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THE EFFECT OF MACROECONOMIC ENVIRONMENT ON PRODUCTIVE PERFORMANCE IN TURKISH BANKING

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Abstract

The goal of this paper is to understand the effect of macroeconomic conditions on performance in Turkish banking. Turkey has experienced a series of financial distresses in the past three decades. This has served as a "negative externality" on banking performance despite important improvements in managerial performance during the period. This study is to show the relative magnitude of internal (managerial) and external (macroeconomic) factors on the survival performance of Turkish banks. By using 30-year data, and employing a non-parametric approach, we calculate the various productive performance indicators such as technical, managerial, scale, allocative and cost efficiencies of the Turkish commercial banks for the period 1970-2000. In order to investigate the causes of bank survival performance, we develop six probit early-warning regression models using efficiency as a proxy for management quality along with macroeconomic factors such as liquidity. Adding the efficiency measures (managerial factors) increases the classification accuracy of our early-warning model, and cost efficiency proves to be the best among the other efficiency measures in terms of increasing the classification accuracy. Also, illiquidity caused mainly by macroeconomic conditions is found to be the major cause of bank failures and successes in Turkey, indicating heavy burden from policy mistakes on banking performance.

ملخص

تهدف هذه الورقة إلى فهم تأثير ظروف الاقتصاد الكلي على أداء البنوك في تركيا. فقد شهدت تركيا العديد من المحن المالية في العقود الثلاثة الأخيرة. وقد أدت تلك المحن إلى إعطاء الأداء البنكي مظهراً خارجياً سلبياً رغم التحسنات المهمة في الأداء الإداري في نفس تلك الفترة. وتوضح هذه الورقة المقدار النسبي للعوامل الداخلية (الإدارية) والخارجية (الاقتصاد الكلي) وتأثير ذلك على الأداء التي انتهجته البنوك التركية للبقاء في السوق. وباستخدام بيانات 30 سنة وتوظيف طريقة غير وسيطية نستطيع أن نحسب مؤشرات الأداء الإنتاجي مثل الكفاءة الفنية والإدارية والقياسية والحصصية والتكاليفية للبنوك التركية التجارية في الفترة بين 1970 و2000. ولكي نبحث في أسباب أداء البنوك للبقاء في السوق سوف نطور ست وحدات احتمالية لنماذج انحدار للإنذار المبكر باستخدام دليل لكفاءة الإدارة باعتبارها كاشفة الجودة إلى جانب عوامل الاقتصاد الكلي مثل السيولة. وبإضافة مقاييس الكفاءة (للعوامل الإدارية) نزيد من دقة التصنيف لنموذج الإنذار المبكر ويعتبر مقياس كفاءة التكلفة من أفضل المقاييس من ناحية زيادة دقة التصنيف. وتعتبر عدم السيولة، التي تحدث غالبا بسبب ظروف الاقتصاد الكلي ، من أكبر أسباب نجاح وفشل البنوك في تركيا مما يعني حملا ثقيلاً على أداء البنوك نتيجة أخطاء السياسة الاقتصادية.

1. Introduction

A key role of a country's financial institution regulator is to limit systemic risk – the risk that the problems of a few institutions spread to many other institutions that are otherwise solvent and liquid. This protects the money supply and payment system from being severely disrupted and involves the management of bank failures. Bank failures have increased all over the world, which lead to the quest of figuring out what the root causes were and the differences between surviving banks and failing ones. Is there a way to detect problem banks prior to their failure so that preventive measures could be taken? The literature developed early warning models but the studies mostly focused on US banks [Wheelock and Wilson, 1995 and Barr and Seiford, 1996]. The main finding was that most bank failures were directly related to having a large number of problem loans, a low capital position, a weak or negative cash flow, and poor management quality.

The research on bank failures in developing countries is very limited due to the lack of data availability and the problems which arise when working with very small number of banks. The purpose of this paper is to study the banking failures in Turkey using a dataset from 1970 to 2000. To the best of our knowledge, this is the first study on banking failures in a developing country spanning over such a long time horizon. The bank failures have increased tremendously in Turkey in the last five years. Between 1970 and 1996, only 17 banks failed; but between 1997 and 2002, a total of 22 banks did. Apparently, most failures occurred during times of financial crises. (1983, 1994, 1999-2001). This paper is also different from earlier papers in that most of the failures we will look at are the result of a financial crisis. Some studies focused on the causes of financial crises using cross-country [Demirguc-Kunt, Hardy and Pazarbasioglu] or time-series macroeconomic data [Canova] and applied multivariate logit or probit models to identify factors with the greatest influence on the crisis. Our goal however is to identify the characteristics of the banks that separate surviving banks from the failed ones, rather than to predict the time or probability of a financial crisis.

Since Thomas [1935], bank failure studies have concluded that the primary cause of bank failures was management incompetence. We use efficiency as a proxy for management quality. We find that the banking institutions showed low efficiencies prior to failure. We use Data Envelopment Analysis (DEA) technique to benchmark the relative performance of banks. DEA is a linear programming technique where the set of best practice or frontier observations are those for which no other decision making unit or linear combination of units has as much or more of every output (given inputs) or as little or less of every input (given outputs). DEA efficiency scores should be good proxies for managerial quality since the bank managers must integrate policies and techniques for transforming inputs into outputs. Non-parametric efficiency approach does not impose a particular functional form on the frontier while the drawback is to assume that there is no random error. In order to enhance the interpretation, we calculated five efficiency measures: technical, pure technical, scale, allocative and cost efficiencies. Previous studies [Siems, Wheeloch, 1995] only used technical efficiency as a proxy for management, but we also look at other efficiencies as possible proxies for management quality. The details are presented in the methodology section.

In the last part of the paper, we present a probit-regression bank failure prediction model using efficiency measure as one of the regressors. Efficiency was found to be important in the regression, and the classification results show that including the efficiency increases the accuracy of the prediction ability of the early warning model. However, the problem that contributes the most to bank failure is the illiquidity faced by these institutions.

We believe that the results of this study will be beneficial for improving government policy targeting the banking sector in Turkey and possibly other developing countries since an accurate and timely identification of a bank's potential for failure would assist in audits targeting and would allow for more effective allocation for resources.

This paper is divided into seven sections. Following the introduction, Section 2 presents the literature review. Section 3 provides an overview of the Turkish Banking System. Section 4 presents the methodology and data. The point estimates of various efficiency measures and sample statistics of inputs, outputs and input prices are discussed in this section. Section 5 provides the empirical results. We compare the efficiencies of surviving and failed banks. Section 6 develops the early warning model by examining the relationship between failure, efficiency and some other bank characteristics. Section 7 concludes the paper.

2. Literature Review

In this section, we review the relevant empirical studies on the relationship between the productive performance and failure of financial institutions.

Meyer and Pifer [1970]: Using only balance sheet ratios, the authors used multivariate analysis to discriminate between failed and survived banks in the US from 1948 to 1965. They used 32 financial ratios and their growth rates in the last five years (total of 160 variables) and used step-wise regression to let the data speak for itself. Approximately 80% of the observations were correctly classified.

Wheelok and Wilson [1995]: They used micro-level historical data to examine the causes of bank failures in Kansas from 1910 to 1928. They used balance sheet information, deposit insurance system membership status and a measure of technical efficiency to explain failure and survival of individual banks. They were the first to use an efficiency measure in an early-warning model. They found that insured banks were more likely to fail (moral hazard problem) and that technical efficiency could improve failure prediction. Rather than a probit or a logit model, they used proportional hazards model developed by Cox (1972) to model the time-to-failure for banks. Since they lacked price data, they were only able to measure technical efficiency and they suggested that including the allocative efficiency would strengthen the results.

Barr and Siems [1996]: They tried to predict bank failures in the US using the data from December 1984 to June 1987. They used a technical efficiency measure they calculated using DEA in their prediction model. Along with their DEA results, which represent Management Quality "M" in the CAMEL rating, they used financial ratios representing soundness of Capital, Asset Quality, Earnings and Liquidity. They found that using the DEA Efficiency Score in the regression increased the accuracy of classification results from 89% to 92.4% and that the new model was superior to previous early-warning models.

