*Topics in Middle Eastern and African Economies*
*Vol. 14, September 2012*

# EFFECTS OF STRUCTURAL CHANGES IN THE TURKISH BANKING SECTOR SINCE 2001 CRISIS AND A RISK ANALYSIS FOR THE SECTOR

**Kenan LOPCU**
Department of Econometrics
Çukurova University
Adana-Turkey
klopcu@cu.edu.tr

**Süleyman Bilgin KILIÇ**
Department of Econometrics
Çukurova University
Adana-Turkey
sbilgin@cu.edu.tr

Prepared for presentation at the 10th Annual
International Meeting of the MEEA
June 23-24, 2011, Barcelona, Spain

## Abstract

The objective of this paper is to measure the failure risk of Turkish commercial banks. We use 29 financial ratios across 1996-2000 and apply principal component analysis to determine significant changes in the financial conditions of banks. We then employ these financial conditions, captured in factor scores, in the logit analysis to build an early warning model. Finally, we predict the probabilities of failure for 25 commercial banks from 2002-to date. The results overall indicate that almost all 25 banks currently operating in the Turkish banking sector are quite sound and far from failure.

*JEL Classification*: G33; C25; C52; C58; G21

*Keywords:* Bank Failures, Principal Component Analysis, Logit Model

## 1. Introduction

Bank failures bring to bear high costs on economies as well as on governments and eventually on the public and the taxpayers. During the past two decades, many developed and developing economies have experienced large scale bank failures, and estimates for average bank restructuring costs range from 6% to 10% of the Gross Domestic Product (GDP) (Hutchison and McDill, 1999). In Turkey the amount of restructuring is approximately 30% of the GDP (Kılıç, 2003). Obviously, if bank failure were a predictable event, bank restructuring costs could be minimized. Additionally, if early warning systems are used effectively, the regulatory actions necessary to prevent banks from failing could be taken in advance or in the least a more orderly process of bank closures could be administered.

Early bank failure studies employed multivariate statistical analyses, including regression analysis. For example, Meyer and Pifer (1970), and Rose and Kolari (1985) used discriminant models; Sinkey (1975) used logit models; Cole and Gunther (1998), and Pantolone and Platt (1987) used probit models.

In terms of American industrial firms, Zavgren (1985) applied Shannon's (1949) entropy measure and found that the information content of the logit model is significant even five years prior to failure, and increases up to one year immediately prior to failure. Keasey and McGuinness (1990) tested to determine if the entropy measure of the information contained in logit functions as developed by Zavgren (1985) offered comparable results when used for UK industrial firms. In that study, they concluded that the measurement was not applicable to UK industrial firms.

Some studies combine nonparametric approaches with parametric multivariate statistical methods including discriminant or logit analysis for bank failure prediction. For example, Tam and Kiang (1992) introduce the neural network approach to perform discriminant analysis as a promising method of evaluating banking conditions. Jo and Han (1996) suggest an integrated model approach for bankruptcy prediction using discriminant analysis and two artificial intelligence models, namely, neural network and case-based forecasting. They conclude that integrated models have higher prediction accuracy than individual models. Alam, Booth and Thordarson (2000) state that a fuzzy clustering algorithm and self-organizing neural networks provide valuable information to identify potentially failing banks. Kolari et al. (2002) use both parametric logit analysis and the nonparametric trait approach to develop computer-based early warning systems to identify large bank failures. They conclude that the system provides valuable information about the future viability of large banks. Lam and Moy (2002) combine several discriminant methods and perform simulation analysis to enhance the accuracy of results for classification problems in discriminant analysis.

Kılıç (2003), and Canbaş, Çabuk and Kılıç (2005) combined Principal Component analysis (PCA) with discriminant, logit and probit models to develop an Integrated Early Warning System for predicting bank failures in the Turkish banking sector one year prior to the failure. More recently, Shin and Kılıç (2006) used a PCA-based neural network committee model for early warning of bank failure. Additionally, Shin, Lee, and Kılıç (2006) used ensemble prediction of bank failure through diversification of input features.

In the current study, as a follow-up to the study by Canbaş, Çabuk and Kılıç (2005), an expanded data set of commercial banks are pooled and the principal component analysis and the logit analysis are combined to estimate the probabilities of banks to fail. In particular, we attempt to build a model to predict bank failures one year in advance of the failure. In particular, representing the banks by a dummy dependent variable, $y_{bt}$, we assign the value of 1 in year *t-1* and *t* for the banks that have failed in year *t*. We then exclude those banks from the analysis after the year failure has been announced. Next, using the PCA, the ratios of banks are grouped under financial factors, which can significantly explain the changes in financial conditions of banks before failure. Factor scores are estimated for each bank, and these scores are then used as independent variables in estimating the logit model and failure probabilities.

