contrasts with that of 0.668 for the largest branches. This finding is consistent with an "asymmetric U-shaped average cost curve" in building society branching and is also consistent with the findings of Drake and Howcroft (1994). These findings of a relatively low MES at the branch level may also provide at least a partial explanation for the typical finding that, at the industry level, economies of scale in building societies tend to be exhausted at relatively low output levels (see Hardwick (1989, 1990 and Drake, 1992)

5. Conclusions

This study is innovative in two respects. First, to the author's knowledge it is the first study of the efficiency of UK building society branches. Secondly, it is the first study to combine both parametric and non-parametric frontier distance function analysis in the context of financial sector efficiency.

In respect of technical efficiency, there is a significant positive correlation between the two sets of distance function measures which suggests that both are credible methodologies for relative efficiency analysis. The degree of correlation appears to be insufficiently high to warrant exclusive reliance, as a management tool for example, on either technique. For those branches deemed efficient according to DEA, for example, the SDF technique produced efficiency scores ranging from 0.96 to 0.79. Hence, in order to produce some consensus regarding the relative efficiency results, the two alternative measures were combined by taking the mean of the SDF and DEA scores. This produced technical efficiency measures ranging from 0.98 to 0.58, with a mean efficiency level of 0.86. The latter contrasts with the figure of 0.94 for UK bank branches found by Drake and Howcroft (1994) using DEA. Furthermore, this relatively high degree of technical inefficiency is somewhat surprising given the evidence typically provided by cost-income ratios, etc, suggesting that UK building societies are more cost efficient than UK banks (see Drake (1989).

A second stage Tobit regression revealed that the most important correlates with respect to technical efficiency were "branch appearance" and risk/loan quality, as proxied by the number of loans over two months in arrears. The former result confirms the potential importance of the marketing function in influencing branch level performance and efficiency, while that latter is consistent with a good deal of empirical literature suggesting that risk/loan quality can have a significant negative impact on the efficiency of financial firms. It should be noted, however, that this finding has typically related to studies of bank efficiency at the industry level, much of it US based (see, for example, Mester 97, Berger et al 97). Hence, the significant negative impact of arrears on efficiency found in this study is particularly interesting as the impact is evident at the branch level in a sector where bad debt problems are typically much less severe than in commercial banking, due to the dominance of secured mortgage lending.

The latter part of the paper focuses on scale efficiency, and in particular, the size-efficiency relationship. In contrast to the technical efficiency results, a marked size-scale efficiency relationship is evident in building society branches. Furthermore, the relationship appears to be asymmetric in the sense that the scale inefficiencies attributable to operating above the MES appear to be much greater than those associated with operating with increasing returns to scale. Finally, the MES itself appears to be at a mean staff level of around 6

FTEs. While this optimal scale of operation may seem surprisingly low, the result is consistent with the findings of Drake and Howcroft (1994) in respect of bank branches. This evidence of a low MES in branch production may also provide at least a partial explanation for the typical finding that economies of scale in financial institutions are exhausted at relatively low asset levels (see Berger and Humphrey, 1997 and Drake, 1992).

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Figure 1. Farrell Efficiency