Kraft, Hofler and Payne [2002]: Using bank balance sheet data for 1994-2000, they calculated the efficiencies of Croatian banks using a parametric Fourier-flexible frontier cost function. They found that foreign banks and old banks had higher cost efficiencies. Using efficiency, ownership and size in their simple logit model, they found that more efficient banks were less likely to fail.

3. Overview of the Turkish Banking Sector during the Study Period

The banking sector accounts for about 75% of the total assets of the financial sector. Total assets of the banking sector increased from USD 20.8bn (28.6% of GNP) in 1980, to USD 58.2bn (38.2% of GNP) in 1990 and to USD 155bn (76.9% of GNP) in 2000.

A major structural change in the banking industry was the liberalization program that started in the early 1980s. The abolition of interest rate ceilings, financial taxes, and restrictions on foreign exchange operations, as well as barriers to entry and exit, provided a more liberal financial environment. The number of banks operating in Turkey has increased considerably over time, mainly due to these liberal policies. For example, the number of banks increased from 43 in 1980 to 66 in 1990 and to 79 by the end of 2000. The number of foreign banks increased from 4 in 1980 to 18 in 2000. The upward trend in the number of banks in the system indicates that the existing traditional have faced an increasing level of competition from both inside and outside of the country. In this new more liberal environment with increased competition, the management of the banks became more important for the survival of the banks, especially when a financial crisis hits the country.

Turkey passed through a fierce financial crisis in 1994. This crisis was also an early warning signal for more financial disruptions to come in the country such as November 2000 and February 2001 crisis. In the aftermath of the 1994 crisis, the Turkish economy shrunk by 6%, the Turkish lira was devaluated by more than 50% against the $US. Banking firms lost 30% of their average total assets. Three small banks were put on liquidation process. However, the banking sector recovered rapidly and posted an average annual growth rate of 18% in the post 1995 period. However, the East Asia and Russian crisis of 1997-98 and the two devastating earthquakes of 1999 had a negative impact on the Turkish economy and the banking sector. Six banks failed that year and were taken under the management of the Savings Deposit Insurance Fund (SDIF). Turkey adapted a comprehensive disinflation program at the beginning of 2000; however adverse international capital market conditions and the heavy financing needs of Turkey as well as the sharply widening current account led to a general loss of credibility of the disinflation program. The outflow of foreign funds from Turkey and the sharp increase in Treasury bill rates led to financing difficulties by some private and state banks. The subsequent November 2000 crisis led to a significant erosion of the capital base of the banking sector and revealed further fragility of the banking system. The rapid announcement of the additional USD7.5bn from IMF could only calm the market for a limited period. The escalating political uncertainties and the loss of credibility of the exchange rate regime and finally the abolition of the exchange rate peg in February 2001 further hit the already weak banking sector. Three banks failed in late 2000 and a record of nine failed in 2001. The government adapted a new program "Transition to a Strong Economy" in order to eliminate the confidence crisis and the financial instability. An important pillar of the program consists of a renewed effort to eliminate structural weaknesses, particularly by strengthening governance and good economic management.

4. Data and Measurement of Bank Productive Performance

In order to assess the performance of financial institutions, one should find a way to separate the firms that perform well from the firms that perform poorly. Since the production function of the fully efficient firm is not known in practice, it must be estimated from observations on a sample of firms in the industry concerned. Frontier methods are basically sophisticated ways to "benchmark" the relative performance of firms or decision making units (DMU's) as they tend to be called in the literature. The "best-practice" frontiers have been estimated using many different techniques over the past four decades. These techniques can be grouped under parametric and nonparametric frontier approaches which entail econometric and mathematical programming methods respectively.

Both techniques utilize all the information contained in the data. In the parametric approach, a single optimized regression equation is assumed to apply to each DMU. Whereas a nonparametric technique optimizes the performance measure of each DMU, there is no consensus in the banking literature on the preferred approach for determining the best-practice frontier against which relative efficiencies are computed. In their excellent survey paper, Berger and Humphrey (1997) reported that there are 69 applications of nonparametric methods and 60 applications of parametric methods in the financial institutions efficiency literature. This practically equal split among researches mainly stems from the fact both approaches are far from perfect.

Nonparametric approaches impose relatively little structure on the "benchmark" frontier and thus do not require any explicit specification of functional form. Despite its relative immunity to specification error, nonparametric approaches are subject to another problem; they do not allow for random error owing to luck, data problems or inaccuracies created by accounting rules. On the other hand, although parametric techniques recognize the presence of random error, they necessitate the imposition of a specific functional form (such as a regression equation, a production function, etc.) relating the independent variable(s) to the dependent variable(s). The functional form chosen also demands specific assumption about the distribution of error terms (e.g. standard normal) and inefficiencies (e.g. half normal, truncated normal, gamma, exponential) and many other constraints (e.g. factors earning the value of their marginal product). Therefore both approaches have both blessings and curses. If random error is present and a nonparametric approach is employed, then obtained efficiency may be confounded (contaminated) with these random deviations from the true frontier. If a parametric approach is used to overcome this problem, but the functional form is incorrectly specified or distributional form of error terms or/and inefficiencies is not estimated correctly, then obtained efficiency indices may be confounded (contaminated) with the specification errors.

Of the available methods in the financial institution efficiency literature, in this paper we prefer "the optimization of the performance of each DMU" (nonparametric approach) to "the single optimized regression equation, or a mythical 'average' for each DMU" (parametric approach). Hence, in order to measure the efficiency of the Turkish banks, we employ a nonparametric method, Data Envelopment Analysis (DEA). The DEA is a linear (mathematical) programming technique which forms a nonparametric surface / frontier (more formally a piecewise-linear convex isoquant) over the data points to determine the efficiencies of each DMU relative to this frontier. The main reason to choose the DEA is the expressed interest by the Turkish banking industry to reduce costs in recent years owing to the increased competition fostered by liberal policies. The DEA allows us to focus on the input saving (cost) efficiency, which can be detailed into technical and allocative efficiency components. It also permits us to further itemize technical efficiency into its pure technical and scale efficiency components. In doing so, we hope that further details will provide us with significant additional information when comparing failed and survived banks.

Farrel (1957) posited that the overall *cost (economic) efficiency (CE)* of a firm can be decomposed into two components: (1) *technical efficiency (TE)*, which reflects the ability of a firm to generate maximum output from a given set of factors of production, and (2) *allocative efficiency (AE)*, which reflects the ability of a firm to use the factors of production in optimal proportions, given their respective prices. Many studies have also decomposed the overall technical efficiency into two components, one due to *pure technical efficiency (PTE)* and one due to *scale efficiency (SE)*.

The *AE* and *TE* concepts can be better illustrated under the assumption of constant returns to scale (*CRS*), thinking of a hypothetical firm, f, which uses only two factors of production, say labor (L) and capital (K) to produce a single good, y, as in Figure 1, the further decomposition of *TE* into its *PTE* and *SE* components can be better depicted with one input (L) and one output (y) case relaxing the *CRS* assumption as in Figure 2.

If we know the unit isoquant (production technology) of the *best-practice firm*, such as $I\text{-}I'$ in Figure 1 and *0n* or *prstuv* in Figure 2, we can measure the overall cost and technical efficiency of our hypothetical firm *f*. Isoquant $I\text{-}I'$ shows the whole set of technologically efficient combinations of *K* and *L* for producing a given level of output, y_1 . Isoquants further to the right are associated with higher levels of output, those to the left with lower levels of output. For instance, the output level corresponding to isoquant $III\text{-}III'$, y_3, is greater than y_1.

The isocost line, as represented by $c\text{-}c'$ in Figure1, shows alternative combinations of *K* and *L* that the firm can buy for a given outlay. Obviously the slope of the isocost line reflects relative factor (input) prices. The least cost position is given graphically by the tangency point between the isoquant and the isocost line. Given the factor prices and available technology, the optimal combination in Figure 1 is at point *e*. Any alternative combination of the inputs along the $c\text{-}c'$ isocost line would bring about less output for the same cost. If the observed combination of inputs used by our hypothetical firm, *f*, to produce y_1 is at point *f* in Figure 1, it can be seen that the firm is inefficient because the point *e* was shown above to correspond to the most efficient combination of *K* and *L* to produce y_1.