Bank failures can be considered as a continuous process in time, although failure is recorded at a specific point in time. We maintain that failure is mainly due to continuously worsening financial conditions attributable to a bank's misguided internal management policies over a number of years. Financial ratios provide valuable quantitative information about changes in financial conditions of banks. Decision makers should examine banks over time to capture information about the progress towards failure.

The major contribution of this study to the literature is the use of information provided by the financial factors in estimating a model. As explained in more detail in section 2.2, the use of uncorrelated financial factors provides more refined and enhanced information to the decision makers than the direct use of financial ratios.

The rest of this article is organized as follows: Section 2 reports the methodology and results, including the sample and variable selection; the determination of significant financial factors; and the estimation and interpretation of the results from the logit model. Then, Section 3 concludes the article. Finally Section 4 provides a brief summary of the early warning system developed in this paper.

## 2. Data Methodology and Results

### *2.1. Data, sample and variable selection*

The sample set covers all commercial banks in the Turkish banking sector for the period of 1996-2009 (Tables 6 and 9)[1], including 22 banks that failed between 1997 and 2003. In 1999 and 2000 the Banks Association of Turkey (BAT) published 49 financial ratios annually for each bank operating in the Turkish banking sector. Data started in 1988 and included ratios for banks whose failures had been announced and whose operations had been transferred to the Savings Deposits Insurance Fund (SDIF).[2, 3] While the data started in 1988, many of the ratios for a number of banks were missing for the initial years and became more regular after 1996, although a few banks still were missing a few ratios.[4]

Starting with 2002 the BAT began to publish 66 annual ratios for each bank.[5] The ratios published before and after 2001 are inconsistent in term of the banks operating in the industry and the ratios published for each bank. However, 29 ratios are compatible in the data published prior to 2001 and after 2001 (Table 1). Thus, our data set includes 29 common annual ratios covering the period 1996 to 2009, with the exception of 2001.[6] All the branch and activity ratios in current TL are converted to 2005 TL using the revaluation index according to the tax procedure laws.[7] None of these ratios turns out to be significant in the ANOVA, except net income per branch (R26). Using the CPI and the PPI from the OECD database for Turkey produces similar conversion rates for these ratios.

[1] The number of banks in the sector changes from year to year because of mergers, buyouts and failures. The maximum number included in the analysis is 46 for 1997. As of 2011 25 commercial banks operate in the Turkish banking sector.

[2] The SDIF was managed by the Turkish Central Bank during the 1983-2000 period, but was transferred to the Banking Regulation and Supervising Agency (BRSA) on August 31, 2000.

[3] In Turkey, the BRSA is a legal entity with administrative and financial autonomy which is responsible for ensuring application of the Banks Act No 4389 issued July 1999. It is charged with laying down rules governing incorporation, management, operations, acquisition, merger, liquidation and supervision of banks in order to protect the rights and interests of depositors, and ensuring an efficient functioning of the credit system by giving due consideration to the confidence and stability of financial markets and the requirements of economic development.

[4] Missing ratios for the year 1996 and after are calculated by the authors using the averages of nearby years and sector and group shares.

[5] The former 49 and the 66 ratios in effect can be found at the BAT web address: http://www.tbb.org.tr/eng/Banka_ve_Sektor_Bilgileri/Istatistiki_Raporlar.aspx

[6] Ratios were not published by BAT for 2001. 2001 was the year of financial and economic crises in Turkey. Starting on February 21, 2001, the Turkish lira lost it value sharply, interest rates sky-rocketed, and inflation began to soar. The Turkish GDP was reduced significantly in the same year. After the 2001 crisis, as part of a larger economic reform package the banking sector was reorganized. Of the 22 failed banks included in our data set, 14 failed during the period between October 2000 and July 2003 (Table 6).

[7] The revaluation index used can be found at the web address: http://www.ivdb.gov.tr/pratik/oranlar/kirk.htm

