PREDICTION OF FAILURE OF COMMERCIAL BANKS IN TURKEY

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PREDICTION OF FAILURE OF COMMERCIAL BANKS

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By

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AUGUST 1996

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ABSTRACT

PREDICTION OF FAILURE OF COMMERCIAL BANKS IN TURKEY

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The aim of this study is failure prediction in Turkish Banking Sector. The results of four prediction models are compared to find out the most efficient one. The models used in this study are: Discriminant Analysis, Logit Analysis, Factor-Logistic Analysis and Alternative Accounting Measures for Prediction.

According to the results of this study, Discriminant Analysis has the best predictive ability. Logit Analysis, Beaver's Method and Factor-Logistic Analysis are ranked after the Discriminant Analysis from best to worst predictive ability.

Key Words: Failure, Prediction, Discriminant Analysis, Logit Analysis, Factor-Logistic Analysis, Beaver's Method.

ÖZET

TÜRKİYEDE'Kİ TİCARİ BANKALARIN İFLAS TAHMİNLERİ

BÜLENT YAĞLI

İŞLETME YÜKSEK LİSANS TEZİ

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Bu çalışmanın amacı en etkili iflas tahmin yöntemini bulmak için iflas tahmin modellerinin sonuçlarını karşılaştırmaktır. Bu çalışmada kullanılan modeller: Diskriminant Analizi, Lojit Analizi, Faktör-Lojistik Analizi ve Tahmin İçin Alternatif Muhasebe Ölçüleri.

Bu çalışmanın sonuçlarına göre Diskriminant Analizi en fazla tahmin gücüne sahiptir. Daha sonra sırasıyla Lojit Analizi, Beaver Metodu ve Faktör-Lojistik Analizi en iyi tahmin gücüne sahiplerdir.

Anahtar Kelimeler : İflas, Tahmin, Diskriminant Analizi, Lojit Analizi, Faktör-Lojistik Analizi, Beaver Metodu.

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TO MY FAMILY

1. INTRODUCTION

In 1994, there was an economic crisis in Turkey. Because of this economic crisis, many companies and banks had financial difficulties and some of them had failed. Between 1989 and 1993, there was short term foreign capital inflow (foreign portfolio investments inflows) because of the high interest rates. This capital inflow has a speculative purpose and it goes to the Country where the interest rates are high and leaves that country immediately when it finds higher interest rates. This short term capital inflow had increased the demand for TL and devaluation of the TL against other major currencies slowed down. In other words, TL became overvalued. As a result of this, imports had reached the highest level (30 Billion $ in 1993) in Turkey's history. This had caused a continuous deficit in the balance of payments and this is not a sustainable position in the long term. In the beginning of 1994, Turkey reached the limit that it could not sustain this position anymore.

In the second half of 1993, government tried to decrease the interest rates and this is difficult to reach in a country where the public sector borrowing requirement reached very high levels (Internal Debt: 70.338 billion TL, Foreign Debt: 67.174 billion TL). As a consequence of the decrease in the interest rates, an outflow of short term capital was observed. The exchange rates began to increase (TL was devaluated from 22.150 TL/$ to 39.875 TL/$ in two days). Here are the major results of the 1994 economic crisis:

1. Reduction in the Production: The economic growth in 1994 was -6.1%, and income per capita had decreased by 9%.
2. Reduction in the Investments: In 1994, there was a 21% reduction in the fixed capital investments. Private sector investments had decreased by 38%.
3. Inflation: In 1994, inflation was 150% (State Statistics Institute).
4. Unemployment: At the end of 1994, unemployment rate was 20% (State Planning Institute).

During the 1994 crisis three commercial banks had failed and some of them had merged with other banks in order to come over the failure. Banks are crucial financial institutions in an economy. When Turkey is considered as a developing country where the capital markets are not developed enough to be an alternative for the investors, banks have an important role as the most preferred financial institutions in the financial system. In Table 1, there are the ratios of fund flows to GNP. Moreover, being the major investment alternative in the financial system of Turkey, small investors will be affected as well as the institutional investors and producers and this gives us a clue about the enormous social effect of the failure of the commercial banks.

TABLE 1

RATIOS OF FUND FLOWS TO GNP

	1986	1987	1988	1989	1990	1991	1992	1993	1994
BANK LOANS	10.3	10.2	7.1	6.4	7.4	9.0	10.3	10.5	8.1
COMMERCIAL BANKS	8.8	8.0	5.2	6.0	7.2	5.7	7.6	7.8	5.9
INVESTMENT BANKS	0.8	0.6	1.0	0.4	0.4	0.9	0.5	0.6	0.6
CENTRAL BANK	0.7	1.6	0.9	0.1	0.2	2.3	2.2	2.0	1.7
CAPITAL MARKET INSTRUMENTS	2.1	4.2	3.7	4.9	4.5	5.8	9.3	7.4	8.4
PUBLIC SECTOR	1.6	2.7	2.4	3.0	2.5	2.9	7.8	6.3	7.4
TREASURY BONDS	0.6	1.5	0.5	0.4	0.5	2.0	2.2	1.1	6.1
STATE BONDS	0.9	1.2	1.9	2.6	2.0	0.9	5.6	5.2	1.3
PRIVATE SECTOR	0.5	1.6	1.3	1.8	2.0	2.9	1.5	1.1	0.9
STOCKS	0.4	1.1	1.2	1.6	2.0	2.8	1.5	1.1	0.9
BONDS	0.1	0.4	0.1	0.1	0.2	0.0	0.0	0.0	0.0
FINANCING BONDS	0.0	0.1	0.1	0.2	-0.1	0.1	0.0	0.0	0.0
FINANCE COMPANIES	0.1	0.1	0.2	0.1	0.1	0.2	0.3	0.4	0.4
TOTAL	12.5	14.5	10.9	11.5	12.0	15.0	19.9	18.3	16.9

1.1 TURKISH BANKING SYSTEM

It could be said that Turkish Commercial Banking Sector reached at the developed countries level. Commercial Banks provide numerous services in the financial system. The services can be broadly classified as follows: (1) individual banking; (2)institutional banking and (3) global banking.

Individual banking encompasses consumer lending, residential mortgage lending, consumer installment loans, credit card financing, automobile and boat financing, brokerage services, student loans and individual-oriented financial investment services such as personal trust and investment services. Interest and fee income are generated from mortgage lending and credit card financing. Fee income is generated from brokerage services and financial investment services.

Loans to non financial corporations, financial corporations (such as insurance companies), and government entities (state and local governments) fall into the category of institutional banking. Also included in this category are commercial real estate financing, leasing activities and factoring.

It is in the area of global banking that banks have begun to compete head to head with investment banking (or securities) firms. Global banking covers a broad range of activities involving corporate financing and capital market and foreign exchange products and services. Most global banking activities generate fee income rather than interest income.

There are three of funds for banks: (1) Deposits; (2) Non-deposit borrowing; and (3) Common stock and retained earnings. Banks are highly leveraged financial institutions, meaning that most of their funds come from borrowing-the first two sources we refer to.

The operations of the banking system in Turkey had began with the Galata Bankers in the second half of the 19th century. However, the development of the Turkish Banking System had began with the foundation of the Turkish Republic. Development of the Turkish Banking System can be studied in four main phases.

1. 1923-1938 Period: The Turkish Republic Central Bank has been founded and the foundation of many state and private banks had followed. The characteristic of this period is the foundation of the banks that have only one branch. In the early 1930, these banks had either bankrupted or merged.
2. 1939-1962 Period: Because of the Second World War between 1939-1944 , there was not any development in the sector. Between 1945-1960, the number of the private banks had increased and the number of the foreign

banks had decreased. There was an economic crisis in the Turkish Economy in the late 1950's and as a result of the crisis, a great number of banks had bankrupted.

3. 1963-1980 Period: The most important characteristic of this period is the importance that had been placed to the foundation of the investment banks. In this period, banks placed importance to open more branches.
4. After 1980: In this period, some regulations have been passed to make banks to improve their financial positions and to operate more rationally and transparently. Moreover, the foundation of the commercial banks was regulated again. Another important characteristics of this period is the increase in the bad loans. Because of the depreciation in TL, the companies that are heavily dependent on the foreign resources felt short in paying their obligations to banks. As a result of this, the percentage of the loans of the banks became bad loans. Hence, in this period four banks were forced to be the acquisition of the bought by Ziraat Bankasi and one bank had bankrupted. As a result of the economic crisis in 1994, three commercial banks had bankrupted.