In Figure 1, to demonstrate allocative and technical efficiency of the firm, a line is drawn from the origin, *0*, to the point *f (*dotted line, *Of)*. Farrell proposes that the technical inefficiency (*TIE*) of the firm could be represented by the distance *bf*, which is the amount by which *K* and *L* could be proportionally reduced without a reduction in output. Stated differently, the combination of *K* and *L* associated with point *f* should enable the firm to produce a level of output, y_3, which is greater than y_1. Efficiency (inefficiency) measures are generally stated in percentage terms. For example, the *TIE* of the firm *f* is represented by the ratio $bf / 0f$, which reflects the percentage by which all inputs could be reduced. Thus the overall ***technical efficiency* (*TE*)** of the firm is given by: $TE = 1 - TIE = 1 - (bf / 0f) = 0b / 0f$. *TE* will take a value between zero and one and a value of one will indicate that the firm is fully technically efficient. For instance, if both firms *b* and *f* produce y_1 level of output, the firm *b* which lies on the frontier is fully technically efficient, whereas *f* is not. If the *TE* of the firm *f* is say 80%, then this implies that *f* would be able to reduce the consumption of all inputs (*K* and *L*) by 20% without reducing its output if it were operating on the frontier like the firm *b*.

Allocative efficiency (*AE*) stems from the right input combinations given input prices. If we also know the input price ratio, represented by the isocost line $c\text{-}c'$, we can also measure allocative (price) efficiency. The ***allocative efficiency (AE)*** of our hypothetical firm operating at *f* is expressed as follows: $AE = 0a / 0b$. The firm *f* is also allocatively inefficient since the distance *ab* represents the potential reduction in *f's* production costs that would occur if production were to occur at the allocatively (and technically) efficient point *e*, instead of at the technically efficient, but allocatively inefficient, point *b*. Hence, the distance *ab* corresponds to additional production expenses resulting from the suboptimal allocation of inputs.

The distance *af* can also be regarded as a potential for cost reduction. It shows the amount by which the total production costs of the firm *f* can be lowered by eliminating both technical inefficiency (the distance *bf*) and allocative inefficiency (the distance *ab*). This gives rise to overall ***cost efficiency (CE)*** measure, which is simply the product of allocative and technical efficiency: $CE = AE \times TE$, in other words, $CE = (0a / 0b) \times (0b / 0f) = 0a / 0f$.

The *CRS* assumption is only justifiable when all firms are operating at an optimal scale (i.e. one corresponding to the flat portion of the long run average cost curve). However, firms in practice might face either economies or diseconomies of scale because of imperfect competition, constraints on finance, etc. In 1984, Banker, Charnes and Cooper proposed an extension of the *CRS* model to account for variable returns to scale (*VRS*) cases. If one makes the *CRS* assumption when all firms are not operating at the optimal scale, the computed measures of *TE* will be confounded (contaminated) with *scale efficiencies (SE)*. The *VRS* assumption, on the other hand, will provide the measurement of *"pure" technical efficiency (PTE)*, which is simply *TE* devoid of these *SE* effects. Further decomposition of *TE* into its *PTE* and SE components can be accomplished by conducting both a CRS and VRS specification upon the same data. If there appears to be a difference in the two *TE* scores for a particular firm, then this indicates that the firm has scale inefficiency. Thus the scale inefficiency can be obtained from the difference between the *VRS TE* and the *CRS TE* score.

Figure 2 illustrates the decomposition of *TE* for one input (*L*) and one output (*y*) case by means of *CRS* and *VRS* frontiers. Under both assumptions, the firm which operates at point *f* in Figure 4 is technically inefficient. Under *CRS*, the technical inefficiency of the point *f* is the distance *mf*, while under VRS the technical inefficiency would only be *sf*. The difference between these two measures, *ms*, is attributed to scale inefficiency, which simply indicates that the firm *f* can produce its current level of output with fewer inputs if it attains *CRS*. In Figure 2, *CRS* frontier is represented by *0n*, and it simply depicts the optimal level of output which can be obtained for given input levels. In other words, *CRS* frontier shows what is attainable and what is unattainable with the given technology, and thus the firms either lie on or below it. The constituents of overall technical efficiency (*TE*), *PTE* and *SE*, for the firm *f* can also be expressed in ratio form: $PTE = ks / kf$, and $SE = km / ks$. The technical efficiency of the firm *f* is thus simply the product of *PTE* and *SE*: $TE = PTE \times SE = (ks / kf) \times (km / ks) = km / kf$.

As expressed before, unfortunately the production function of the *best-practice (fully efficient) firm* in an industry is not known in practice and thus must be estimated from a sample of observations on the firms operating in the industry. The DEA linear programming model, as a member of nonparametric frontier family, estimate a non-stochastic envelopment frontier over the data points such that all observed points lie on or below the frontier. Thus the frontier represents the set of best-practice observations for which no other DMU or linear combination of units employs as little or less of every input without changing the output quantities (input-orientated efficiency frontier) or produces as much or more of every output without altering the input quantities used (output-orientated efficiency frontier).

To formulate the linear programming problem with the DEA to calculate each efficiency measure, let's assume that there *N* banks (DMUs), each producing *O* different outputs employing *I* different inputs. Also, let's assume that x_i represents the amount of input employed and y_i represents the amount of output produced by the *i*-th bank. Thus, the data of all banks in the sample are represented by the $O \times N$ output matrix, *Y*, and $I \times N$ input matrix, *X*. Since there are *N* banks, the linear programming problem is solved *N* times, once for each bank in the sample.

The CRS TE: To simplify the problem, let's consider that these *N* banks, as in Figure 3, operate under the *CRS* and employ two inputs (*K* and *L*) to produce a single output. The formal problem for the technical efficiency (*TE*) can conveniently be expressed in the following way:

$$
\begin{aligned}
&Min_{TE,w}\ TE_i \\
&s.t. \\
&Y \,.\, w_i \geq y_i \\
&X \,.\, w_i \leq TE_i \,.\, x_i \\
&w_i \geq 0 \qquad (1)
\end{aligned}
$$

where TE_i, is a scalar and represents the technical efficiency measure (index) for the ***i***-th bank. w_i is the $1 \times N$ vector of intensity weights defining the linear combination of efficient banks to be compared with the ***i***-th bank. The inequality ($Y \,.\, w_i \;\geq\; y_i$) implies that the observed outputs must be less or equal to a linear combination of outputs of the banks forming the efficient frontier. The inequality ($X \,.\, w_i \;\leq\; TE \,.\, x_i$) assures that the use of inputs at the linear combination of the efficient banks must be less or equal to the use of inputs of the ***i***-th bank. The formulation will mandate that $TE_i \leq 1$. According to the Farrel (1957), an index value of 1 refers to a point on the frontier and thus to a technically efficient bank.

The VRS TE (PTE): The CRS assumption will be incorrect if all banks are not operating at an optimal scale. In this case, the CRS specification will bias the estimation of the TE by confounding scale effects. But, the substitution of the CRS with variable returns to scale (VRS) assumption brings about the estimation of the pure technical efficiency (PTE), i.e. TE devoid of the scale effects. This can be achieved by adding a convexity constraint $(N_1 \,.\, w_i = 1)$ to (1) which allows VRS as demonstrated below:

$$\begin{aligned}
&Min_{TE,w}\;\; TE_i \\
&s.t. \\
&Y \,.\, w_i \;\geq y_i \\
&X \,.\, w_i \;\leq TE_i \,.\, x_i \\
&N_1 \,.\, w_i = 1 \\
&w_i \;\geq\; 0 \qquad (2)
\end{aligned}$$

where N_1 is an $1 \times N$ vector of ones. The VRS frontier obtained this way envelops the data more tightly than the CRS frontier and thus generates TE scores which are greater than or equal to those obtained from the CRS frontier.

The SE: If there is a difference between the *CRS TE* and the *VRS TE (PTE)* for a specific bank, then this means that the bank has scale inefficiency. The scale inefficiency for the bank, thus, can be computed from the difference between the *CRS TE* and the *VRS TE*. Since, *TE(CRS) = TE(VRS)*SE*, where *TE(CRS) = TE*, and *TE(VRS) = PTE*, then, ***SE = TE / PTE***.