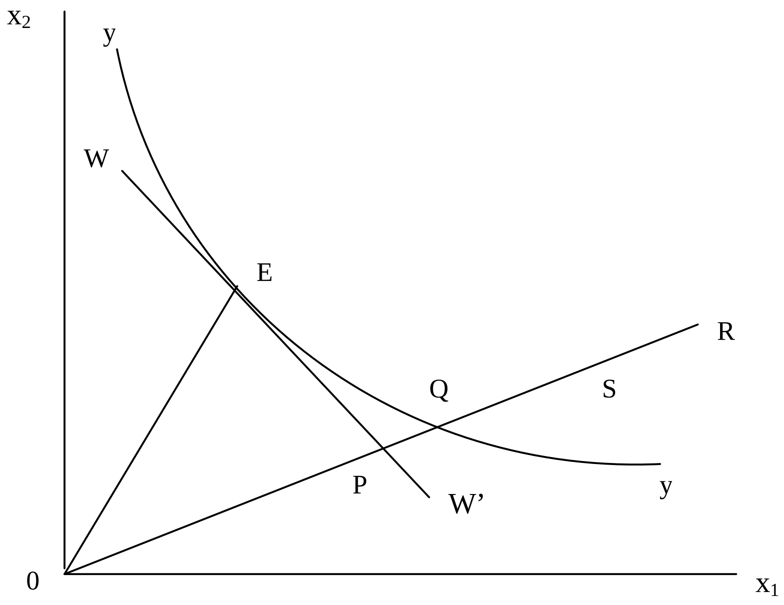

Figure 2. Scale and Technical Efficiency

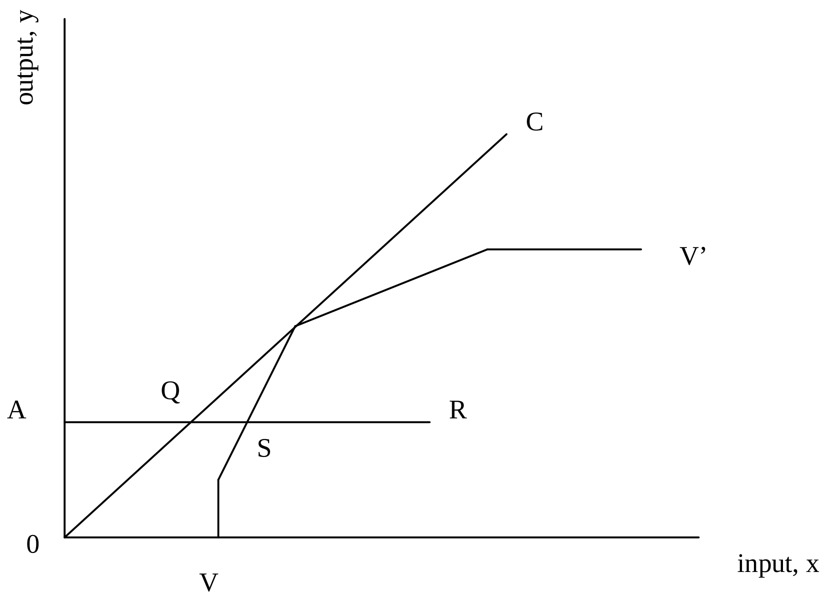

Figure 3
Technical Efficiency

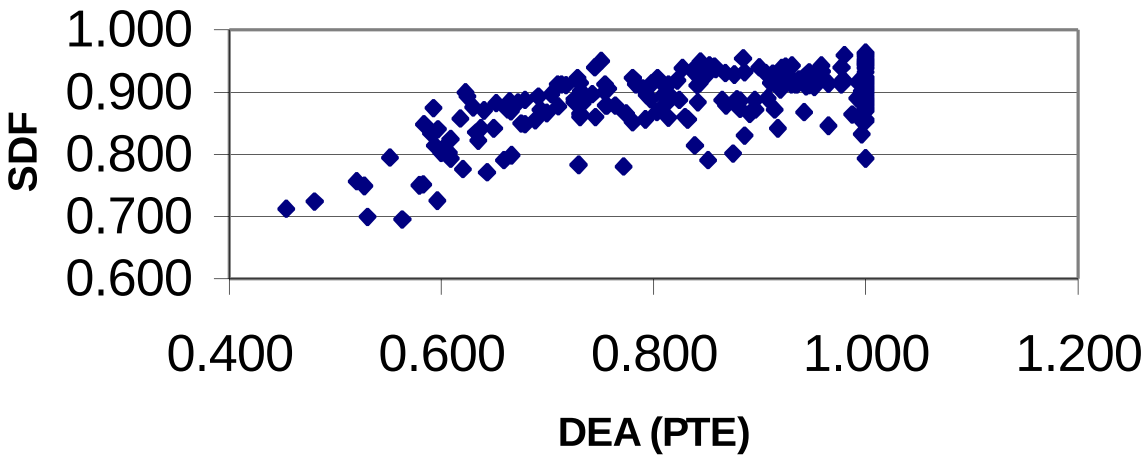

Table 1

Branch Efficiency Results

Branch	1 SDF	2 PTE	3 Mean (1 & 2)	4 OE	5 SE	6 Returns to Scale
1	0.912	1.000	0.956	0.568	0.568	D
2	0.899	1.000	0.950	0.670	0.670	D
3	0.857	1.000	0.928	0.683	0.683	D
4	0.842	0.917	0.879	0.819	0.894	D
5	0.801	0.875	0.838	0.796	0.910	D
6	0.852	0.780	0.816	0.672	0.862	D
7	0.783	0.729	0.756	0.498	0.683	D
8	0.901	0.996	0.949	0.921	0.925	D
9	0.883	0.842	0.862	0.779	0.925	D
10	0.849	0.678	0.764	0.608	0.896	I
11	0.891	0.992	0.941	0.871	0.878	D
12	0.880	0.868	0.874	0.861	0.992	D
13	0.795	0.552	0.673	0.518	0.940	I
14	0.865	0.891	0.878	0.839	0.941	D
15	0.869	1.000	0.935	0.905	0.905	D
16	0.871	0.693	0.782	0.682	0.984	I
17	0.832	0.996	0.914	0.996	1.000	I
18	0.791	0.659	0.725	0.648	0.982	D
19	0.882	0.733	0.807	0.726	0.991	I
20	0.886	1.000	0.943	1.000	1.000	C
21	0.824	0.608	0.716	0.586	0.963	I
22	0.910	1.000	0.955	1.000	1.000	C
23	0.878	0.754	0.816	0.749	0.993	I
24	0.914	1.000	0.957	1.000	1.000	C
25	0.939	0.827	0.883	0.818	0.989	I
26	0.919	1.000	0.959	0.675	0.675	I
27	0.959	1.000	0.980	0.861	0.861	I
28	0.872	0.896	0.884	0.896	1.000	I
29	0.917	1.000	0.958	1.000	1.000	C
30	0.871	0.662	0.767	0.662	1.000	I
31	0.937	0.842	0.890	0.837	0.994	D
32	0.931	0.922	0.926	0.896	0.972	D
33	0.938	0.921	0.929	0.913	0.991	D
34	0.896	0.742	0.819	0.737	0.993	D
35	0.871	0.640	0.755	0.625	0.977	I
36	0.904	1.000	0.952	1.000	1.000	C
37	0.963	1.000	0.982	1.000	1.000	C
38	0.944	1.000	0.972	1.000	1.000	C
39	0.878	1.000	0.939	1.000	1.000	C
40	0.852	0.997	0.924	0.827	0.829	D
41	0.889	0.797	0.843	0.732	0.918	I
42	0.914	0.910	0.912	0.822	0.903	D
43	0.888	0.865	0.876	0.834	0.965	I
44	0.913	0.916	0.915	0.784	0.855	D
45	0.945	1.000	0.973	1.000	1.000	C
46	0.879	0.756	0.818	0.752	0.994	I