1.2. MAJOR REASONS OF THE FAILURE OF THE COMMERCIAL BANKS IN 1994

In Turkey, commercial banks are heavily dependent on the short term funding, especially customer short term funding. The repayment of the customer short term funds can not be predicted easily. Customers can withdraw their money whenever they want. In times of panic, all of the customers can withdraw their money and cause a bank to fail. Hence, it is very risky to depend on customer short term funding. Because of the economic conditions in Turkey, it is not easy for commercial banks to find long term funds (internal or external). Especially the credibility of the small scale commercial banks is low. Therefore, they are very dependent on short tern funding. When the maturity date of the repayment of the short term funding comes, the only way for banks to pay this debt is to find short term funds again. This is a vicious cycle. The Customer Short Term Funding / Total Liabilities ratios are (Bankscope): In 1994 0.95, in 1993 0.86, in 1992 0.84, in 1991 0.80, in 1990 0.82. When the date of failure (in this study, date of failure is 31st December 1994) approaches, the dependence on the Customer Short Term Funding increases.

In 1994, just before the crisis, commercial banks were excessively dependent on the short term funding. And with the crisis, they could not find any source (even short term funds) for the repayment of the short term debts which are due because both foreign and domestic financial institutions cut off the credit lines available. Here we can explicitly see the importance of the liquidity. The banks which are not liquid enough had failed.

Another major reason for the bank failure in 1994 is their being short in US. Due to slow depreciation of TL against foreign currencies and high interest rates on TL based Treasury Bills, banks buy TL with the foreign currency funds they hold. When the maturity date of the repayment of these funds come, they buy USD with TL and they can make profit. This is called Open Position. However, with the rapid depreciation of the TL in 1994, they began to incur losses and they could not pay their obligations.

As mentioned above, Turkish Banking Sector History is full of bank failure examples. Consequently a research on the prediction of failure of the commercial banks in Turkey is motivated by the examples in the history

2. BANK FAILURE PREDICTION MODELS

Since 70's, numerous models have been proposed to predict failure of the commercial banks. Perhaps the most widely used method is the multidimensional discriminant analysis (DA). Originally suggested by Altman (1968) as a tool to predict corporate failure, the DA method has been employed to asses financial distress across different industries and different countries.

In this study the results of the Discriminant Analysis, Logit Analysis, Factor-Logistic Analysis and Beaver's Method are compared. DA is a parametric function which assumes the normal distribution. However, normal distribution assumption of DA is frequently violated. Logit Analysis does not require the normal distribution assumption and it can be used when this assumption likely to be violated. Logit Analysis can be extended to Factor-Logistic Analysis. In Factor-Logistic Analysis, first the important factors are identified by the factor analysis and then factor scores are used instead of financial ratios in the logit function. Logit Analysis is an alternative for DA when the Normal distribution assumption is violated. Beaver's Method is a completely intuitive method and does not require any assumption.

2.1. Discriminant Analysis

The DA model used in this study is constructed by using the Fischer procedure (Fischer 1936) of maximizing the ratio between-groups and within-groups variances. Classification rules derived from the Fischer procedure were shown to be optimal in minimizing the expected cost of misclassification, provided the following conditions are satisfied:

(1) Each group follows a multivariate normal distribution.

(2) The covariance matrices of each group are the same.

(3) The mean vectors, the covariance matrices, the prior probabilities, and the cost of misclassifications of each group are known.

In the case of binary classification the discriminant function can be stated as

$$\mathbf{D}(X) = X'\Sigma^{-1}(\mu_1 - \mu_2) - \mathbf{1/2}(\mu_1 - \mu_2)^T\Sigma^{-1}(\mu_1 + \mu_2)$$

where μ_1 , μ_2 and Σ^{-1} are the group means and the inverse of the common covariance matrix respectively. The decision rule is to classify X to group 1 if $\mathbf{D}(X) \geq \ln(C_{21}\,\pi_1 \,/\, C_{12}\,\pi_2)$; otherwise X is assigned to group 2. The variables C_{12}, C_{21}, π_1 and π_2 denote the costs of misclassification and prior probabilities of each group, respectively. The model is a linear function which relates a set of independent variables to a scoring variable. The function actually represents a hyperplane dividing the variable space into two partitions.

A linear discriminant function offers minimum expected misclassification cost if the normality and equal dispersion assumptions are satisfied. Unfortunately, violations of these two assumptions are highly likely in real-life applications. It is common that individual variables are not univariate normally distributed. Examples can be found where variables are bounded from below or above, or assume categorical values. A study by Deakin (1976) suggested that financial ratios are not normally distributed but are positively skewed (i.e. clustered more to the left of the mean with a fewer number of extreme values to the right of it). Violation of the normality assumption may lead to biased and overly optimistic results, thus limiting the usefulness of the model. Transformations of variables such as taking the natural logarithm are suggested to obtain an approximate normal distribution of the values in this case; however, the transformed variables may be difficult to interpret.

If the equal covariance matrices assumption is violated, a quadratic function instead of a linear function should be employed. Quadratic functions may be quite accurate for classifying original samples, yet they do not perform as well as linear models in holdout sample tests (Altman,Avery,Eisenbeis and Sinkey 1981). Lachenbruch *et al.* (Lachenbrauch, Sneeringer, Revo 1973) reported a similar conclusion after comparing the two models under various multivariate non-normal distributions.

Whether the function is linear or quadratic, a fundamental condition that must be satisfied is that the two groups must be discrete and identifiable. Cases where this condition may be violated arise if observations of each group form clusters which scatter in different regions of the variable space. Depending on the number of clusters in each group, a discriminant function (linear or quadratic) may incur a high error rate for both the original and holdout samples.

Very often, assumptions of DA are violated. A common practice is to concept the results if the assumptions are satisfied. Altman *et al.* (Altman, Avery, Eisenbeis, Sinkey 1981) identified four related problems in the use of DA techniques in classification: (1) relative significance of individual variables; (2) reduction of dimensionality; (3) elimination of insignificant variables; (4) existence of time series relationships.

2.2. Logit and Factor-Logistic Analysis

In order to avoid the pitfalls of the conventional DA methods, logit analysis is suggested by McFadden (1976) and Martin (1977) as an alternative. A virtue of the logit approach is that it does not require the assumptions of normality and equal dispersion. Unlike DA models, a non-linear logistic function is used. The logistic function has the following form:

$$Y = 1 / (1 + e^{y'}) , \qquad y = c_0 + \sum_{i=1}^{n} c_i X_i$$

where X_i $1 \leq i \leq n$ represent the ith financial ratio, c_i is the coefficient of the ith ratio and Y is an index indicating the likelihood of failure. Since Y falls between 0 and 1, it is usually interpreted as the probability of failure.

Since logistic regression does not assume any probability distribution, it is often preferred over DA (Press and Wilson 1978). Harell and Lee (1978) contended that even when all assumptions of DA are, logistic regression is virtually as efficient as DA.

West (1985) extended the logistic approach by augmenting it with factor analysis. The model is constructed in two stages. First, a factor analysis is performed on the observations to identify important factors that influence the financial condition of the bank. In the second stage, instead of using financial ratios directly, each observation is described by its factor scores. The transformed observations are then used to estimate the coefficient of the logit model. Using West's model, y is no longer a function of X_i, $1 \leq j \leq m$, but a function of its factor scores, i.e.

$$Y = 1 / (1 + e^{y'}) \qquad y = k_0 + \sum k_J F_J$$

where F_J $1 \leq j \leq m$ and $m < n$ is the score of the jth factor of a bank. Each bank is assigned a probability (i.e. Y) of being a problem institution.

2.3. k Nearest Neighbor (kNN)

k Nearest Neighbor (kNN) (Tam 1991), a nonparametric method, is used when groups have radically non-normal distributions, particularly in cases where observations belonging to the same group form clusters in the variable space (i.e. multi-modal distribution). Compared with parametric techniques, kNN is applicable under less restrictive assumptions regarding the underlying population distribution.

The kNN model not only relaxes the normality assumption, it also eliminates the functional form of the model required by the previous techniques. The group assignment of an observation is decided by the group assignments of its first k nearest neighbor. The distance d(x,y) between any two observations x and y is defined by $d(x,y) = (x-y)' \; COV^{1} (x-y)$, where COV^{1} is the inverse of the pooled covariance matrix. An observation will be assigned to the group to which majority of its k nearest neighbors belong.