The Non-IRS TE: With this *SE* specification, however, it is not clear whether the bank is operating in area of IRS (increasing return to scale) or DRS (decreasing return to scale). To determine this, an additional DEA problem is run to construct a frontier which allows for only non-increasing returns to scale (Non-IRS), such as *0mtuv* in Figure 4. This can be accomplished by substituting the constraint $(N_1.\; w_i \;=\; 1)$ in (2) with $(N_1.\; w_i \;\leq\; 1)$ as demonstrated below:

$$\begin{aligned}
&Min_{TE,w}\;\; TE_i \\
&s.t. \\
&Y.\, w_i \;\geq y_i \\
&X.\, w_i \;\leq TE_i \,.\, x_i \\
&N_1.\, w_i \leq 1 \\
&w_i \;\geq\; 0 \qquad (3)
\end{aligned}$$

The type of scale inefficiencies (IRS or DRS) for a specific bank can be determined as follows:

If VRS TE ≠ Non-IRS TE, then the bank is operating at IRS, If VRS TE = Non-IRS TE, then the bank is operating at DRS.

If data on prices for inputs are available, one can measure both technical (TE) and allocative efficiencies (AE), whose product leads to overall cost efficiency (CE). For the VRS case, to obtain the CE, one first should compute the cost minimizing vector of input quantities, x^*, by running the (2) DEA. Then, the following cost minimization DEA is run:

$Min_{w,x^*}\ p_i \,.\, x_i^*$

s.t.

$Y.\, w_i \geq y_i$

$X.\, w_i \ \leq x_i^*$

$N_1.\, w_i = 1$

$w_i \geq 0$ (4)

where p_i is a vector of input prices for the *i*-th bank and x_i^* is the cost minimizing vector of input quantities for the *i*-th bank, given the input prices p_i and the output levels y_i.

The overall cost efficiency (CE) of the *i*-th bank could be obtained as follows:

$$CE = \frac{p_i' x_i^*}{p_i' x_i} = \frac{minimum\ cost}{observed\ cost}.$$

Since CE = AE × TE, then AE can be calculated residually: AE = CE / TE.

4.1 Empirical Design for Efficiency Calculations

Rather than estimating a common frontier across time, we preferred to estimate three separate annual efficiency frontiers specifically for the years from 1970 to 2000. We believe that the principal advantage of having panel data is the ability to observe each bank more than once over a period of time. This is a critical issue in a continuously changing business environment because the technology or bank that is most efficient in one year may not be the most efficient in another year. Furthermore, by doing so, we also wish to alleviate, at least to an extent, the problems related to the lack of random error in DEA efficiency estimation by allowing an efficient (inefficient) firm in one year to be inefficient (efficient) in another year assuming that the errors owing to luck or data problems are not consistent over time. Taking the volatility and ongoing restructuring of bank market in Turkey into consideration a separate frontier for different years would hopefully reflect the changes better in the macro-economy and the regulatory treatment of banks over time.

In order to have 'reliable' efficiency indices we need to have appropriate definitions and certain assumptions regarding the measurement of variables: inputs, outputs and input prices. The exclusion of certain important bank inputs (outputs) might bias the final efficiency measures by distorting the frontier (the locus of the efficient combination of inputs and outputs). To determine what constitutes inputs and outputs of banks, thus, one first should decide on the nature of banking technology. In the literature on the theory of banking, there are two main approaches competing with each other in this regard, production and intermediation approaches.

Production approach considers banks as firms producing services for customers such as performing transactions and processing documents. Since such production requires only physical inputs such as labor, capital and material, total costs should be exclusive of interest expenses. Therefore, inputs are measured by physical units and outputs are measured by the number and type of transactions or documents processed over a given time period (but in practice proprietary nature of such flow variables might necessitate the usage of stock variables for outputs instead: such as the number of deposit or loan accounts serviced). On the other hand, under the alternative ***intermediation approach***, banks are viewed as the conduit of funds between depositors and borrowers. Banks incur labor, capital and loanable funds expenditures to transfer funds from those with surplus to those with shortage of funds. Thus total costs should include interest expenses as well as operation costs.

According to Berger and Humphrey [1997], the production approach might be better for branch efficiency studies because they basically process customer documents and bank funding and investment decisions are mostly not under the control of branches. Whereas, the intermediation approach might be more suitable for studying the efficiency of entire financial institutions because interest expenses might indeed compose a large portion (as high as one-half to two-thirds) of bank total costs depending on the phase of the interest rate cycle. Also, in practice, availability of flow data required by the production approach is usually exceptional rather than common.[1]

4.2 Data Description

The data used in this study was obtained from various issues of the Banks Association of Turkey (BAT), which includes all banks operating in Turkey as members and publishes annual balance sheets and income statements of its members each year. The data collection process took a lot of time since the soft copies of the financial information were not available for the period before 1988 and we had to enter the relevant information by hand from the hard copy of the annual reports.

By definition, nonparametric best-practice frontiers are determined by extreme values in the dimensional space created by the choice of inputs and outputs. Unlike parametric approaches that are nondeterministic, a single outlier can have much greater effects on measured efficiency. In other words, single outliers can significantly influence the calculated efficiency measure for each firm using the nonparametric DEA approach (Evanoff and Israilevich, 1991). Thus, in order not to bias the construction of the efficiency frontier against which the efficiency of all banks in the sample is relatively measured, we eliminated a few bank observations because of their either suspicious values or outlier nature. For instance, for some banks, input prices could not be constructed because either the required relevant stock value for the input or flow value for the expense was reported as zero. At times, even though input prices could be constructed, they were unrealistically large or small. Therefore, despite the expense of losing some information, we excluded those observations whose input prices could not be obtained and/or are more than 2.5 standard deviations away from the mean value of the respective year if obtained.

As a result of this data filtering process, we lost approximately 3-4 observations in each year. We also took out the investment banks from the sample since their technology is quite different from that of commercial banks, so we did not want to compare them with the commercial banks using a common frontier. After filtering, we had a total of 1342 observations for the 30 year period. Also, some of the banks that failed were small, local banks and they did not have adequate reporting and thus had zero for some of their input prices, and thus were excluded them from the data since their efficiency measures could not been calculated. We used 28 of the total 36 banks that failed in the 30-year time period. Others were excluded since they were either outliers or had zero input variables.

[1] Humphrey (1985) presents an extended discussion of the alternative approaches over what a bank produces.

4.3 Definition of Inputs, Input Prices and Outputs

This study adopts the intermediation approach to define outputs, inputs and input prices of banks. All variables, except for the input factor labor, are measured in Turkish lira which is inflation adjusted to the base year 1968.

The ***input vector*** used here in calculation of various efficiency measures are (1) labor [LABOR], (2) capital, [CAPITAL], and (3) loanable funds [FUNDS]. We measure the quantity of labor by the number of full-time employees on the payroll, capital by the book value of premises and fixed assets, and loanable funds by the sum of deposit (demand and time) and non-deposit funds as of the end of the respective year[2]. Hence the total costs include both interest expense and operating costs and are proxied by the sum of labor, capital and loanable funds expenditures. Obviously, all ***input prices*** are calculated as flows over the year divided by these stocks: (1) price of labor [P(LABOR), total expenditures on employees such as salaries, employee benefits and reserves for retirement pay divided by the total number of employees], (2) price of capital [P(CAPITAL), total expenditures on premises and fixed assets plus depreciation expense divided by book value of premises and fixed assets plus the depreciation expense], and (3) interest rate on loanable funds [P(FUNDS), total interest expenses in deposit and non-deposit funds divided by loanable funds]. Expenditures on these inputs account for the vast majority of all banking costs in Turkey.

On the other hand, the ***output vector*** includes (1) [LOANS] and (2) [SECURITIES]. Securities are calculated by subtracting loans from total assets. Some studies separate loans into short-term and long-term loans; but because of data limitations before 1980, only total loans were reported, so to be consistent for the 30 year period, we had total loans as the output.