**Table 1: Ratios**

| Code | Ratio Categories and Names | Code | Ratio Categories and Names |
|---|---|---|---|
| | **Assets Quality, %** | | **Share in Group, %** |
| ***R1*** | Total Loans/Total Assets | ***R17*** | Total Assets |
| ***R2*** | Non Performing Loans/Total Loans | ***R18*** | Total Loans |
| ***R3*** | Permanent Assets/Total Assets | ***R19*** | Total Deposits |
| | **Liquidity, %** | | **Branch Ratios, Million TRY** |
| ***R4*** | Liquid Assets/Total Assets | ***R20*** | Total Assets / No. of Branches |
| ***R5*** | Liquid Assets/(Deposits + Non-deposit Funds) | ***R21*** | Total Deposits / No. of Branches |
| ***R6*** | Fx Liquid Assets/Fx Liabilities | ***R22*** | TL Deposits / No. of Branches |
| | **Profitability, %** | ***R23*** | Fx Deposits / No. of Branches |
| ***R7*** | Net Income(Loss)/Average T.Assets | ***R24*** | No. of Personnel / No. of Branches |
| ***R8*** | Net Income(Loss)/Shareholder's Equity | ***R25*** | Total Loans / No. of Branches |
| ***R9*** | Income Before Tax / Average Total Assets | ***R26*** | Net Income / No. of Branches |
| | **Income-Expenditure Structure, %** | | **Activity Ratios** |
| ***R10*** | Interest Income/Total Expense | ***R27*** | (Salary and Emp'ee Bene.+Res. for Retire.)/No.of Pers.(Billion TL) |
| ***R11*** | Interest Income/Interest Expenses | ***R28*** | Reserve for Seniority Pay/No.of Personnel (Billion TL) |
| ***R12*** | Non-Interest Income/Non-Interest Expenses | ***R29*** | (Salaries and Emp'ee Benefits+Reserve for Retirement)/T.Assets |
| ***R13*** | Total Income/Total Expenditure | | |
| | **Share in Sector, %** | | |
| ***R14*** | Total Assets | | |
| ***R15*** | Total Loans | | |
| ***R16*** | Total Deposits | | |

*TL: Turkish Lira, FX: Foreign Exchange*

We partitioned the data set into two sub-samples; one is the model sample covering the period 1996-2000, and the other is the test (holdout) sample covering the period of 2002-2009. We use the model sample to estimate the model. Then, using the estimated model we predict the failure risk of the banks for the holdout sample.

Using the uni-variate analysis of variance (ANOVA), we determine the most relevant financial ratios for bank failures. The null hypothesis in ANOVA is the equality of the means of the failed and non-failed banks for a given ratio. Table 2 presents the results of the ANOVA tests, including the F statistics and the corresponding significance levels for the selected ratios for each year. The table reveals that a total of 18 out of 29 ratios emerge as statistically significant. We select the ratios that are significant at the 5% level. These are the relevant financial ratios that have a high discriminating ability for the two groups, failed versus non-failed banks.