2.4. Classification Tree

To deal with category variables, a symbolic method employing machine learning techniques has recently suggested by Messier and Hansen (1988). Instead of generating a decision rule in the form of discriminant function, the ID3 method creates a classification tree that best discriminates the original sample. Frydman (Frydman, Altman, Kao 1985) *et al.* applied a similar technique called recursive partitioning to generate a discriminant tree. Both methods employ a non-backtracking splitting procedure that recursively partitions a set of examples into disjointed subsets. They differ in their splitting criteria: the ID3 method intends to maximize the entropy of the split subsets, while the recursive partitioning technique is designed to minimize the cost of misclassification.

2.5. Alternative Accounting Measures as Predictors of Failure

The evaluation of alternative accounting measures is one of the most difficult tasks facing the accounting profession. Although *a priori* arguments have been advanced in support of each alternative, it is difficult to decide which arguments to accept or reject based solely upon their *a priori* appeal. There is general recognition that empirical research will be needed for a meaningful evaluation but little effort has been directed toward specifying what the nature of the empirical study should be.

Beaver (1968) conducted a study (1) to emphasize the need for empirical verification of *a priori* beliefs, by citing one area where widely held beliefs were found to be erroneous when examined by empirical evidence, and (2) to illustrate a method for empirically evaluating alternative accounting measures. According to this method, alternative measures would be evaluated in terms of their ability to predict events of interest to users of accounting data. The measure with the greatest predictive ability with respect to a given event would be considered the best measure for that particular purpose.

Beaver had chosen the event of failure for his study, because accounting data in the form of financial ratios are in widespread use as predictors of failure. According to Beaver's model the evidence was analyzed at two levels. (1) The Dichotomous Classification Test, (2) The comparison of mean values of financial ratio components.

The purpose of Beaver's study was to discover how well financial ratios could predict failure relative to random prediction. The major result of the study is: based solely upon a knowledge of the financial ratios, the failure status of firms can be correctly predicted to a much greater extent than would be expected from a random prediction.

All these methods, with the exception of the linear and quadratic DA models are generally called distribution-free techniques since they do not require any distribution assumption. In the current study, performances of linear DA method ,logit method, factor-logistic method Beaver's model are compared.

3. DATA AND MODEL CONSTRUCTION

The findings presented here are based upon an investigation of the financial statement data of 22 failed and 34 non-failed commercial banks that were operated as of December 1994. The group of commercial banks consist of 8 state banks, 32 private commercial banks and 16 foreign commercial banks. The data consists of financial statements of banks between one and five years prior to failure. These years are 1990, 1991,1992, 1993 and 1994. Involving banks from the same country, instead of those from other countries, increase the population's homogeneity. The names of the commercial banks used in this study are listed in Appendix B.

Instead of bankruptcy, the long term ratings of the Capital Intelligence Rating Company have been used to define failure. These ratings assess the bank's capacity for timely repayment on an 8 point scales. In this study, the banks that are rated B or less than B are classified as failed. B means that, fundamental weaknesses are present either in bank's financial condition or trends, and other factors are unlikely to provide strong protection from unexpected adversities. Highest rating AAA means that bank is in extremely strong condition with satisfactory trends; other factors also support this as an unquestioned obligor. The lowest ratio DDD means that bank falls below usually acceptable standards and may be in an untenable condition. The meanings of the other ratings are shown in Appendix C.

The financial statements of the commercial banks are drawn from a software named Bankscope. Bankscope is a software of Capital Intelligence Rating Company and it is used for the commercial purpose. It is sold to financial institutions, especially commercial banks in all over the world. Financial statements of the commercial banks are included in the Bankscope. These include the balance sheets, income statements, financial ratios. Shareholders and Banking Subsidiaries are also included in the software.

Each bank is described by 13 financial ratios that are used by the Capital Intelligence Rating Company in the rating of the commercial banks. The list of the ratios are shown in Table 2. These 13 ratios are grouped into four different categories, each describing a unique financial characteristics of a bank. No explicit ratio is used for the management criterion, since it is logical to think that quality of the management, which is difficult to quantify, will eventually be reflected by the above mentioned ratios.

Liquidity ratios measures the banks debt payment ability. Capital adequacy ratios shows if the banks capital is enough for the operation of the banks without financial difficulties. Profitability Level ratios measures the profit making ability

TABLE 2

LIST OF THE FINANCIAL RATIOS

RATIOS

LIQUIDITY RATIOS

Net Loans / Total Assets

Net Loans / Customer and Short Term Funding

Liquid Assets / Customer and Short Term Funding

CAPITAL ADEQUACY

Equity / Total Assets

Equity / Loans

Equity / Customer and Short Term Funding

Equity / Liabilities

PROFITABILITY LEVEL

Net Income / Equity

Net Income / Total Assets

Net Interest Revenue / Total Assets

LOAN LOSS COVERAGE

Loan Loss Provisions / Loans

Equity / Loan Loss Provisions

Loan Loss Reserves / Loans

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of the commercial banks. Loan Loss Coverage ratios shows if a commercial bank have enough provisions and reserves for bad loans.

There are some expressions that need further explanation. Net Income means profits of the banks after the taxes. Loan Loss Provisions are the provisions for the bad loans and they are used as same as the other provisions in the balance sheet. Loan Loss Reserves are the part of the profits that are set aside for bad loans as a part of the capital and it is regulatory.

However, it is important to consider the scale differences between the commercial banks. These scale differences can affect the financial positions of the commercial banks and so the financial ratios of the banks can be affected.

All of the data are analyzed with the help of the SPSS for Windows.

3.1. Discriminant Analysis Model

First of all, the Kolmogorov-Smirnov test was performed for each of the 13 financial ratios in the original population to check if the univariate normal distribution assumption was satisfied. The test indicated that some of the ratios are not normally distributed. For those ratios that failed the test[1] the natural logarithm transformation was performed to approximate normality. The

[1] The significance level of the test is 5%.

Kolmogorov-Smirnov test was then repeated for the transformed ratios. Since no significant improvement was made, we decided to use the original ratios to construct the DA models. The results of the Kolmogorov-Smirnov test before and after natural logarithm transformation are shown in TABLE A3,. In the Table A3 the financial ratios are stated as R1, R2,......, R13 according to the sequence in the List of Financial Ratios in Table 2.

Discriminant function used in this study can be stated as

$$Y = \sum v_i x_i$$

v_i : weights

x_i : ith financial ratio

In discriminant analysis, The weights are derived so that the variation in Y scores between the groups is as large as possible, while the variation in Y scores within the groups is small as possible. That is, the weights are derived so that the ratio

$$\frac{\text{Between-group variation}}{\text{Within-group variation}}$$

is maximized. This makes the groups as distinct as possible with respect to new index scores.

3.1.1. Interpreting the Discriminant Function

Discriminant coefficients reflects the relative contribution of a unit change of the independent variables (financial ratios in this study) on the discriminant function. A small coefficient means that one-unit change in that particular ratio produces a small change in the discriminant function score, and vice versa. The problem here is that if the unit measurement for one or more variables were to be changed, the discriminant function would also change. To remove the arbitrary scale-of-measurement effects, the discriminant weights that would be applied to the predictors in *standardized form* are employed when comparing the individual contributions of the individual ratios. The relative magnitudes of these standardized weights are determined by multiplying each determinant weight by the *pooled standard deviation* of the corresponding ratio. Standardized weight (v_k^*) can be stated as

$v_k^* = v_k \, s_k$

v_k = weight of the kth ratio

s_k = pooled standard deviation of the kth ratio

To assist in interpretation, the mean discriminant score for each group could be calculated. To do this, it is simply necessary to substitute the mean values of the variables for each group into the calculated discriminant function.

To determine whether the discriminant function provides meaningful practical differentiation (versus statistical differentiation) between two groups (Failed and Non-failed), it is possible to apply the discriminant function to each bank to predict the bank's score and, on the basis of the generated score, to classify the bank as bankrupt or non-bankrupt. We could then compare the prediction with the bank's actual classification to determine whether the derived function provides meaningful discrimination. We can create a predicted classification for each sample member using a very simple decision rule: *If a bank's discriminant score is closer to the mean score for failed banks than for non-failed banks, classify the bank as a failed bank; otherwise, classify it as a non-failed bank.*

Results of the discriminant analysis are presented in Tables A2 through A6. In order to identify the important financial ratios that determine the failure, the standardized discriminant coefficients and Univariate F-Ratios that are stated in Tables A2, A3, A4, A5, and A6 must be investigated. The bigger the coefficient and the univariate F-Ratio the higher the explanatory power of the ratio.