Table 1 displays summary statistics for outputs, inputs and input prices of the surviving and failed commercial Turkish banks for the 1970-2000 period. All variables are expressed in 1968 Turkish Lira (i.e. adjusted for inflation using 1968 as the basis year). If a bank has failed in time period t, all its data before time t is included in the failed bank data, whereas, if a bank has never failed, all its years of existence are included in the survivor banks data.

5. Empirical Results and Analysis

5.1 General Trend of Efficiency Scores

In this part of the analysis we compare the efficiency results of the failed and survived banks. We first grouped the banks based on how many years they have until the failure date and compared their efficiency scores with the 30-year average efficiencies of the surviving banks. Table 2 shows the mean values for each type of the efficiency scores. Figures 4 to 8 also depict the efficiencies of failed and survivor banks.

We see that there is a general trend towards lower efficiency values as the banks approach their failure date. The CRS technical efficiency (TE) and cost efficiency (CE) means for the failed banks are lower starting from five years prior to failure and the gap is the greatest when they have one year to failure and they have the greatest decrease in efficiency one year prior to failure. For instance, the TE score decreased from 0.68 to 0.58 (14% decrease) and CE from 0.55 to 0.43 (21% decrease) for failed banks. Allocative efficiency (AE), although lower for failed banks one year prior to failure, shows more variation in the average efficiency scores throughout the years and may not be a discriminative measure between failed and survivor banks.

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[2] Non-deposit funds include borrowed funds from interbank, central bank, domestic banks, abroad and others as well as funds raised by issuing securities.

5.2 Statistical Comparison of Efficiency Scores

We first compare statistically the 30-year average efficiency values for the failed and survived banks [Table 3]. If a bank failed in period t, then all its previous year efficiencies until 1970 (or its establishment year if it is established after 1970) are taken in the failed sample. We had a total of 1,342 observations: 585 belong to failed banks and 757 to survivor banks. For each efficiency measure, these tests assess the hypothesis that the different samples (failed and surviving) in the comparison were drawn from the same distribution or from distribution with the same median. Four tests were applied: Median Test, Kruskal-Wallis and Mann-Whitney and ANOVA, the first three being nonparametric statistical tests [Table 4]. All tests except the Median test confirm that TE was different for failed and survived banks at the 1% significance level. TE for failed banks was 0.66 and it was 0.71 for the survived banks.

Although figures 4 to 8 that compare the efficiency performance of failed banks vis a vis those of survivors suggest that the biggest difference in the efficiencies was one year prior to failure, actually the performance of failed and survived banks over the thirty years was also statistically different even though the average mean efficiency difference is not that substantial. The strongest result was in the difference of their pure technical efficiencies (PTE). PTE was 0.75 for the failed banks and 0.84 for the survivors. All four tests give us statistical difference of PTE between failed and survived banks at the 1% level. However, scale efficiency (SE) does not appear to be different. Scale inefficiency refers to a non-optimal choice of production scale in terms of cost control and since production scale is partly related to the size of the banks, management may not be able to have full control over it. This does not mean however that the bank managers do not have any control over the scale; it means that their scale adjustments are somehow restricted. For example, if there are increasing returns to scale (IRS), efficiency gains could be obtained by expanding production levels, but management might have some size limitations and thus may not be responsible for the total part of scale efficiency.

However, PTE is defined as managerial inefficiency devoid of scale effects, thus it results directly from management errors. For this reason the strong result of statistical difference in PTE shows that the management of failed banks was less competent or had other motivations than improving the efficiency of their banks. Allocative efficiency (AE) was not different among these two groups either. This result was expected when the relevant figure was analyzed in the previous section. Allocative inefficiency occurs when inputs are combined in sub-optimal proportions given their prices. Regulation and external factors are typically given as major sources of allocative inefficiency, and since most of the banks in the sample failed during financial crises, external factors were common to the banks that they were not easy to anticipate. High fluctuation and instability in factor prices due to inflation leads to allocative inefficiency because if bank managers are uncertain about prices, they are likely to make inefficient decisions. Also the overall AE is greater than TE for both the failed and surviving banks, which shows that the dominant source of cost inefficiency in technical (managerial) rather than allocative (regulatory). Hence, the overall cost inefficiency in Turkish banks may be attributed, to a great extent, to underutilization or wasting of resources rather than choosing the incorrect input mix and it is the case that failed banks wasted more of their resources compared to surviving banks. Cost Efficiency (CE) was 0.52 for failed banks and 0.56 for surviving banks and all four tests showed that the difference is significant. When decomposed into Scale, PTE and AE, it is clear that the main reason for this difference is PTE which solely stems from managerial incapability. So these results reinforce the earlier findings that managerial discretion is very important for the survival of the banks.

We then statistically compare the surviving banks with the final year of the failed banks [Tables 5 and 6]. We again have 757 surviving banks like the previous test, but this time we have only 28 observations for the failed banks since we took only the final year of their existence. As expected from the earlier graphs, the difference in their efficiency values was large and they were statistically different except for the AE. Although we found that over the thirty years, failed banks and surviving banks did not have scale efficiency differences, their scale efficiencies were statistically different in the final year of the failed banks and the average SE of the failed banks had constantly decreased in the last three years of their existence. The reason for this result could be that at the time of the financial crisis, there was a sudden decline in the market demand and due to lack of confidence, customers withdrew their deposits. The banks could not make the necessary adjustment in their scale in the short term, probably they were outgrown in the period of growth of the economy and now they were left with branches and employees that were not much use to them. Although both the survivor and failed banks experienced the same shock, it could be that the managers of failed banks were less cautious of their growth policy in the years preceding the crisis and thus they were less prepared for it. Also, since the failed banks were concentrated at the later time period of our 30 year period when the banks experienced a financial crisis and the surviving banks were mostly concentrated at the earlier section of the period, it could be that the period chosen might have had an effect on our results.

In order to check for the sensitivity of the period chosen for the statistical comparison, we took the period 1997-2000 and performed the same tests for tests of equality [Tables 7 and 8]. We especially chose that period because most of the failures occurred within it. Some 19 banks failed during that period, and we were able to use 17 of them in our analysis. (If a bank failed in 2001, since its one year prior to failure data is in 2000, it could be included in our analysis). We compared the surviving banks with the final year of the failed banks like in the previous comparison, except that the time period is now much smaller to capture the time effects. The results are consistent with the earlier ones. The mean efficiency results were lower for the failed banks and the differences were statistically significant for TE, PTE and CE at the 1% level. SE and AE are different only at the 10% level. This shows that SE and AE, which are mainly affected by external factors such as regulation, financial crisis, change in the growth of demand, size limitations are statistically less different between the failed and surviving banks.

6. Probit Models (Early Warning Models)

In order to understand the relationship between failure and efficiency, we develop an early warning model using a probit model and use failure as the dependent variable. We use the data period 1997-2000 for our regression analysis because almost half of the bank failures (19 bank failures) occurred during this period when compared to the past thirty years. When a bank fails at time t, we use its financial data at period t-1 for the prediction model, so 9 bank failures in 2001 were included in the regression since their data in 2000 was available. Two of the 19 banks were eliminated since their input prices were outliers and thus we could not calculate efficiencies for these two banks. Our regression includes 144 surviving bank observations and 17 failed banks one year prior to failure.

Early Warning Models have been very popular since the costs associated with the bankruptcy of the banks are pretty high and some preventive measures could be taken if some signal could be received prior to failure by the bank authorities. The choice of independent variables is very important. We use the five separate efficiency measures as a proxy for management quality in five different models and compare them with the model where we do not use efficiency. The bank failures probably depend on other characteristics in addition to management quality.

To develop our early warning model using a probit model, we regress failure on a set of possible explanatory variables:

Failure=Failure (Age, Ownership, Size, Efficiency, Capital, NP_Loans, Liquidity) + ε

The standard probit methodology is used to develop models that would classify banks as either survivors or failures. The models are configured so that the dependent variable takes on the value of zero (0) for survivors and one (1) for failures. Hence, a negative (positive) coefficient means that the variable is inversely (directly) related to failure.