47	0.872	0.914	0.893	0.910	0.996	I
48	0.799	0.666	0.732	0.486	0.730	D
49	0.860	0.731	0.795	0.712	0.974	I
50	0.916	0.731	0.823	0.695	0.952	I
51	0.941	0.840	0.891	0.839	0.999	D
52	0.890	0.732	0.811	0.726	0.992	D
53	0.858	0.618	0.738	0.601	0.972	D
54	0.803	0.607	0.705	0.607	0.999	D
55	0.842	0.637	0.739	0.624	0.980	I
56	0.937	0.858	0.898	0.847	0.987	D
57	0.912	0.930	0.921	0.807	0.868	I
58	0.914	0.798	0.856	0.635	0.796	I
59	0.934	0.836	0.885	0.836	0.999	D
60	0.928	0.876	0.902	0.829	0.947	I
61	0.923	0.780	0.852	0.774	0.993	D
62	0.906	1.000	0.953	0.812	0.812	I
63	0.945	1.000	0.972	0.923	0.923	I
64	0.914	0.934	0.924	0.708	0.758	I
65	0.921	0.937	0.929	0.697	0.744	I
66	0.884	0.672	0.778	0.656	0.976	I
67	0.914	0.965	0.939	0.619	0.642	I
68	0.854	1.000	0.927	0.713	0.713	D
69	0.923	0.729	0.826	0.678	0.931	I
70	0.963	1.000	0.981	1.000	1.000	C
71	0.939	0.900	0.919	0.887	0.986	D
72	0.941	0.924	0.933	0.924	1.000	D
73	0.955	0.884	0.919	0.807	0.913	D
74	0.952	1.000	0.976	0.915	0.915	D
75	0.903	1.000	0.951	0.905	0.905	D
76	0.875	1.000	0.938	0.799	0.799	D
77	0.906	0.757	0.831	0.741	0.979	I
78	0.912	0.783	0.848	0.781	0.997	I
79	0.726	0.596	0.661	0.555	0.931	D
80	0.920	1.000	0.960	1.000	1.000	C
81	0.888	0.824	0.856	0.778	0.944	D
82	0.889	0.725	0.807	0.723	0.996	I
83	0.913	0.935	0.924	0.934	0.998	D
84	0.902	0.732	0.817	0.719	0.983	I
85	0.957	1.000	0.979	1.000	1.000	C
86	0.895	0.815	0.855	0.756	0.928	I
87	0.877	0.710	0.793	0.632	0.891	I
88	0.910	0.943	0.927	0.941	0.997	D
89	0.858	0.814	0.836	0.739	0.908	I
90	0.929	0.912	0.921	0.891	0.978	D
91	0.906	0.790	0.848	0.768	0.972	I
92	0.920	0.822	0.871	0.821	1.000	D
93	0.848	0.584	0.716	0.568	0.973	I
94	0.923	0.804	0.864	0.630	0.784	I
95	0.889	0.878	0.884	0.809	0.921	I
96	0.912	0.718	0.815	0.709	0.988	I
97	0.926	0.955	0.940	0.915	0.958	D
98	0.900	0.622	0.761	0.616	0.989	I
99	0.923	0.927	0.925	0.900	0.971	D
100	0.803	0.600	0.701	0.554	0.924	D
101	0.884	1.000	0.942	0.740	0.740	D