In the DA of one year prior to failure, Liquid Assets / Customer Short Term Funding, Equity / Total Assets, Equity / Customer Short Term Funding, Net Income / Equity and Net Income / Total Assets have greater predictive ability. In two years prior to failure, Equity / Total Assets, Equity / Loans, Equity / Customer Short Term Funding, Equity / Liabilities, Net Income / Total Assets have greater predictive power. In three years prior to failure, Equity / Loans, Equity / Customer Short Term Funding, Net Income / Equity, Loan Loss Provisions / Loans have greater predictive ability. In four years prior to failure, Net Loans / Customer Short Term Funding, Liquid Assets / Customer Short Term Funding, Equity / Total Assets, Equity / Customer Short Term Funding, Net Income / Equity, Net Income / Total Assets have greater predictive ability. In five years prior to failure, Net Loans / Customer Short Term Funding, Equity / Total Assets, Equity / Customer Short Term Funding, Net Income / Equity, Loan Loss Provisions / Loans, Loan Loss Reserves / Loans have greater predictive ability.

When the results of the analysis are investigated according to the ratio groups, it is observed that Capital Adequacy ratios and Profitability Level Ratios have greater predictive ability. However, Capital Adequacy ratios have superior performance when it is compared with all other ratio groups. In one, four and five years prior to failure, Liquidity ratios have greater predictive ability and it is the proof of the importance of the liquidity. In three and five years prior to failure , Loan Loss Coverage ratios have grater predictive ability. In three and five years prot to failure, Loan Loss Coverage ratios have grater predictive ability.

In the discriminant functions stated below, the financial ratios are stated as R1, R2,......, R13 according to the sequence in the List of Financial Ratios in Table 2.

$$Y_1: -2.07763 R1 - 2.94406R2 + 6.51111 R3 + 4.37874R4 + 1.98527R5 - 5.35010R6 + 0.02113R7 + 6.40643R8 - 5.34852R9 - 1.59128R10 - 2.74195R11 - 0.87540R12 + 1.68098R13$$

$$Y_2: -1.16684R1 + 2.11750R2 - 1.75585R3 - 1.67368R4 + 2.45319R5 + 1.10359R6 + 1.02778R7 - 0.70754R8 - 1.66840R9 + 1.03213R10 + 0.78121R11 - 0.48981R12 + 0.58022R13$$

Y_3 : -0.86505R1 + 2.24978R2 - 1.69216R3 - 1.36868R4 + 2.78076R5 - 1.44032R6 + 0.92308R7 - 2.60782R8 + 0.58808R9 - 0.26021R10 + 2.24385R11 - 0.60349R12 - 0.78628R13

Y_4 : 3.07993R1 + 2.11223R2 - 2.32153R3 -12.63549R4 + 0.28962R5 + 11.11393R6 + 1.14755R7 - 4.45447R8 + 2.43866R9 + 1.58130R10 - 2.43528R11 - 2.83807R12 + 2.94972 R13

Y_5 : 0.82463R1 - 3.54492R2 - 0.75121R3 - 3.39189R4 + 1.48799R5 - 11.86657R6 - 2.22878R7 - 7.82774R8 - 0R9 - 0R10 - 12.95730R11 - 3.34280R12 + 4.73240R13

Classificatory results of DA are presented in Table 3. The numbers stated as percentages in Table 3 shows the accuracy of the classificatory results for the discriminant analysis. According to the classificatory results, overall classificatory accuracy is 100%.

TABLE 3

CLASSIFICATORY RESULTS OF DISCRIMINANT ANALYSIS

CONFUSION MATRIX OF ACTUAL VERSUS PREDICTED GROUP MEMBERSHIP

1 YEAR PRIOR TO FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-FAILED	FAILED	TOTAL
NON-FAILED	34 (100 %)	0	34
FAILED	0	22 (100 %)	22
			56 (100%)

2 YEARS PRIOR TO FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-FAILED	FAILED	TOTAL
NON-FAILED	34 (100%)	0	34
FAILED	0	22 (100%)	22
			56 (100%)

3 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-FAILED	FAILED	TOTAL
NON-FAILED	34 (100%)	0	34
FAILED	0	22 (100%)	22
			56 (100%)

4 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-FAILED	FAILED	TOTAL
NON-FAILED	34 (100%)	0	34
FAILED	0	22 (100%)	22
			56 (100%)

5 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-FAILED	FAILED	TOTAL
NON-FAILED	34 (100%)	0	34
FAILED	0	22 (100%)	22
			56 (100%)

3.2. Logit Model

The logit model is of the form

$$Y = 1 / (1 + e^{y}) \qquad\qquad y = c_0 + \sum_{I=1}^{n} c_i x_i$$

Y: Likelihood of failure (falls between 0 and 1)

x_i : ith financial ratio

c_i : coefficient of the ith financial ratio

The cutoff point used in this study is 0.5. If the likelihood of failure of a bank is below 0.5, it is accepted as failed and if Y is above 0.5, the bank is accepted as non-failed.

Cutoff points other than 0.5 are used in order to improve the classification accuracy but the results could not been improved.

The classificatory results of the Logit analysis are shown in Table 4. According to the results of the logit analysis, overall classification accuracy is 90%.

TABLE 4
CLASSIFICATORY RESULTS OF LOGIT ANALYSIS

1 YEAR BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	32 (93.75%)	2	34
BANKRUPT	2	20 (90.91%)	22
			56 (92.86%)

2 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	32 (93.75%)	2	34
BANKRUPT	7	15 (68.18%)	22
			56 (83.93%)

3 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	34 (100%)	0	34
BANKRUPT	6	16 (72.73%)	22
			56 (89.29%)

4 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	34 (100%)	0	34
BANKRUPT	7	15 (68.18%)	22
			56 (87.5%)

5 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	34 (100%)	0	34
BANKRUPT	2	20 (90.91%)	22
			56 (96.43%)

3.3. Factor-Logistic Model

In the factor-logistic analysis, factors accounting for the variances are identified by the factor analysis. The factor scores of each observation are used as the independent variables of a logit regression. In other words, factor analysis is performed on the observations to identify the important factors that influence the financial condition of the bank. Then, factor scores are used instead of financial ratios. There are two assumptions for factor analysis:

1. Variables should be normally distributed
2. Population should be equal or more than three times of the variables.

As mentioned in the discriminant analysis, the first assumption of the factor analysis is violated.

The logit model is of the form

$$P(X) = (1 + e^{-Y})^{-1}$$

$$Y = a + \sum \beta_i X_{iJ}$$

a : constant

β_i : coefficient of the *i*th factor

X_{iJ} : factor scores of the *i*th factor for the *j*th observation

The cutoff point used in this study is 0.5. If the likelihood of failure of a bank is below 0.5, it is accepted as failed and if *Y* is above 0.5, the bank is accepted as non-failed. Cutoff points other than 0.5 are used in order to improve the classification accuracy but the results could not be improved.

The classificatory results of the factor-logistic model are shown in Table 5. According to the results of the factor-logistic analysis, overall accuracy is 86.07%.

3.4. Beaver's Model

The analysis was made at three levels: (1) The Dichotomous Classification Test, (2) The comparison of mean values of ratio components.

TABLE 5

CLASSIFICATORY RESULTS OF FACTOR-LOGISTIC ANALYSIS

1 YEAR BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	34 (100%)	0	34
BANKRUPT	2	20 (90.91%)	22
			56 (90.43%)

2 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	27 (79.41%)	7	34
BANKRUPT	7	15 (68.18%)	22
			56 (75%)

3 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	30 (88.24%)	4	34
BANKRUPT	4	18 (81.82%)	22
			56 (85.71%)

4 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	34 (100%)	0	34
BANKRUPT	4	18 (81.82%)	22
			56 (92.86%)

5 YEARS BEFORE FAILURE

	PREDICTED CLASSIFICATION		
ACTUAL CLASSIFICATION	NON-BANKRUPT	BANKRUPT	TOTAL
NON-BANKRUPT	30 (83.33%)	4	34
BANKRUPT	7	15 (68.18%)	22
			56 (80.36%)

3.4.1. Dichotomous Classification Test

The dichotomous classification test (DCT) provides one index of predictive ability. The DCT predicts the failure status of a bank based solely upon the knowledge of the values of the financial ratios. First the banks are randomly divided into two subgroups. For a given ratio, the data of the first subsample are arrayed in ascending order. The array is inspected to find an optimal cut off ratio, a cut off point that minimizes the percentage of incorrect predictions. In other words, a cutoff point that most successfully discriminates the failed and non-failed is looked for. If a bank's ratio is below the cut off ratio, the bank is classified as failed. If the bank's ratio is above the cut off ratio, the bank is classified as non-failed. The classifications are compared with the actual failure status of the banks and the percentage of incorrect classifications are computed. The process of finding an optimal cut off point is largely one of trial and error. The procedure just described may be repeated for several tentative cut off points, before an optimal one is found.