Age could be an important factor in the survival of a bank, and we expect young banks to fail more since it is more difficult to establish and gain a customer base in the beginning. The banks are classified as young if they are less than ten, and old if otherwise. Also we expect foreign banks to fail more since domestic banks are more used to the environment. Domestic banks have a dummy of zero, and foreign banks have a dummy of one. We also include size as a possible explanatory variable. Large banks could have a scale advantage and more excess to funds and thus fail less. We use the average of the total assets of the banks as a cut-off value and assign a dummy zero for banks which have fewer assets than that, and a dummy of one for large banks. Total Equity/Total Asset is used as a proxy for capital adequacy and Liquid Assets/Total Funds is used as a proxy for liquidity. We expect both the coefficients on Capital and Liquidity to be negative. Since most of the failures in our sample are a result of financial crisis, we believe that liquidity plays a very important role. Lastly, nonperforming loans/total assets is used to control for the asset quality, we expect the coefficient to be positive.

Classification is a standard way of measuring the accuracy of the prediction models and a means to compare them. The estimated equation assigns a score to each bank and using a threshold each bank is classified into the surviving or the failed group. We chose 0.6 as the cutoff score so if a bank gets a score higher than 0.6, it is classified as a failed bank (based on the probit, probability of failure increases at an increasing rate after 0.6). The results from the six regressions are presented in Table 9.

All the efficiency coefficients are negative as expected. TE is only significant at the 10% level and scale and cost efficiencies are significant at the 5% level. Also, in absolute value terms, it has the second largest coefficient. Ownership is found to be significant at the 5% level; foreign banks tend to fail more as expected. However, the most striking result is that of liquidity. In all the models, liquidity is significant at the 1% level and its effect is found to be very large. This result confirms the fact that the main problem of banks in times of financial crisis is that of liquidity. Although management is important, maybe these banks would not have failed if there hadn't been a financial crisis, leading to a liquidity problem for the banks.

Since the other goal of this regression is to assess the importance of the efficiency measures in the prediction of bank failures, we present the classification results with and without the efficiency measures. When no efficiency measure is used, the model correctly classified 69% of the survivors and 76% of the failures, having a total of 70% of the banks to be correctly classified. Using efficiency measures increased the accuracy of classification except for PTE (Accuracy results for PTE was the same). The most accurate model was the one which used cost efficiency as an explanatory variable. Approximately 75% of the survivors and 82% of the failed banks were correctly classified, having a total of 76% of the banks to be correctly classified. This total score is a 6% increase from the model without efficiency. This shows that the efficiency measure increases the prediction precision of the early warning model and thus should be incorporated in the model.

7. Summary and Concluding Remarks

In this paper, using a data set from 1970 to 2000 on Turkish commercial banks, we try to investigate the relative importance of managerial and macroeconomic factors on productive bank performance. We find that managerial skills — as measured by various productive efficiency measures — have important role in determining the survival performance of banks. There is a clear downward trend in the efficiencies of commercial banks as they approached failure. The overall results indicate that failing banks also tend to be inefficient in transforming bank inputs (such as funds, labor and capital) into various bank services.

In addition, we develop six bank failure prediction models by focusing on the bank failures between the period between 1997-2001 when most of the failures have occurred. Of these models the first does not include an efficiency measure, whereas the remaining five models use one of the five different efficiency measures we calculated as a proxy for management quality. When the management variable (one of the efficiency scores) is removed from the model, the results are worse in terms of the model classification accuracy. The best accuracy is achieved when using the cost efficiency score. These results emphasize the quality of management in the successful operation of banks. However, we find that the most important factor contributing to the failure of banks in Turkey is macroeconomic factors. The clear indication of importance of macroeconomic factors on bank performance was the lack of liquidity during financial distresses. Although liquidity is somewhat under management control, external shocks such as the financial crises experienced in the past two decades in Turkey could have severely limited the resources available to bank managers. Most bank failures in Turkey have occurred during macroeconomic crises and the major cause was lack of liquidity. One implication is that liquidity becomes one of the most important determinants of bank failure during a financial distress. Another implication is that bank failures in developing economies may be driven mostly by environmental factors than by internal factors.

Coefficients with ***, **, and * are statistically different from zero at the 1%, 5% and 10% levels of significance.

Numbers under the coefficients are standard deviations.

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Figure 1: Cost (economic) Efficiency

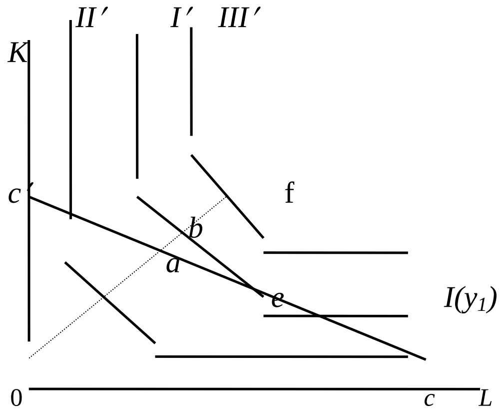

Figure 2: Technical Efficiency

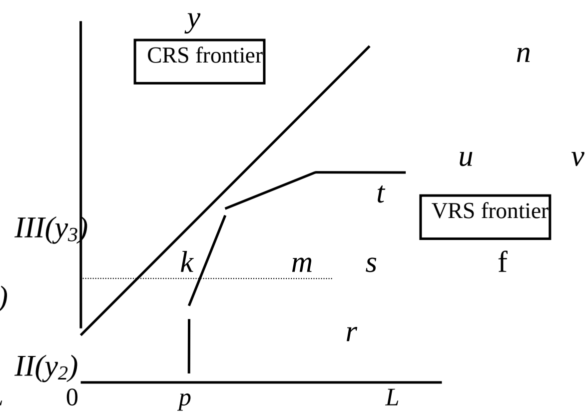

Figure 3

CE = AE × TE
CE = 0a / 0f
AE = 0a / 0b
TE = 0b / 0f

Figure 4

TE = PTE × SE
TE = km / kf
PTE = ks / kf
SE = km / ks

Figure 3: Bank Failures in Turkey

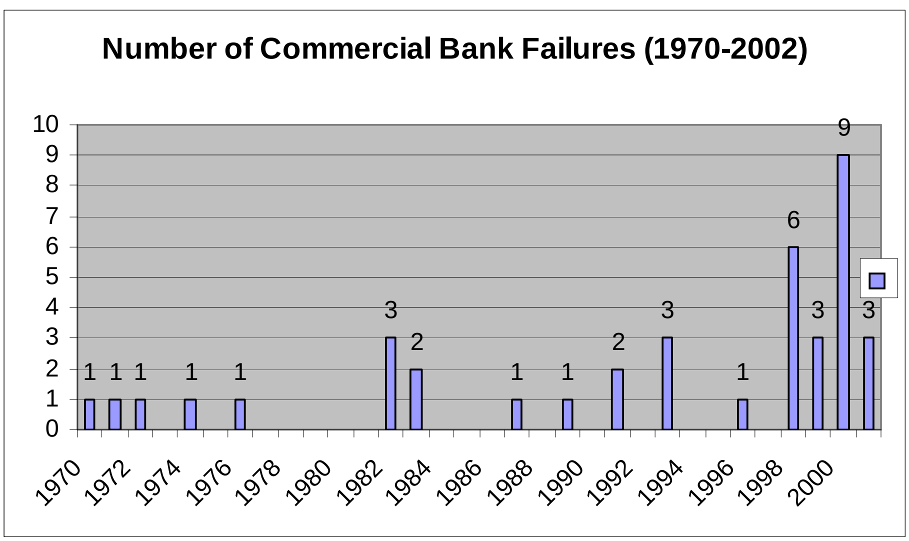

Figure 4: Technical Efficiency (TE) Comparison between Failed and Survived Banks

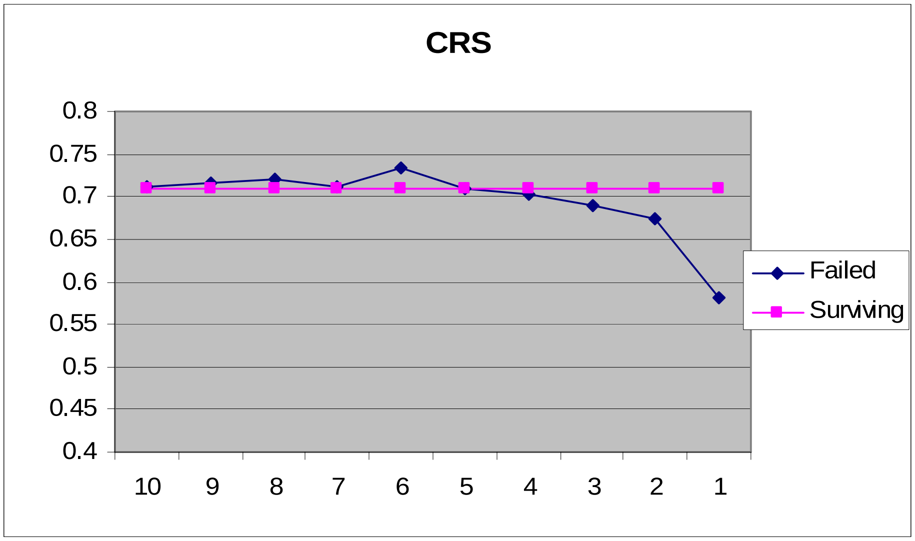

Figure 5: Pure Technical Efficiency (PTE) Comparison between Failed and Survived Banks