**Table 2: Tests of Equality of Group Means**

| | Non-failed | | Failed | | Total | | Test of group means' equality | | |
|---|---|---|---|---|---|---|---|---|---|
| Code | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Wilks' Lambda | F(1,215) | Sig. |
| R1 | 34.1036 | 14.6621 | 30.3384 | 13.8037 | 33.5657 | 14.5716 | 0.9918 | 1.7805 | 0.1835 |
| R2 | 5.7667 | 23.1804 | 160.2178 | 364.2305 | 27.8311 | 147.7170 | 0.8655 | 33.4078 | 0.0000** |
| R3 | 8.8675 | 9.3281 | 16.4104 | 13.2735 | 9.9451 | 10.2954 | 0.9340 | 15.2003 | 0.0001** |
| R4 | 44.5053 | 17.9357 | 33.7179 | 16.5820 | 42.9643 | 18.1115 | 0.9564 | 9.8110 | 0.0020** |
| R5 | 56.8031 | 28.9613 | 32.6135 | 17.9779 | 53.3474 | 28.9007 | 0.9138 | 20.2758 | 0.0000** |
| R6 | 45.4642 | 21.3907 | 25.9413 | 16.4373 | 42.6753 | 21.8244 | 0.9016 | 23.4751 | 0.0000** |
| R7 | 3.4737 | 4.1249 | -31.8493 | 44.9519 | -1.5724 | 21.1828 | 0.6579 | 111.7805 | 0.0000** |
| R8 | 40.3776 | 135.7328 | -464.7252 | 2512.2586 | -31.7799 | 961.1210 | 0.9660 | 7.5616 | 0.0065** |
| R9 | 4.7863 | 5.1964 | -31.5578 | 45.1532 | -0.4058 | 21.6515 | 0.6534 | 114.0583 | 0.0000** |
| R10 | 100.6046 | 21.2771 | 60.4223 | 265.4029 | 94.8643 | 101.8308 | 0.9808 | 4.1986 | 0.0417* |
| R11 | 239.4059 | 345.0996 | 116.3624 | 62.6488 | 221.8283 | 323.1240 | 0.9822 | 3.9048 | 0.0494* |
| R12 | -0.3365 | 123.0795 | -47.3023 | 114.7195 | -7.0459 | 122.7749 | 0.9820 | 3.9412 | 0.0484* |
| R13 | 131.9842 | 37.1055 | 68.0839 | 53.0882 | 122.8556 | 45.5298 | 0.7577 | 68.7581 | 0.0000** |
| R14 | 2.2697 | 3.3797 | 0.9579 | 0.7894 | 2.0823 | 3.1751 | 0.9790 | 4.6115 | 0.0329* |
| R15 | 2.2337 | 3.3960 | 0.8852 | 0.8878 | 2.0410 | 3.1954 | 0.9781 | 4.8152 | 0.0293* |
| R16 | 2.3573 | 3.8761 | 1.3202 | 0.9174 | 2.2092 | 3.6217 | 0.9899 | 2.1909 | 0.1403 |
| R17 | 6.5566 | 10.2492 | 11.3657 | 16.4547 | 7.2436 | 11.4202 | 0.9782 | 4.7948 | 0.0296* |
| R18 | 6.8147 | 11.4505 | 16.0254 | 29.7893 | 8.1306 | 15.6838 | 0.9576 | 9.5259 | 0.0023** |
| R19 | 6.8158 | 11.5265 | 10.6503 | 13.4050 | 7.3636 | 11.8557 | 0.9871 | 2.8028 | 0.0956 |
| R20 | 110.8392 | 257.9485 | 50.4794 | 38.1760 | 102.2164 | 240.0805 | 0.9922 | 1.6849 | 0.1957 |
| R21 | 62.8361 | 169.3690 | 47.1761 | 35.9900 | 60.5990 | 157.4134 | 0.9988 | 0.2621 | 0.6092 |
| R22 | 20.6444 | 56.9123 | 23.8176 | 25.7226 | 21.0977 | 53.5470 | 0.9996 | 0.0929 | 0.7608 |
| R23 | 42.1918 | 117.3095 | 23.3586 | 14.6471 | 39.5013 | 108.9032 | 0.9963 | 0.7939 | 0.3739 |
| R24 | 36.1951 | 98.7178 | 22.4984 | 7.6157 | 34.2384 | 91.5299 | 0.9972 | 0.5939 | 0.4418 |
| R25 | 35.8399 | 91.8582 | 12.9239 | 8.8547 | 32.5662 | 85.4542 | 0.9912 | 1.9190 | 0.1674 |
| R26 | 4.2098 | 14.8976 | -15.9328 | 23.0329 | 1.3323 | 17.7110 | 0.8409 | 40.6825 | 0.0000** |
| R27 | 53.1214 | 25.9585 | 56.7137 | 12.9024 | 53.6346 | 24.5325 | 0.9974 | 0.5686 | 0.4516 |
| R28 | 1.3451 | 1.8359 | 1.3076 | 1.4451 | 1.3397 | 1.7824 | 0.9999 | 0.0117 | 0.9140 |
| R29 | 2.5742 | 2.0631 | 3.4525 | 2.3327 | 2.6997 | 2.1204 | 0.9789 | 4.6354 | 0.0324* |
| ** and ** represent %5 and %1 significance level, respectively* | | | | | | | | | |

*2.2. Principal components analysis and determination of the significant financial factors*

The use of PCA and financial factors in estimating a model provides more refined and enhanced information to decision makers compared to the direct use of financial ratios for several reasons. Firstly, PCA allows conversion of a large number of closely related financial ratios into a small number of financial factors and thus helping researchers understand underlying relationships better. Secondly, financial factors permit to explain the percentage of change in the total variance of the financial condition of banks over time.

Furthermore, using financial ratios directly in estimating logistic or other similar models would be problematic because most of the financial ratios are correlated with each other. This leads to a multicollinearity problem among independent variables (ratios). For example, Kılıç (2003) showed that most of the financial ratios in the Turkish banking system are highly correlated. This is an important consideration because a high degree of multicollinearity produces large variation in the estimated coefficients of the ratios. Particularly, the coefficients can change substantially depending on which variables are in or out of the model and also the order in which they are placed in the model. In summary, PCA converts a set of closely related (correlated) financial ratios into uncorrelated financial factors. The lack of giving adequate consideration to these issues is an important shortcoming of traditional bankruptcy studies conducted previously.

Applying PCA, we estimate 6 financial factors that could significantly explain the changes in the financial condition of the banks for the period considered (1996-2000). We estimate the total variance explained by each factor (eigenvalues) in order to determine how many factors are needed to represent the selected financial ratios. Table 3 presents the estimated factors and corresponding eigenvalues of the estimated factors. Only those factors that have variances greater than 1 (eigenvalue >1) are selected. Factors with a variance less than 1 are not any better than a single ratio since each standardized ratio has a variance of 1.