A criterion for predictive ability is the percentage error - the lower the error, the greater the predictive power. However, if the percentage error obtained from the first subsample were used, the test can be criticized on the basis that it selects *ex post* (after looking the actual failure status of the banks) the cut off point that will minimize the error. In a decision making situation, one should use this information in making predictions on a new set of banks, i.e. in evaluating the performance of a set of banks different from those used to derive the cut off point.

To make the test conform more closely to the decision-making situation, the optimal cut off point for the first subsample is used to predict the failure status of the banks in the second subsample. Similarly, an optimal cut off point was derived for the second subsample and was used to predict the failure status of the banks in the first subsample. Note that the predictions are always being made on a set of banks different from those used to derive the cut off point. Afterwards the predictions are compared with the actual failure statue and the percentage error was computed. This procedure is conducted for each ratio in each year before failure.

Table 6 shows the accuracy of prediction as percentages for different years and the percentage errors for 13 financial ratios are stated in Table 7.

TABLE 6

CLASSIFICATION ACCURACY, BEAVER'S METHOD

	YEAR 1	YEAR 2	YEAR 3	YEAR 4	YEAR 5
CLASSIFICATION ACCURACY	94.1%	83.3%	86.6%	74.9%	92%

According to these results, overall accuracy of prediction is 86.18%. However, Beaver puts emphasis on the predictive power of the financial ratios individually. Therefore, it will is useful to analyze talk about the predictive ability of the individual financial ratios.

As the ratio classes can be obtained from Table 7, there is inconsistency in the prediction errors of liquidity, capital adequacy, profitability level and loan loss coverage ratios. Furthermore, there is almost no relation between the prediction errors associated with individual financial ratios over subsequent ratios. However, the following four ratios having consistently lower percentage errors and they are consistently superior to the others: Liquid Assets/Customer Short Term Funding, Equity/Liabilities, Net Income/Equity and Net Interest Revenue/Total Assets. Among these ratios, Equity/Liabilities has the lowest

TABLE 7

PERCENTAGE ERROR FOR 13 RATIOS

RATIO	YEAR BEFORE FAILURE				
	5	4	3	2	1
LIQUIDITY					
NET LOANS/TOTAL ASSETS	0.35	0.33	0.39	0.33	0.30
NET LOANS/CUSTOMER S.T. FUNDING	0.35	0.38	0.40	0.30	0.47
LIQUID ASSETS/CUSTOMER S.T. FUNDING	0.25	0.19	0.25	0.30	0.22
CAPITAL ADEQUACY					
EQUITY/TOTAL ASSETS	0.40	0.57	0.36	0.43	0.30
EQUITY/LOANS	0.35	0.47	0.37	0.40	0.26
EQUITY/CUSTOMER S.T. FUNDING	0.47	0.28	0.39	0.43	0.30
EQUITY/LIABILITIES	0.35	0.30	0.26	0.26	0.00
PROFITABILITY LEVEL					
NET INCOME/EQUITY	0.05	0.35	0.14	0.29	0.20
NET INCOME/TOTAL ASSETS	0.21	0.55	0.14	0.35	0.52
NET INTEREST REVENUE/TOTAL ASSETS	0.16	0.35	0.27	0.28	0.25
LOAN LOSS COVERAGE					
LOAN LOSS PROVISIONS/LOANS	0.38	0.35	0.45	0.48	0.18
EQUITY/LOAN LOSS PROVISIONS	0.23	0.55	0.59	0.34	0.27
LOAN LOSS RESERVES/LOANS	0.25	0.31	0.33	0.48	0.33

percentage errors and its predictive ability increases in the short term (as the date of the failure approaches).

The literature asserts that liquidity ratios must have superior predictive ability, however, results presented in Table 7 indicate that except for Liquid Assets/Customer Short Term Funding ratio, all other liquidity ratios have larger percentage errors. As mentioned before, liquidity is crucial for commercial banks in Turkey and as experienced during the crisis in 1994 but, an observation contradicting the results of the DCT analysis.

The most striking feature of the findings presented in Table 7 is the superior performance of the profitability ratios rather than the liquidity ratios. Except Net Income/Total Asset ratio, profitability ratios have smaller percentage errors. One possible interpretation of this observation is the following: if a bank is in a poor liquidity position but has good profit prospects, it is more likely that it will be able to obtain necessary funds to meet maturing obligations.

As mentioned before, Equity/Liabilities ratio has the best prediction ability. This shows that capital adequacy is one of the most important factors that determines the failure of a bank. This can also be observed in practice. In times of financial trouble, capital adequacy is a determining factor for failure like liquidity. As can be obtained from Table 7 the percentage error of Equity/Liabilities is zero one year before failure. However, other capital adequacy ratios do not show consistent predictive performance.

According to the results of the DCT, the loan loss coverage ratios have high percentage errors. It can therefore be concluded that they have inferior predictive ability.

A possible reason for the observed differences in predictive ability is that popularity is itself defeating. The less frequently advocated measures, Net Income/Equity and Net Interest Revenue/Total Assets (profitability ratios), outperformed the two more frequently advocated measures, Net Loans/Total Assets and Net Loans/Customer Short Term Funding (liquidity ratios). It is argued that widely used ratios are manipulated by management in a manner that mitigates the measures' usefulness. However, this explanation is not saticfactory, because the profitability ratios are also popular measures, especially for rating companies, and as can be seen in Table 7, they have good predictive ability.

3.4.2. Comparison of Mean Values of Ratio Components

To gain more insight into the differences in the predictive ability, it is useful to examine the behavior of the ratio components.

As can be seen in Table 8, for the most part, the behavior of the failed banks is what would be expected. For all of the eleven financial statement items, non-failed banks have larger values than the failed banks. Failed banks have less loans and liquid assets, they generate less interest revenue and net income. This combination causes a marked deterioration in their solvency positions.

As mentioned above, liquidity is the most important factor that determines the failure. Table 8 shows that the means of liquid assets and loans for non-failed banks are consistently three times of the means of the liquid assets and loans of the failed banks.

As can be seen in Table 8, Loan Loss Reserves and Loan Loss Coverages of the failed banks are smaller than the non-failed ones. This is an indicator that the failed banks are risk takers.

TABLE 8

COMPARISON OF MEANS FOR 11 FINANCIAL STATEMENT ITEMS

ITEM	COMPARISON OF MEANS FOR 11 FINANCIAL STATEMENT ITEMS YEAR BEFORE FAILURE 5	4	3	2	1
EQUITY					
NF	420.64	758.40	1116.22	2081.11	4746.33
F	201.37	288.17	351.10	647.83	2125.40
DIFFERENCE	219.28	470.23	765.12	1433.28	2620.93
TOTAL ASSETS					
NF	4259.43	9924.87	11090.67	22060.56	46612.22
F	1605.83	3007.50	3950.50	6902.75	23094.80
DIFFERENCE	2653.60	6917.37	7140.17	15157.81	23517.42
CUSTOMER & S.T. FUNDING					
NF	3233.14	5362.67	8721.89	17382.94	41122.89
F	1080.83	2091.83	2867.20	5275.83	18167.60
DIFFERENCE	2152.31	3270.83	5854.69	12107.11	22955.29
LIABILITIES					
NF	4130.00	6620.00	10270.00	19990.00	41111.00
F	1389.17	2718.67	3598.90	6245.50	20967.80
DIFFERENCE	2740.83	3901.33	6671.10	13744.50	20143.20
LOANS					
NF	1837.21	2877.47	4535.39	9329.78	17295.11
F	741.80	1565.17	1969.10	3340.58	11974.80
DIFFERENCE	1095.41	1312.30	2566.29	5989.19	5320.31
LIQUID ASSETS					
NF	1747.07	4985.93	4961.39	8779.72	21050.67
F	543.73	892.40	1318.40	2512.42	7903.80
DIFFERENCE	1203.34	4093.53	3642.99	6267.31	13146.87
NET INCOME					
NF	130.71	334.60	301.67	745.06	1585.06
F	10.77	235.38	56.00	100.32	417.16
DIFFERENCE	119.95	99.22	245.67	644.74	1167.90
NET INTEREST REVENUE					
NF	286.50	537.93	830.50	2069.28	4365.28
F	33.65	152.03	263.37	448.29	2255.68
DIFFERENCE	252.85	385.90	567.13	1620.99	2109.60
LOAN LOSS PROVISIONS					
NF	21.05	28.96	33.31	116.40	180.17
F	10.16	9.48	30.92	47.94	323.93
DIFFERENCE	10.89	19.48	2.39	68.46	-143.76
LOAN LOSS RESERVES					
NF	25.79	39.03	73.69	174.11	255.97
F	19.38	28.50	62.83	115.11	183.00
DIFFERENCE	6.42	10.53	10.86	59.00	72.97