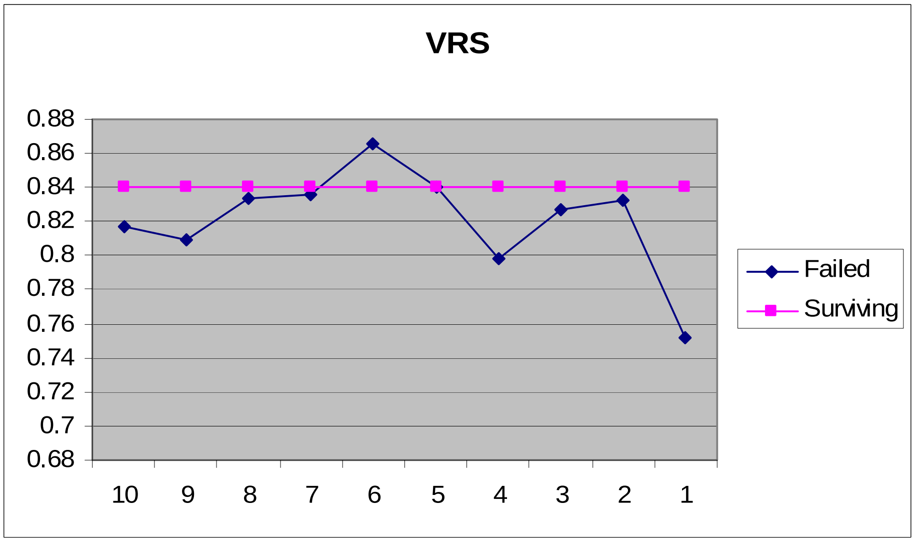

Figure 6: Scale Efficiency (SE) Comparison between Failed and Survived Banks

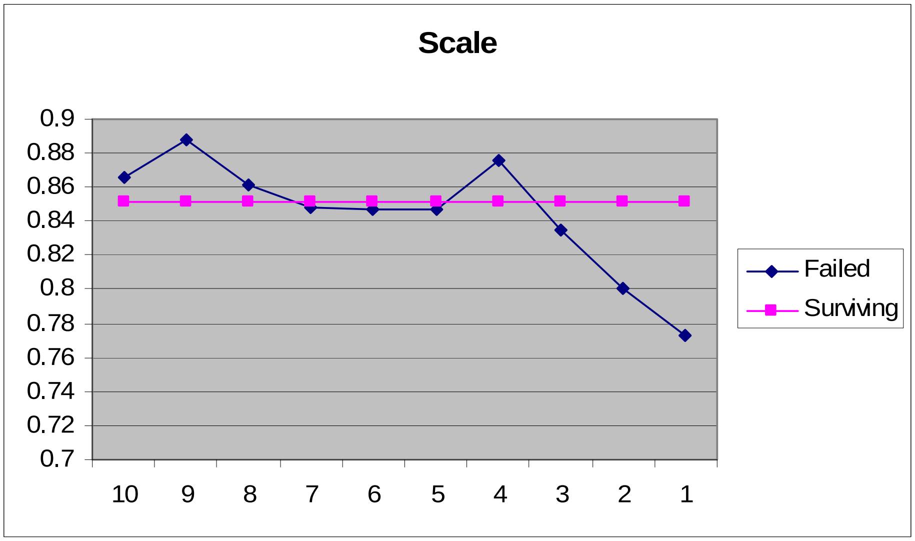

Figure 7: Allocative Efficiency (AE) Comparison between Failed and Survived Banks

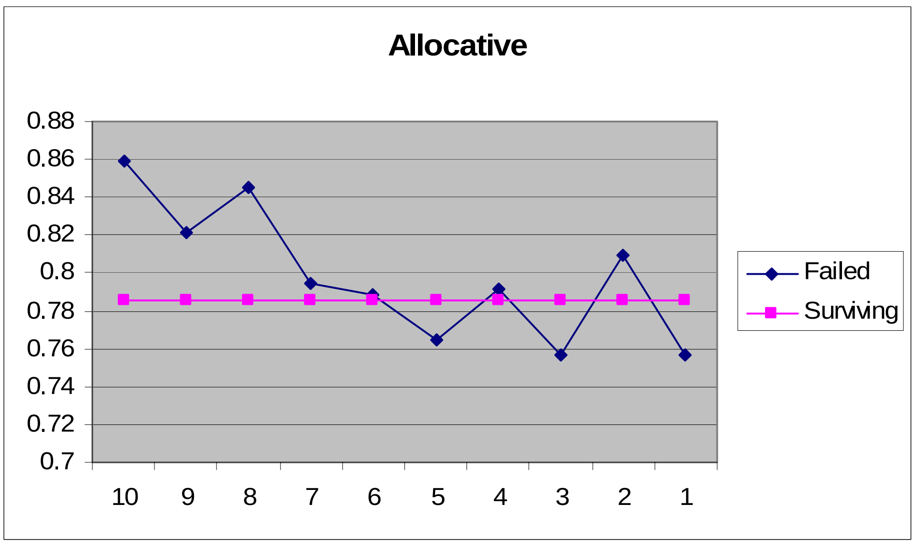

Figure 8: Cost Efficiency (CE) Comparison between Failed and Survived Banks

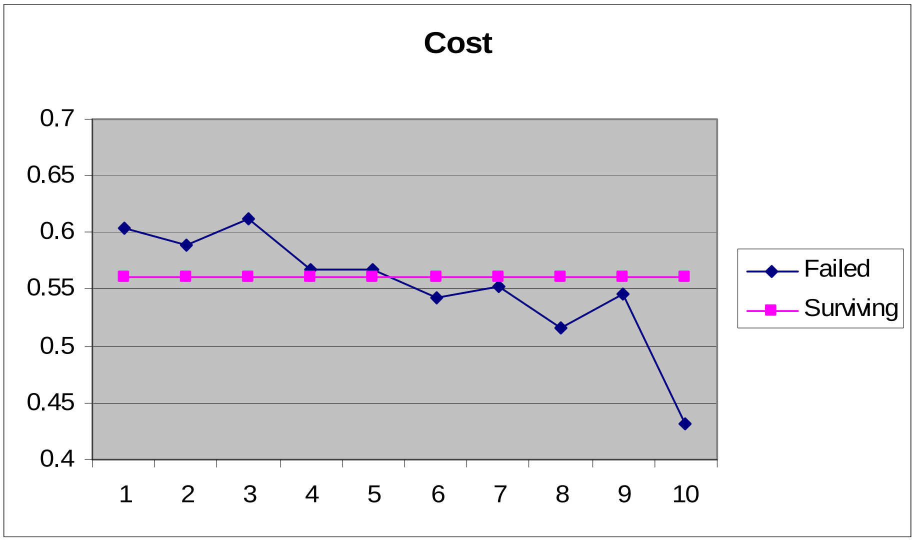

Table 1: Sample Statistics of Variables: Outputs, Inputs and Input Prices (Million TL – adjusted for inflation using 1968 as the basis year)