**Table 3: Total variance explained by the selected factors**

| | Variance Explained | | |
|---|---|---|---|
| **Component** | **Eigenvalue** | **% of Variance** | **Cumulative %** |
| ***F1*** | 4.55 | 25.27 | 25.27 |
| ***F2*** | 3.53 | 19.62 | 44.89 |
| ***F3*** | 1.78 | 9.90 | 54.79 |
| ***F4*** | 1.37 | 7.59 | 62.39 |
| ***F5*** | 1.16 | 6.46 | 68.85 |
| ***F6*** | 1.02 | 5.69 | 74.54 |

For the period 1996-2000, F1 is the most important factor in explaining changes in the financial conditions of the banks. It explains 25.27 % of the total variance of the statistically significant financial ratios, whereas factor F2 explains 19.62 % of the total variance. The 6 common factors together explain 74.54 % of the total changes in the financial conditions of the commercial banks for the period considered.

After the determination of the significant factors, we calculate the regression factor scores estimated for each bank and each year. We, then, use these factor scores as independent variables in estimating the logit model and the probabilities of failure.

*2.3. Estimation of the logit model*

The basic assumption in the estimation of the logit model is that banks can be split into two groups, namely, the non-failed group and the failed group. Thus, banks can be represented by a dummy dependent variable $y_{bt}$ . This variable takes the value of *1* in year *t-1* and *t* if the bank *b* has failed in year *t* and 0 otherwise. The logit analysis is based on a cumulative logistic distribution function providing the probability of a bank belonging to one of the prescribed classes given the financial characteristics of the bank.

As mentioned earlier, the factor regression scores obtained from the PCA serve as independent variables in estimating the logit model. We employ the backward Wald method in estimating the logit model. This is a stepwise method which eliminates variables from the model based on the probabilities of the Wald statistic, providing the most parsimonious model. Hence, among the 6 factors that were previously determined, and the constant, $\alpha$, the backward Wald stepwise method selects only factors F1, F3, F4 and F5 as independent variables.

**Table 4: Estimated logit model**

| Factors | $\hat{\beta}$ | Exp ( $\hat{\beta}$ ) | S.E. | Wald | P-Value |
|---|---|---|---|---|---|
| ***F1*** | -3.915 | 0.020 | 0.900 | 18.937 | 0.000 |
| ***F3*** | -1.498 | 0.224 | 0.458 | 10.701 | 0.001 |
| ***F4*** | -1.632 | 0.195 | 0.697 | 5.486 | 0.019 |
| ***F5*** | -0.561 | 0.571 | 0.264 | 4.514 | 0.034 |
| ***Constant*** | -2.630 | 0.072 | 0.405 | 42.160 | 0.000 |

**Model summary**

| -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|
| 89.276 | 0.336 | 0.600 |

Table 4 presents the test statistics for the estimated coefficients of the logit model. Here, all of the coefficients of the estimated logit model are now statistically significant. Thus, the cumulative logistic distribution function used in calculating the failure probabilities for each bank, *b*, in year *t* is given by

$$p(y_{bt}=1)=\frac{1}{1+e^{-(-2.63-3.915F1_{bt}-1.498F3_{bt}-1.632F4_{bt}-0.561F5_{bt})}}$$

The lower panel of Table 4 presents the overall test statistics for the estimated logit model. The likelihood ratio test is statistically significant at the 1% level; Cox & Snell R Square is 33.6 %; and Nagelkerke R Square is 60 %. Given the limitations in data, such as starting with a limited number of ratios and not being able to include 2001 in the analysis when 9 of the failures were announced, we interpret these results as the model having a reasonably high explanatory power.

The performance of the estimated logit model can also be evaluated according to the classification achievements. Considering the cutoff point as 0.500, our null hypothesis is that a bank will fail, and the alternative hypothesis is that it will not fail. The summary of the classification results are presented in Table 5. Here, overall classification accuracy is very high (92.63%). Type I error (the probability of rejecting the null hypothesis when it is correct) is 41.94 % (13/31). We must note that the failures of 7 of these banks are correctly predicted by the model for the year of failure but not one year prior to the failure.[8] For 4 of these banks the year of failure is not included in the analysis as they failed in 2001, the year for which data were not available.[9] Type II error (the probability of accepting the null hypothesis when it is not correct) is 1.64 % (3/186), noting that two of these banks eventually failed (Bank Express and Milli Aydın Bankası). Here, a type I error means that an actually failed bank is classified as non-failed, while a type II error means that an actually non-failed bank is classified as failed by the estimated model. A type I error is more important than a type II error because, as stated previously, the international average for bank failure costs was estimated to be 6 to 10% of GDP, prior to the recent global turmoil in the financial markets. If a bank failure is predicted in advance, the cost of the failure can at least be minimized, even if it cannot be completely eliminated.