F denotes failed, NF denotes non-failed banks
Mean values are expressed in Billion TRL

One of the reasons for the differences in means is the differences in the size of the failed and non-failed banks. The size of the failed banks tend to be smaller than the non-failed banks. The difference in the size, in part, accounts for the smaller means of the financial items of the failed banks. However, even the financial statement items were deflated for asset size, the same differences would be observed. The differences are apparent five years prior to failure and increases as we move in time.

The analysis of ratio components has limited explanatory power because, it solely relies on the comparison of the means of the financial statement items. Differences in the means are difficult to interpret without having additional knowledge about ratio the distributions, like the variability of the individual ratios.

3.5. COMPARISON OF DIFFERENT PREDICTION METHODS

First of all, it will be useful to compare the statistical methods and then make an overall comparison including the Beaver's method.

The fundamental assumption that should be satisfied for the linear DA is the multivariate normal distribution and the equality of covariances in the two groups. In this study, this assumption is not satisfied.

To avoid the pitfalls of the conventional linear DA models, logit analysis which requires no distributional assumptions is suggested. Assumptions of the factor-logistic analysis:

1. Variables should be normally distributed
2. Population should be equal or more than three times of the variables

Furthermore, factor-logistic analysis is performed with the important factors that influence the financial condition of a bank. In the factor-logistic analysis, important factors (factor scores) accounting for the variances is used like in the logit analysis.

It is asserted that, even when all assumptions of DA hold, logit is virtually as efficient as DA. In the factor-logistic method, the percentage of the variances explained by the factors changes because of the limitations in the computation and these factors are identified by the computer by itself. To conclude, in most cases logit model is superior to the factor-logistic model and linear DA model.

Beaver's method is an empirical procedure. However, it allows for the investigation of the behavior of individual ratios over time. Table 9 summarizes the results of these four methods by their accuracy in the prediction of failure.

TABLE 9

COMPARISON OF THE ACCURACY OF THE METHODS

METHOD	OVERALL ACCURACY
DISCRIMINANT ANALYSIS	100 %
LOGIT ANALYSIS	90 %
BEAVER'S METHOD	86.18 %
FACTOR-LOGISTIC ANALYSIS	86.07

As can be obtained from Table 9, DA seems to have more predictive power than both the logit and factor-logistic analysis. The reason of this result is that DA method is more appropriate for continuous variables and logit models are more appropriate for categorical variables (i.e. small, medium, large). The variables that are used in this study are continuous. Another reason for this is that the distributional assumptions are not met by the data set.

It is not surprising that, Beaver's method performs as well as the factor-logistic method. The most important reason for this is that the assumptions of the factor-logistic analysis are not met by the data set. Furthermore, the percentages that are explained by the factors changes because of the limitations in the computations.

In the prediction studies it is generally expected that the accuracy of prediction increases when prediction date approaches. It is interesting that there is no relation between the years prior to failure and accuracy of prediction for all methods used in this study. Similarly, there is no relation between the overall accuracy and the accuracy of prediction according to years prior to failure.

In Table 10, important ratios according to the DA and Beaver's Method can be seen. According to the results of the DA, Capital Adequacy and Profitability Level ratios are important for all years. Capital Adequacy and Profitability ratios are also important in Beaver's Method. Liquidity ratios are important in 1,4 and 5 years prior to failure according to DA. In the Beaver's Method, Liquidity ratios are important in 2,3 and 5 years prior to failure. Loan Loss Coverage ratios are important in 3 and 5 prior to failure in DA and they are important in 5 years prior to failure in Beaver's Method. Capital Adequacy and Profitability Level ratios have greater predictive power in both of the methods in all of the years prior to failure. So it can be asserted that Capital Adequacy and Profitability Level ratios are the determinant factors of the failure of the commercial banks in Turkey.

TABLE 10

IMPORTANT RATIOS ACCORDING TO THE METHODS

YEAR	METHOD: DISCRIMINANT ANALYSIS	METHOD: BEAVER'S METHOD
1	LIQUID ASSETS/CUSTOMER SHORT TERM FUNDING EQUITY/TOTAL ASSETS EQUITY/CUSTOMER SHORT TERM FUNDING NET INCOME/EQUITY NET INCOME/TOTAL ASSETS	EQUITY/LOAN LOSS COVERAGE NET INCOME/EQUITY NET INCOME/TOTAL ASSETS NET INTEREST REVENUE/TOTAL ASSETS
2	EQUITY/TOTAL ASSETS EQUITY/LOANS EQUITY/CUSTOMER SHORT TERM FUNDING EQUITY/LIABILITIES NET INCOME/TOTAL ASSETS	EQUITY/CUSTOMER SHORT TERM FUNDING EQUITY/LIABILITIES LIQUID ASSETS/CUSTOMER SHORT TERM FUNDING
3	NET INCOME/EQUITY EQUITY/LOANS EQUITY/CUSTOMER SHORT TERM FUNDING LOAN LOSS PROVISIONS/LOANS	NET INCOME/EQUITY NET INCOME/TOTAL ASSETS NET INTEREST REVENUE/TOTAL ASSETS LIQUID ASSETS/CUSTOMER SHORT TERM FUNDING
4	NET LOANS/CUSTOMER SHORT TERM FUNDING LIQUID ASSETS/CUSTOMER SHORT TERM FUNDING EQUITY/TOTAL ASSETS EQUITY/CUSTOMER SHORT TERM FUNDING NET INCOME/EQUITY NET INCOME/TOTAL ASSETS	EQUITY/LIABILITIES NET INCOME/EQUITY NET INTEREST REVENUE/TOTAL ASSETS
5	NET LOANS/CUSTOMER SHORT TERM FUNDING EQUITY/TOTAL ASSETS EQUITY/CUSTOMER SHORT TERM FUNDING NET INCOME/EQUITY LOAN LOSS PROVISIONS/LOANS LOAN LOSS RESERVES/LOANS	LIQUID ASSETS/CUSTOMER SHORT TERM FUNDING EQUITY/LOANS EQUITY/LIABILITIES NET INCOME/EQUITY NET INTEREST REVENUE/EQUITY NET INTEREST REVENUE/TOTAL ASSETS LOAN LOSS PROVISIONS/LOANS

4. DISCUSSION AND CONCLUSION

In this study, a comparison of the prediction ability of four methods for prediction of bank failure is presented. All of these methods uses financial ratios in order to predict the failure. Among these four methods, Discriminant Analysis have the best predictive power. According to the results of the DA, it is found that Capital Adequacy and Profitability Levels are the major determinants of the failure.

However, it is crucial to mention some of the limitations that affect the results of the four methods.

First, commercial banks are experts in changing their financial statements in the borders of the law. In other words, they are professional "window dressers" For example in the Balance Sheet of the banks, there are Bad Loans in the Total Assets. However, banks always try to hide it and they are very successful about it. Hence, when we investigate the financial statements of the banks, there are a lot of hidden things that we can not realize and we can not see the truth when we analyze the financial statements. Consequently there can be differences between reality and our analysis because of this manipulation.

Macroeconomic conditions in Turkey is another limitation for this study. There is not a stable economic environment, and economic conditions are changing rapidly and unexpectedly. The financial ratios of the banks are changing in a manner that the banks can not control.

In this study, there are state owned commercial banks and private commercial banks. In Turkey, the reason for the existence of the state owned commercial banks is not just profit making. This factor can cause a big difference between the financial statements of the state owned and private owned commercial banks. Moreover, state owned commercial banks are under the protection of the state and these reasons can violate the results of our analysis.