	Survivor Commercial		Failure Commercial		All Commercial	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
OUTPUTS						
Total Loans	2760.318	5448.17	1032.709	1817.033	2015.549	4362.509
Securities	3464.616	8487.503	1386.669	2268.52	2568.817	6650.984
INPUTS						
Capital	545.4341	1399.33	332.9783	1045.825	453.8448	1263.127
Funds	5456.846	11230.77	2105.108	3793.695	4011.918	8981.713
Labor	3999.399	7493.546	1355.383	2136.663	2859.569	5967.395
INPUT PRICES						
p1	0.184247	0.21121	0.160954	0.182908	0.174206	0.199765
p2	0.163442	0.192153	0.165604	0.196423	0.164374	0.193936
p3	0.065883	0.050838	0.048119	0.042861	0.058225	0.048354

Table 2: Mean Efficiency Comparison between Surviving and Failed Banks

	TE	**PTE**	**SE**	**AE**	**CE**
Years Prior to Failure					
10	0.7108	0.8165	0.8659	0.8589	0.6033
9	0.7154	0.8097	0.8883	0.8210	0.5888
8	0.7205	0.8335	0.8616	0.8453	0.6128
7	0.7120	0.8360	0.8483	0.7948	0.5672
6	0.7337	0.8652	0.8467	0.7890	0.5678
5	0.7085	0.8405	0.8475	0.7649	0.5430
4	0.7029	0.7987	0.8755	0.7920	0.5521
3	0.6904	0.8267	0.8347	0.7571	0.5162
2	0.6750	0.8325	0.8007	0.8091	0.5466
1	0.5814	0.7523	0.7726	0.7567	0.4315
Survivor Long Run Ave.	0.7104	0.8397	0.8518	0.7855	0.5611

Table 3: Mean and Standard Deviations of Failed and Surviving Banks for the period 1970-2000 (30 year comprehensive failure data)

	Type	Count	Mean	SD
TE	Survived	757	0.709889	0.21591
	Failed	585	0.661133	0.23466
	All	1342	0.688636	0.225491
PTE	Survived	757	0.839531	0.193982
	Failed	585	0.759988	0.227606
	All	1342	0.804857	0.212911
SE	Survived	757	0.851358	0.172697
	Failed	585	0.87107	0.147221
	All	1342	0.859951	0.162321
AE	Survived	757	0.785705	0.192288
	Failed	585	0.782624	0.178467
	All	1342	0.784362	0.186328
CE	Survived	757	0.560741	0.228384
	Failed	585	0.516099	0.221851
	All	1342	0.541281	0.226561

Table 4: Statistical Tests of Equality between the Distributions of Failed and Surviving Banks for the period 1970-2000 (30 year comprehensive failure data)

	Median Test	Kruskal-Wallis	ANOVA	Mann-Whitney
TE	3.529618	14.19969	15.5952	3.768177
	0.0603	0.0002	0.0001	0.0002
PTE	34.1321	41.76563	47.6607	6.462562
	0	0	0	0
SE	0.14849	0.076683	4.880543	0.276846
	0.7	0.7818	0.0273	0.7819
AE	0.604886	0.873452	0.090192	0.934516
	0.4367	0.35	0.764	0.35
CE	8.51241	13.28723	12.92589	3.645094
	0.0035	0.0003	0.0003	0.0003

Table 5: Mean and Standard Deviations of Failed and Surviving Banks for the period 1970-2000 (0-12 months prior to failure)

	Type	Count	Mean	SD
TE	Survived	757	0.709889	0.21591
	Failed	28	0.579429	0.21585
	All	785	0.705236	0.217124
PTE	Survived	757	0.839531	0.193982
	Failed	28	0.748821	0.221876
	All	785	0.836296	0.195612
SE	Survived	757	0.851358	0.172697
	Failed	28	0.773679	0.146654
	All	785	0.848587	0.172359
AE	Survived	757	0.785705	0.192288
	Failed	28	0.7485	0.177909
	All	785	0.784378	0.191812
CE	Survived	757	0.560741	0.228384
	Failed	28	0.425964	0.184104
	All	785	0.555934	0.228231

Table 6: Statistical Tests of Equality between the Distributions of Failed and Surviving Banks for the period 1970-2000 (0-12 months prior to failure)

	Median Test	Kruskal-Wallis	ANOVA	Mann-Whitney
TE	2.349173	7.994373	9.858367	2.827008
	0.1253	0.0047	0.0018	0.0047
PTE	5.175949	6.306592	5.842192	2.510868
	0.0229	0.012	0.0159	0.012
SE	11.76331	8.717935	5.515971	2.952191
	0.0006	0.0032	0.0191	0.0032
AE	1.317468	2.111117	1.015904	1.452544
	0.251	0.1462	0.3138	0.1464
CE	5.23847	10.2999	9.518295	3.208921
	0.0221	0.0013	0.0021	0.0013

Table 7: Mean and Standard Deviations of Failed and Surviving Banks for the period 1997-2000

	Type	Count	Mean	SD
TE	Survived	144	0.729618	0.179729
	Failed	17	0.576444	0.238514
	All	161	0.712599	0.192431
PTE	Survived	144	0.892639	0.143922
	Failed	17	0.758278	0.22709
	All	161	0.87771	0.160116
SE	Survived	144	0.81959	0.151344
	Failed	17	0.753222	0.160424
	All	161	0.812216	0.153295
AE	Survived	144	0.772694	0.175755
	Failed	17	0.6905	0.167794
	All	161	0.763562	0.176297
CE	Survived	144	0.56609	0.207969
	Failed	17	0.379611	0.155689
	All	161	0.54537	0.210787

Table 8: Statistical Tests of Equality between the Distributions of Failed and Surviving Banks for the period 1997-2000

	Median Test	Kruskal-Wallis	ANOVA	Mann-Whitney
TE	4	7.257733	10.75172	2.691353
	0.0455	0.0071	0.0013	0.0071
PTE	8.671075	8.907067	12.03923	2.981806
	0.0032	0.0028	0.0007	0.0029
SE	3.781441	2.944899	3.036966	1.713406
	0.0518	0.0861	0.0833	0.0866
AE	2.25	4.331125	3.532594	2.078471
	0.1336	0.0374	0.062	0.0377
CE	9	15.03227	13.49442	3.874483
	0.0027	0.0001	0.0003	0.0001

Table 9: Probit Regression (Early Warning Models)

	Probit Regressions for Failure (1=failed)					
Variable	**Model 0 (-)**	**Model 1 (TE)**	**Model 2 (PTE)**	**Model 3 (SE)**	**Model 4 (AE)**	**Model 5 (CE)**
CONSTANT	0.31	1.63*	1.22	2.66**	0.75	1.2**
	0.56	0.94	1.32	1.24	0.78	0.7
AGE	0.27	0.36	0.32	0.26	0.27	0.38
	0.37	0.38	0.38	0.38	0.37	0.38
OWNERSHIP	0.77	1.09**	0.81*	1.27**	0.75	1.03**
	0.48	0.52	0.48	0.55	0.48	0.5
SIZE	-0.64	-0.71	-0.56	-0.94**	-0.64	-0.71
	0.43	0.45	0.44	0.48	0.43	0.44
EFFICIENCY		-1.74*	-1.07	-2.63**	-0.87	-2.37**
		1	1.38	1.21	1.05	1.15
CAPITAL	-0.47	-0.53	-0.42	-0.9	-0.38	-0.37
	0.97	1.08	0.97	1.44	0.94	1.01
NP_LOANS	-0.35	-1.37	-0.84	-1.16	-0.09	-0.82
	1.75	1.9	1.84	2.13	1.74	1.75
LIQUIDITY	-3.49***	-3.91***	-3.57***	-4.09***	-3.11***	-3.12***
	1.11	1.15	1.11	1.18	1.17	1.07
adj R^2	0.24	0.27	0.25	0.29	0.25	0.28
	Percent Correctly Classified					
Survivors	69.44	70.83	69.44	72.92	71.53	75
Failure	76.47	82.35	76.47	82.35	76.47	82.35
Total	70.19	72.05	70.19	73.91	72.05	75.78