**Table 5: Classification results for the model sample (1996-2000)**

| **Actual Observed** | **Predicted** | | |
|---|---|---|---|
| | **Non- Failure (0)** | **Failure (1)** | **Percentage Correct** |
| **Non-Failure (0)** | 183 | 3 | 98.36 |
| **Failure (1)** | 13 | 18 | 58.06 |
| **Overall Percentage** | | | 92.63 |
| *The cut value is 0.500* | | | |

[8] These banks are Bank Ekspres, Bank Kapital, Egebank, Eskişehir Bank, Etibank, Sümerbank and Türk Ticaret Bank.
[9] These are Bayındırbank, Kentbank, Toprakbank and Türkiye Emlak Bank.

# Table 6: Estimated failure probabilities for 1996-2000

| BANKS | Failure | 1996 | 1997 | 1998 | 1999 | 2000 | Average |
|---|---|---|---|---|---|---|---|
| Adabank A.Ş. | - | 0.0139 | 0.0207 | 0.0277 | 0.0096 | 0.0026 | 0.0149 |
| Akbank T.A.Ş. | - | 0.0020 | 0.0037 | 0.0019 | 0.0026 | 0.0077 | 0.0036 |
| Alternatif Bank A.Ş. | - | 0.0076 | 0.0830 | 0.0550 | 0.0038 | 0.1075 | 0.0514 |
| Anadolubank A.Ş. | - | N. A. | 0.0000 | 0.0011 | 0.0516 | 0.0577 | 0.0276 |
| Arap Türk Bankası A.Ş. | - | 0.0077 | 0.0253 | 0.0092 | 0.0022 | 0.0068 | 0.0102 |
| Denizbank A.Ş. | - | N. A. | 0.0042 | 0.0270 | 0.0521 | 0.1223 | 0.0514 |
| Fiba Bank A.Ş. | - | 0.0094 | **0.5370*** | 0.1065 | 0.0113 | 0.0951 | 0.1519 |
| Finans Bank A.Ş. | - | 0.0076 | 0.0111 | 0.0083 | 0.0079 | 0.0212 | 0.0112 |
| HSBC Bank A.Ş. | - | 0.0164 | 0.0362 | 0.2146 | 0.0000 | 0.0094 | 0.0553 |
| Koçbank A.Ş. | - | 0.0020 | 0.0311 | 0.0188 | 0.0055 | 0.1081 | 0.0331 |
| MNG Bank A.Ş. | - | 0.0001 | 0.0001 | 0.0011 | 0.0218 | 0.1427 | 0.0332 |
| Osmanlı Bankası A.Ş. | - | 0.0170 | 0.0555 | 0.0437 | 0.0206 | 0.0589 | 0.0391 |
| Oyak Bank A.Ş. | - | 0.0001 | 0.0034 | 0.0016 | 0.0129 | 0.2885 | 0.0613 |
| Şekerbank T.A.Ş. | - | 0.0684 | 0.1217 | 0.0637 | 0.0461 | 0.0730 | 0.0746 |
| Tekstil Bankası A.Ş. | - | 0.0241 | 0.0333 | 0.0113 | 0.0256 | 0.0508 | 0.0290 |
| Türk Dış Ticaret Bankası A.Ş. | - | 0.0113 | 0.0684 | 0.0043 | 0.0088 | 0.0047 | 0.0195 |
| Türk Ekonomi Bankası A.Ş. | - | 0.0228 | 0.0473 | 0.0131 | 0.0125 | 0.0232 | 0.0238 |
| Turkish Bank A.Ş. | - | 0.0346 | 0.0218 | 0.0134 | 0.0188 | 0.0058 | 0.0189 |
| T.C. Ziraat Bankası A.Ş. | - | 0.0352 | 0.0661 | 0.1034 | 0.1116 | 0.1038 | 0.0840 |
| Türkiye Garanti Bankası A.Ş. | - | 0.0181 | 0.0158 | 0.0105 | 0.0214 | 0.0273 | 0.0186 |
| Türkiye Halk Bankası A.Ş. | - | 0.0387 | 0.0515 | 0.1019 | 0.0751 | 0.1382 | 0.0811 |
| Türkiye İş Bankası A.Ş. | - | 0.0067 | 0.0076 | 0.0100 | 0.0043 | 0.0157 | 0.0089 |
| Türkiye Vakıflar Bankası T.A.O. | - | 0.0287 | 0.0123 | 0.0193 | 0.0233 | 0.0932 | 0.0354 |