Another shortcoming of this study is the data that is used in this study. The data used in this study is taken from Bankscope which is the software of the rating company Capital Intelligence. Another rating company can use different financial data to rate the banks. So it could be said that the data used in this study is biased because of the subjective opinion of the Capital Intelligence Rating Company.

The findings of this study can be useful to a wide range of people from finance specialists to management students. Even small investors can examine the financial statements of the banks and they can give their decisions according to the findings of this study.

REFERENCES

1. Tam KY (1991), Neural Network Models and the Prediction of Bank Failure. *OMEGA Int. J. of Mgmt Sci., Vol. 19, No. 5, pp.429-445.*

2. Altman EI (1994), Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (The Italian Experience). *Journal of Banking and Finance 18, pp. 505-529.*

3. Oral M, Kettani O, Cosset JC, Daaouas M (1992), An Estimation Model for Country Risk Rating. *International Journal of Forecasting 8, pp. 583-593.*

4. Tam KY, MY (1992), Managerial Applications of Neural Networks: The Case of Bank Failure Predictions. *Management Science, Vol 38, No.7, pp.926-947.*

5. Platt HD, Platt MB (1991), A Note on the Use of Industry-Relative Ratios in Failure Prediction. *Journal of Banking and Finance 15, pp. 1183-1194.*

6. Casey C, Bartczak N (1982), Operating Cash Flow and The Prediction of Failure: An Empirical Study.

7. Beaver W (1968), Alternative Accounting Measures As Predictors of Failure. *The Accounting Review, January 1968, pp. 113-122.*

8. Altman EL (1968), Financial Ratios, Discriminant Analysis and The Prediction of Bankruptcy. *Journal of Finance 23 (3), pp. 559-609.*

9. Fischer RAE, The Use of Multiple Measurements In Taxonomic Problems. *Ann. Eugenics 7, pp. 179-188.*

10. Deakin BE (1976), Distributions of Financial Accounting Ratios: Some Empirical Evidence. *Accounting Review (January), pp. 90-96.*

11. Altman EL, Avery R, Eisenbeis RAE and Sinkey J (1981), Applications of Classification Techniques in Business, Banking and Finance. *JAI Press, CT.*

12. Lachenbrauch PA, Sneering C and Revo L (1973), Robustness of the Linear and Quadratic Discriminant Function to certain type of Normality. *Commun. Statist. 1 (1), pp. 39-56.*

13. McFadden D (1976), A Comment on Discriminant Analysis versus Logit Analysis. *Ann. Econ. Social Measurement, pp. 511-523.*

14. Martin D (1977), Early Warning of Bank Failure, A Logit Regression Approach. *J. Banking and Finance 1 (3), 249-276.*

15. Press SJ and Wilson S (1978), Choosing Between Logistic Regression and Discriminant Analysis. *J. Am. Statist. Assoc. 73, pp. 699-705.*

16. Harell FE and Lee KL (1985), A Comparison of The Discrimination of Discriminant Analysis of Logistic Regression Under Multivariate Normality. *In Biostatistics: Statistics in Biomedical, Public Health and Environmental Sciences (Edited by Sen PK), North Holland, Amsterdam.*

17. West RG (1985), A Factor-Analytic Approach To Bank Condition. *J. Banking and Finance 9 (2), pp. 253-266).*

18. Messier WF and Hansen J (1988), Inducing Rules For Expert System Development: An Example Using Default and Bankruptcy Data. *Mgmt. Sci. 34 (12), pp. 1403-1415.*

19. Frydman H, Altman EL and Kao D (1985), Introducing Recursive Partioning For Financial Classification: The Case of Financial Distress. *J. Fin. 40 (1), pp.269-291.*

20. Aruoba C , Alpar C, Ocal T (1992), Turkiye Ekonomisi " Sektorel Gelismeler ". *Turkiye Ekonomi Kurumu 1992, pp.143-166.*

APPENDIX A - TABLES

TABLE A1

RESULTS OF KOLMOGOROV-SMIRNOV TESTS

	RATIOS												
	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13
BEFORE NATURAL LOGARITHM TRANSFORMATION	0.1181	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0352	0.0002	0.0122	0.0003	0.0000	0.0003
AFTER NATURAL LOGARITHM TRANSFORMATION	0.0008	0.0094	0.0132	0.0227	0.0320	0.0026	0.1205	0.0324	0.5006	0.0474	0.0248	0.0436	0.0691

TABLE A2
DISCRIMINANT ANALYSIS - 1 YEAR BEFORE FAILURE

VARIABLES	MEAN		UNIVARIATE F-RATIO	STANDARDIZED DISCRIMINANT COEFFICIENTS
	NON-FAILED	FAILED		
NET LOANS/TOTAL ASSETS	39.51	38.78	0.0310	-2.07763
NET LOANS/CUSTOMER & SHORT TERM FUNDING	50.56	60.07	3.5185	-2.94406
LIQUID ASSETS/CUSTOMER & SHORT TERM FUNDING	59.15	73.32	3.4100	6.51111
EQUITY/TOTAL ASSETS	11.57	20.42	10.1319 **	4.37874
EQUITY/LOANS	33.71	76.91	19.0250 **	1.98527
EQUITY/CUSTOMER & SHORT TERM FUNDING	16.61	45.43	22.7287 **	-5.35010
EQUITY/LIABILITES	15.53	8.28	12.4448 **	0.02113
NET INCOME/EQUITY	42.38	18.89	9.0318 **	6.40643
NET INCOME/TOTAL ASSETS	4.91	8.67	3.2560	-5.34852
NET INTEREST REVENUE/TOTAL ASSETS	13.92	18.73	2.0564	-1.59128
LOAN LOSS PROVISIONS/LOANS	1.89	3.58	8.3755 **	-2.74195
EQUITY/LOAN LOSS PROVISIONS	43.00	14.48	2.3911	-0.87040
LOAN LOSS RESERVES/LOANS	2.33	3.44	3.3959	1.68098

** SIGNIFICANT AT 1%
* SIGNIFICANT AT 5%

TABLE A3
DISCRIMINANT ANALYSIS - 2 YEARS BEFORE FAILURE

VARIABLES	MEAN NON-FAILED	MEAN FAILED	UNIVARIATE F-RATIO	STANDARDIZED DISCRIMINANT COEFFICIENTS
NET LOANS/TOTAL ASSETS	48.23	43.04	0.8739	-1.13684
NET LOANS/CUSTOMER & SHORT TERM FUNDING	61.39	94.09	1.7888	2.11750
LIQUID ASSETS/CUSTOMER & SHORT TERM FUNDING	54.08	106.36	1.5029	-1.75585
EQUITY/TOTAL ASSETS	10.38	21.83	4.4064 *	-1.67368
EQUITY/LOANS	23.79	207.31	3.0494	2.45319
EQUITY/CUSTOMER & SHORT TERM FUNDING	13.77	24.54	4.5960 *	1.10359
EQUITY/LIABILITES	11.28	20.93	9.8337 **	1.02778
NET INCOME/EQUITY	54.77	32.99	6.0916 *	-0.70754
NET INCOME/TOTAL ASSETS	6.05	2.64	4.9774 *	-1.66840
NET INTEREST REVENUE/TOTAL ASSETS	15.00	13.08	0.4241	1.03213
LOAN LOSS PROVISIONS/LOANS	1.34	2.77	2.2784	0.78121
EQUITY/LOAN LOSS PROVISIONS	54.68	32.65	0.8235	-0.48981
LOAN LOSS RESERVES/LOANS	1.42	2.47	2.5213	0.55022