102	0.856	0.832	0.844	0.638	0.766	D
103	0.751	0.579	0.665	0.512	0.884	D
104	0.842	0.649	0.746	0.620	0.955	D
105	0.812	0.602	0.707	0.602	0.999	I
106	0.938	1.000	0.969	1.000	1.000	C
107	0.890	0.908	0.899	0.686	0.755	D
108	0.876	0.630	0.753	0.614	0.975	I
109	0.822	0.635	0.729	0.474	0.747	I
110	0.920	1.000	0.960	1.000	1.000	C
111	0.815	0.594	0.704	0.532	0.896	I
112	0.791	0.851	0.821	0.851	0.999	I
113	0.871	1.000	0.935	1.000	1.000	C
114	0.860	0.829	0.844	0.708	0.855	I
115	0.878	0.868	0.873	0.703	0.809	I
116	0.831	0.885	0.858	0.872	0.984	I
117	0.932	1.000	0.966	1.000	1.000	C
118	0.846	0.965	0.905	0.906	0.939	D
119	0.724	0.481	0.602	0.481	1.000	D
120	0.895	0.793	0.844	0.741	0.934	D
121	0.841	0.597	0.719	0.572	0.958	I
122	0.757	0.520	0.638	0.443	0.853	I
123	0.912	0.977	0.944	0.748	0.766	D
124	0.931	0.906	0.918	0.874	0.965	D
125	0.940	1.000	0.970	0.973	0.973	D
126	0.921	1.000	0.961	0.914	0.914	D
127	0.865	0.731	0.798	0.591	0.809	I
128	0.917	1.000	0.958	1.000	1.000	C
129	0.887	1.000	0.944	0.727	0.727	D
130	0.912	0.709	0.810	0.704	0.993	D
131	0.868	0.803	0.835	0.708	0.883	I
132	0.712	0.453	0.583	0.389	0.857	I
133	0.875	0.593	0.734	0.584	0.986	I
134	0.912	0.814	0.863	0.783	0.963	I
135	0.751	0.583	0.667	0.576	0.989	I
136	0.888	0.679	0.783	0.652	0.961	I
137	0.867	0.699	0.783	0.611	0.874	I
138	0.940	0.744	0.842	0.708	0.951	I
139	0.922	1.000	0.961	1.000	1.000	C
140	0.920	0.978	0.949	0.796	0.814	D
141	0.874	1.000	0.937	0.927	0.927	D
142	0.917	1.000	0.958	0.760	0.760	D
143	0.874	1.000	0.937	0.655	0.655	D
144	0.942	0.958	0.950	0.957	0.999	I
145	0.929	0.850	0.889	0.784	0.922	D
146	0.924	1.000	0.962	1.000	1.000	C
147	0.911	0.841	0.876	0.825	0.982	D
148	0.865	0.988	0.926	0.695	0.704	I
149	0.780	0.772	0.776	0.676	0.877	D
150	0.855	0.688	0.771	0.685	0.996	I
151	0.914	0.843	0.879	0.727	0.862	I
152	0.869	0.942	0.905	0.940	0.998	D
153	0.882	0.812	0.847	0.763	0.940	D
154	0.930	0.867	0.899	0.795	0.917	D
155	0.889	1.000	0.945	1.000	1.000	C
156	0.932	0.946	0.939	0.820	0.866	D