| Yapı ve Kredi Bankası A.Ş. | - | 0.0366 | 0.0231 | 0.0459 | 0.0109 | 0.0108 | 0.0255 |
| Bank Ekspres A.Ş. | Dec. 1998 | 0.0918 | **0.0676*** | 1.0000 | - | - | 0.3865 |
| Bank Kapital Türk A.Ş. | Oct. 2000 | 0.0102 | 0.0502 | 0.0907 | **0.2753*** | 1.0000 | 0.2853 |
| Bayındırbank A.Ş. | July 2001 | 0.0665 | **0.7535*** | 0.0281 | 0.0297 | **0.0294*** | 0.1814 |
| Demirbank T.A.Ş. | Dec. 2000 | 0.0330 | 0.0431 | 0.0148 | **0.0108*** | **0.224*** | 0.0651 |
| Ege Giyim Sanayicileri Bankası A.Ş. | July 2001 | 0.0329 | 0.1244 | 0.1572 | 0.1820 | 0.5422 | 0.2077 |
| Egebank A.Ş. | Dec. 1999 | 0.0913 | 0.0814 | **0.2875*** | 1.0000 | - | 0.3651 |
| Eskişehir Bankası T.A.Ş. | Dec. 1999 | 0.0977 | 0.1330 | **0.4907*** | 0.9999 | - | 0.4303 |
| Etibank A.Ş. | Oct. 2000 | 0.0063 | 0.4424 | 0.0726 | **0.1113*** | 0.9987 | 0.3263 |
| İktisat Bankası T.A.Ş. | March 2001 | 0.0091 | 0.0322 | 0.0912 | 0.0770 | 1.0000 | 0.2419 |
| Interbank | Jan. 1999 | 0.3233 | 0.4088 | 0.9997 | 0.9812 | - | 0.6783 |
| Kentbank A.Ş. | July 2001 | 0.0904 | 0.0838 | 0.1030 | 0.0748 | **0.0828*** | 0.0870 |
| Milli Aydın Bankası T.A.Ş. | July 2001 | 0.1057 | 0.1261 | 0.3109 | **0.6475*** | 0.8214 | 0.4023 |
| Pamukbank T.A.Ş. | June 2002 | 0.2059 | 0.1411 | 0.1233 | 0.0908 | 0.0570 | 0.1236 |
| Sitebank A.Ş. | July 2001 | 0.0000 | 0.0003 | 0.1293 | 0.1526 | 0.6678 | 0.1900 |
| Sümerbank A.Ş. | Dec. 1999 | 0.0317 | 0.0386 | **0.3304*** | 0.9984 | - | 0.3498 |
| Toprakbank A.Ş. | Nov. 2001 | 0.0203 | 0.0270 | 0.0174 | 0.0266 | **0.0933*** | 0.0369 |
| Türk Ticaret Bankası A.Ş. | Nov. 1997 | **0.1480*** | 0.8357 | - | - | - | 0.4919 |
| Türkiye Emlak Bankası A.Ş. | July 2001 | 0.0720 | 0.1370 | 0.1513 | 0.0369 | **0.1372*** | 0.1069 |
| Türkiye İmar Bankası T.A.Ş. | July 2003 | 0.0478 | 0.0318 | 0.0742 | 0.2539 | 0.1150 | 0.1045 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| T.T.Bankası Yaşarbank A.Ş. | Dec. 1999 | 0.1488 | 0.2406 | 0.8262 | 1.0000 | - | 0.5539 |
| Ulusal Bank T.A.Ş. | Feb. 2001 | 0.0257 | 0.0002 | 0.0003 | 0.0019 | 0.9217 | 0.1900 |
| Yurt Ticaret ve Kredi Bankası A.Ş. | Dec. 1999 | 0.1577 | 0.1583 | 0.5497 | 1.0000 | - | 0.4664 |
| **Average** | | **0.0506** | **0.1139** | **0.1310** | **0.1934** | **0.2175** | **0.1413** |
| **Average (Non-Fail)** | | **0.0186** | **0.0533** | **0.0381** | **0.0233** | **0.0656** | **0.0398** |
| **Average (Fail)** | | **0.0826** | **0.1799** | **0.2785** | **0.3975** | **0.3620** | **0.2601** |
| *N.A.: Not available,* ***** *Represents misclassifications by the estimated logit model* | | | | | | | |