** SIGNIFICANT AT 1%
* SIGNIFICANT AT 5%

TABLE A 4

DISCRIMINANT ANALYSIS - 3 YEARS BEFORE FAILURE

VARIABLES	MEAN		UNIVARIATE F-RATIO	STANDARDIZED DISCRIMINANT COEFFICIENTS
	NON-FAILED	FAILED		
NET LOANS/TOTAL ASSETS	47.46	44.49	0.4777	-0.86505
NET LOANS/CUSTOMER & SHORT TERM FUNDING	62.09	78.72	1.2940	2.24978
LIQUID ASSETS/CUSTOMER & SHORT TERM FUNDING	59.37	71.59	0.8789	-1.69216
EQUITY/TOTAL ASSETS	12.11	17.85	1.3943	-1.36868
EQUITY/LOANS	28.24	40.35	1.2868	2.78076
EQUITY/CUSTOMER & SHORT TERM FUNDING	17.46	54.04	2.0965	-1.44032
EQUITY/LIABILITES	12.69	13.63	0.5300	0.92308
NET INCOME/EQUITY	34.30	14.55	17.1152 **	-2.60782
NET INCOME/TOTAL ASSETS	3.49	0.99	13.2817 **	0.58808
NET INTEREST REVENUE/TOTAL ASSETS	11.98	8.09	5.5187 *	-0.26021
LOAN LOSS PROVISIONS/LOANS	1.15	2.27	6.9128 *	2.24385
EQUITY/LOAN LOSS PROVISIONS	381.20	41.37	2.1986	-0.60349
LOAN LOSS RESERVES/LOANS	2.33	1.39	0.6022	0.78628

** SIGNIFICANT AT 1%
* SIGNIFICANT AT 5%

TABLE A5

DISCRIMINANT ANALYSIS - 4 YEARS BEFORE FAILURE

VARIABLES	MEAN		UNIVARIATE F-RATIO	STANDARDIZED DISCRIMINANT COEFFICIENTS
	NON-FAILED	FAILED		
NET LOANS/TOTAL ASSETS	46.40	50.58	2.3074	3.07993
NET LOANS/CUSTOMER & SHORT TERM FUNDING	61.40	87.24	7.6098 *	2.11133
LIQUID ASSETS/CUSTOMER & SHORT TERM FUNDING	55.84	45.64	9.3454 **	-2.32153
EQUITY/TOTAL ASSETS	9.61	18.33	6.7574 *	-12.63549
EQUITY/LOANS	22.15	35.28	5.0149 *	0.28962
EQUITY/CUSTOMER & SHORT TERM FUNDING	12.89	44.02	7.1088 *	11.11393
EQUITY/LIABILITES	10.77	11.56	0.4232	1.14755
NET INCOME/EQUITY	44.27	14.81	28.5301 **	-4.45447
NET INCOME/TOTAL ASSETS	4.30	2.28	8.0655 **	2.43866
NET INTEREST REVENUE/TOTAL ASSETS	10.69	8.81	3.2965	1.88130
LOAN LOSS PROVISIONS/LOANS	1.45	1.79	0.2562	-2.43528
EQUITY/LOAN LOSS PROVISIONS	64.66	14.78	1.0613	-2.83807
LOAN LOSS RESERVES/LOANS	2.29	2.88	0.9273	2.94972

** SIGNIFICANT AT 1%
* SIGNIFICANT AT 5%

TABLE A6

DISCRIMINANT ANALYSIS - 5 YEARS BEFORE FAILURE

VARIABLES	MEAN		UNIVARIATE F-RATIO	STANDARDIZED DISCRIMINANT COEFFICIENTS
	NON-FAILED	FAILED		
NET LOANS/TOTAL ASSETS	47.98	45.91	0.4533	0.82463
NET LOANS/CUSTOMER & SHORT TERM FUNDING	63.35	74.04	1.9034	-3.54492
LIQUID ASSETS/CUSTOMER & SHORT TERM FUNDING	57.71	52.14	0.0224	0.75121
EQUITY/TOTAL ASSETS	10.06	17.79	8.0700 **	-3.39189
EQUITY/LOANS	21.78	39.26	13.5081 **	1.48799
EQUITY/CUSTOMER & SHORT TERM FUNDING	13.52	35.39	7.1555 *	11.86657
EQUITY/LIABILITES	11.47	13.67	4.1584	-2.22878
NET INCOME/EQUITY	40.48	2.96	144.8677 **	7.82774
NET INCOME/TOTAL ASSETS	6.49	0.83	4.8901 *	0.00000
NET INTEREST REVENUE/TOTAL ASSETS	8.96	3.46	45.3732 **	0.00000
LOAN LOSS PROVISIONS/LOANS	1.66	3.42	3.9861	-12.95730
EQUITY/LOAN LOSS PROVISIONS	25.47	37.63	1.3216	-3.34280
LOAN LOSS RESERVES/LOANS	2.21	6.38	27.3123 **	4.73240

** SIGNIFICANT AT 1%
* SIGNIFICANT AT 5%

APPENDIX B - List of the Commercial Banks Used in this Study

I. STATE OWNED COMMERCIAL BANKS

1. Denizcilik Bankası
2. Etibank
3. T.C. Ziraat Bankası
4. T. Emlak Bankası
5. Sümerbank
6. T. Halk Bankası
7. T. Öğretmenler Bankası
8. T. Vakıflar Bankası

II. PRIVATE COMMERCIAL BANKS

9. Adabank
10. Çaybank A.Ş.
11. Akbank
12. Demirbank
13. Egebank
14. Eskişehir Bankası
15. Finansbank
16. İktisat Bankası
17. İnterbank A.Ş.
18. Koç Amerikan Bankası
19. Milli Aydın Bankası
20. Netbank
21. Pamukbank
22. Şekerbank
23. Tekstil Bankası

24. Türk Dış Ticaret Bankası
25. Türk Ekonomi Bankası
26. Türk Ticaret Bankası
27. T. Garanti Bankası
28. T. İmar Bankası
29. T. İş Bankası
30. T. İthalat ve İhracat Bankası
31. T. Turizm Yatırım ve Dış Ticaret Bankası
32. T. Tütüncüler Bankası
33. Yapı ve Kredi Bankası
34. Arap-Türk Bankası
35. Bnp. Ak. Dresdner Bank
36. Birleşik Türk Körfez Bankası
37. Midland Bank A.Ş.
38. Osmanlı Bankası
39. The First National Bank of Bos. A.Ş.
40. Türk Mitsui Bank
41. Bank Mellat
42. Bank of Bahrain and Kuwait
43. Bank of Credit and Commerce
44. Bank di Roma
45. Banque Indosuez
46. Citibank
47. Credit Lyonnais
48. Habib Bank Limited
49. Holantse Bank Uni. N.V.
50. Kıbrıs Kredi Bankası Limited
51. Manufakturers Hanover Bank
52. Saudi Amerikan Bank
53. Socviete Generale
54. The Chase Manhattan Bank
55. Türk Bankası Limited

56. Westdeutsche Landesbank

APPENDIX C

CAPITAL INTELLIGENCE RATINGS

CI Ratings summarise the probability that a bank will require external assistance to overcome adversities, not the likelihood that specific obligations will be repaid in a timely manner. Nevertheless, the ratings address the overall capacity for timely repayment. The ratings exclude, to the extent possible, the impact of transfer risk - the risk that the host country may be unable or unwilling to service its foreign currency obligations.

LONG TERM RATINGS:

AAA	Financially in extremely strong condition with satisfactory trends; other factors also support this as an unquestioned obligor.
AA	Not quite as strong as the highest rating. However, such a bank would be unlikely to have repayment problems over the long term and is unquestioned over the short and medium terms.
A	A strong bank and no cause for concern; any weaknesses in financial condition or trends are compensated by favourable non-financial considerations.
BBB	Basically sound overall; slight weaknesses in financial or other factors could be remedied fairly easily.
BB	One or two significant weaknesses in the bank's financial makeup could cause problems over the medium term. Other supporting factors may not be sufficient to avoid some degree of temporary external support being required in the face of any extraordinary adversities which may occur.
B	Fundamental weaknesses are present either in the bank's financial condition or trends, and other factors are unlikely to provide strong protection from unexpected adversities.
CCC	In a weak condition, either with immediate problems or with limited capacity to withstand adversities. However, this is still bankable obligor, although creditors should take into consideration the quality of their relationship with the bank.
DDD	Falls below usually acceptable standards and may be in an untenable position.

Capital Intelligence appends a "+" to the long term rating where an institution merits a rating higher than similarly rated peers.

SHORT TERM RATINGS:

A-1	Unquestioned capacity for timely repayment that is not likely to be affected by unexpected adversities. Banks with overwhelming strengths have a "+" appended to this rating.
A-2	Very strong capacity for timely repayment but may be affected slightly by unexpected adversities.
A-3	Strong capacity for timely repayment that may be affected by unexpected adversities.
B	Adequate capacity for timely repayment that could be seriously affected by unexpected adversities.
C	Inadequate capacity for timely repayment if unexpected adversities are encountered in the short term.
D	May be in an untenable position and is likely to default if it does not receive immediate external support.