157	0.815	0.839	0.827	0.792	0.945	D
158	0.883	0.725	0.804	0.715	0.986	D
159	0.908	1.000	0.954	1.000	1.000	C
160	0.945	1.000	0.972	0.970	0.970	I
161	0.939	0.977	0.958	0.967	0.990	D
162	0.953	1.000	0.976	1.000	1.000	C
163	0.932	0.957	0.944	0.893	0.933	I
164	0.950	1.000	0.975	1.000	1.000	C
165	0.699	0.530	0.615	0.463	0.875	D
166	0.696	0.563	0.629	0.520	0.924	D
167	0.912	0.933	0.922	0.931	0.998	D
168	0.909	0.952	0.930	0.847	0.890	D
169	0.921	0.844	0.882	0.746	0.884	D
170	0.904	0.919	0.912	0.862	0.937	D
171	0.748	0.527	0.638	0.519	0.984	I
172	0.882	1.000	0.941	0.979	0.979	D
173	0.895	0.809	0.852	0.803	0.993	I
174	0.834	0.590	0.712	0.583	0.988	D
175	0.917	0.993	0.955	0.718	0.723	D
176	0.886	0.881	0.884	0.832	0.944	D
177	0.919	1.000	0.959	1.000	1.000	C
178	0.850	0.675	0.763	0.669	0.992	I
179	0.945	1.000	0.973	1.000	1.000	C
180	0.948	1.000	0.974	0.934	0.934	D
181	0.913	0.809	0.861	0.798	0.986	I
182	0.961	1.000	0.981	0.982	0.982	D
183	0.943	0.853	0.898	0.797	0.935	I
184	0.913	0.713	0.813	0.690	0.967	I
185	0.943	0.930	0.937	0.823	0.884	D
186	0.959	0.980	0.969	0.968	0.988	I
187	0.892	0.691	0.792	0.650	0.940	D
188	0.894	1.000	0.947	1.000	1.000	C
189	0.880	1.000	0.940	1.000	1.000	C
190	0.951	0.751	0.851	0.750	1.000	I
191	0.793	1.000	0.897	0.768	0.768	D
192	0.923	1.000	0.962	1.000	1.000	C
193	0.948	1.000	0.974	1.000	1.000	C
194	0.865	0.774	0.819	0.748	0.967	I
195	0.835	0.632	0.734	0.626	0.989	D
196	0.856	0.792	0.824	0.769	0.971	D
197	0.901	0.754	0.827	0.736	0.977	I
198	0.870	0.665	0.767	0.663	0.996	D
199	0.948	1.000	0.974	0.753	0.753	D
200	0.912	0.754	0.833	0.741	0.982	D
201	0.887	0.895	0.891	0.871	0.974	I
202	0.912	0.947	0.929	0.896	0.947	D
203	0.771	0.643	0.707	0.627	0.976	D
204	0.885	0.664	0.775	0.639	0.962	D
205	0.925	0.928	0.927	0.903	0.973	D
206	0.776	0.620	0.698	0.482	0.777	I
207	0.890	1.000	0.945	1.000	1.000	C
208	0.896	0.704	0.800	0.696	0.989	I
209	0.794	0.609	0.701	0.538	0.884	I
210	0.933	0.959	0.946	0.943	0.983	I
211	0.860	0.745	0.802	0.588	0.789	I

212	0.883	0.652	0.767	0.597	0.916	I
213	0.874	0.881	0.877	0.832	0.944	I
214	0.932	0.886	0.909	0.835	0.942	I
215	0.892	0.625	0.758	0.621	0.994	I
216	0.941	0.857	0.899	0.857	1.000	D
217	0.879	0.763	0.821	0.702	0.919	I
218	0.949	0.844	0.896	0.840	0.996	I
219	0.898	1.000	0.949	1.000	1.000	C
Mean	**0.887**	**0.842**	**0.864**	**0.781**	**0.929**	
Min	**0.696**	**0.453**	**0.583**	**0.389**	**0.642**	
Max	**0.963**	**1.000**	**0.982**	**1.000**	**1.000**	

TABLE 2

TOBIT REGRESSION RESULTS

	Coefficient	Standard Error	T-Stat
Constant	0.9156384	0.44503E-01	20.575
RATIO	0.1365530E-01	0.12196E-01	1.120
MERGER	-0.1310123E-01	0.15360E-01	-0.853
STAFF	0.1855179E-02	0.16388E-02	1.132
APPEAR	0.1918200E-01	0.84504E-02	2.270
LOCATION	0.1060088E-05	0.41400E-03	0.003
MIA	-0.1165970E-02	0.24110E-03	-4.836

TABLE 3

SCALE EFFICIENCY AND BRANCH SIZE

(SIZE BAND MEAN LEVELS)

	SE	FTE Staff	Total Accounts
Band 1	**0.668433**	**29.002**	**32006**
Band 2	**0.836636**	**11.99485**	**12592.08**
Band 3	**0.905058**	**9.540069**	**8339.192**
Band 4	**0.93527**	**7.8157**	**6121.102**
Band 5	**0.97007**	**6.107158**	**4479.394**
Band 6	**0.948622**	**5.190943**	**3209.554**
Band 7	**0.924295**	**5.189938**	**1833.4**