Table 6 shows the probability of failures obtained from the logit model for the model sample which covers the period of 1996-2000. The last row and the last column show the average probabilities of failure. We can explain the underlying relationships among financial ratios and factors by observing factor loadings. Varimax (orthogonal) factor rotation in the PCA is used for this purpose. This method maximizes the variance of loadings within factors and produces a structure that is easier to interpret. Table 7 presents the factor loadings obtained from the orthogonally rotated factor solution. Ratios with factor loadings less than 0.5 are omitted.

According to Table 7 the significant loadings for Factor 1 (F1) are R7, R9, R2, R26, and R13 in a descending order reflecting mostly profitability and income-related ratios and affecting F1 positively with the exception of R2. Hence, as the first component, F1, which contributes the most in explaining the changes in the financial conditions of the banks during the period, can be considered as the income-profitability factor.

The significant loadings for Factor 3 (F3) are R4, R6 and R5, all liquidity ratios, all affecting F3 positively and all reflecting a bank's readiness to absorb TL and FC liquidity risk. Thus, F3 can be thought of as the liquidity factor (TL and FC). Ratios that are significant for Factor 4 are R11 and R13, both reflecting the income-expenditure structure of the banks and both affecting F4 positively. Finally, F5 is affected by R12 and R10, both again reflecting the income-expenditure structure. R12's impact is positive while R10 impacts F5 negatively and indicates the interest rate risk.

**Table 7: Orthogonally rotated factor solutions**

| | ***F1*** | ***F3*** | ***F4*** | ***F5*** |
|---|---|---|---|---|
| ***R7*** (Net Profit (Losses) / Total Assets) | 0.937 | | | |
| ***R9*** (Income Before Taxes / Total Assets) | 0.934 | | | |
| ***R2*** ( Loans under follow-up (net) / Total Loans) | -0.748 | | | |
| ***R26*** (Net Income / No. of Branches) | 0.713 | | | |
| ***R4*** (Liquid Assets / Total Assets) | | 0.846 | | |
| ***R6*** (FC Liquid Assets / FC Liabilities) | | 0.842 | | |
| ***R5*** (Liquid Assets / (Deposits + Non-Deposit Funds)) | | 0.839 | | |
| ***R11*** (Interest Income / Interest Expense) | | | 0.91 | |
| ***R13*** (Total Income / Total Expense) | 0.632 | | 0.667 | |
| ***R12*** (Non-Interest Income / Non-Interest Expense) | | | | 0.773 |
| ***R10*** (Interest Income / Total Expenses) | | | | -0.609 |

Turning to the model's out-of-sample predictive ability for the commercial banks currently operating in the banking industry, tables 8 and 9 provide a summary of classification results, and the probability of failures for the holdout sample 2002-2009, respectively. The last row and last column of table 9 give the average failure probabilities. Here, the overall classification accuracy is extremely high (99.00%). Only in two cases, where the income-profitability ratios of the relevant banks are somewhat problematic, does the model predict failure of actually non-failed banks. In other words, the probability of accepting the null hypothesis when it is not correct (Type II error) is only 1.00 % (2/200).

**Table 8: Classification results for the holdout sample (2002- 2009)**

| **Actual Observed** | **Predicted** | | |
|---|---|---|---|
| | **Non- Failure (0)** | **Failure (1)** | **Percentage Correct** |
| **Non-Failure (0)** | 198 | 2 | 99.00 |
| **Failure (1)** | - | - | - |
| **Overall Percentage** | | | 99.00 |

| |
|---|
| *The cut value is 0.500* |

## Table 9: Predicted failure probabilities for 2002-2009

| | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **Average** |
|---|---|---|---|---|---|---|---|---|---|
| T. C. Ziraat Bankası A.Ş. | 0.0365 | 0.0097 | 0.0060 | 0.0052 | 0.0040 | 0.0040 | 0.0217 | 0.0082 | 0.0119 |
| Türkiye Halk Bankası A.Ş. | 0.0738 | 0.0449 | 0.0723 | 0.0564 | 0.0270 | 0.0227 | 0.0626 | 0.0315 | 0.0489 |
| Türkiye Vakıflar Bankası T.A.O. | 0.0225 | 0.0098 | 0.0055 | 0.0076 | 0.0108 | 0.0161 | 0.0415 | 0.0153 | 0.0161 |
| Adabank A.Ş. | 0.0801 | 0.0632 | **0.6937*** | 0.0012 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.1048 |
| Akbank T.A.Ş. | 0.0021 | 0.0009 | 0.0015 | 0.0027 | 0.0050 | 0.0063 | 0.0295 | 0.0083 | 0.0070 |
| Alternatif Bank A.Ş. | 0.4168 | 0.1231 | 0.0891 | 0.0826 | 0.0589 | 0.0564 | 0.0543 | 0.0844 | 0.1207 |
| Anadolubank A.Ş. | 0.1683 | 0.0665 | 0.0397 | 0.0773 | 0.0753 | 0.0685 | 0.0723 | 0.0484 | 0.0770 |
| Şekerbank T.A.Ş. | 0.1705 | 0.0865 | 0.0239 | 0.0173 | 0.0151 | 0.0425 | 0.1067 | 0.0673 | 0.0662 |
| Tekstil Bankası A.Ş. | 0.0850 | 0.0501 | 0.0702 | 0.0995 | 0.0645 | 0.1270 | 0.1458 | 0.1092 | 0.0939 |
| Turkish Bank A.Ş. | 0.0044 | 0.0043 | 0.0077 | 0.0131 | 0.0097 | 0.0197 | 0.0083 | 0.0162 | 0.0104 |
| Türk Ekonomi Bankası A.Ş. | 0.0162 | 0.0215 | 0.0283 | 0.0446 | 0.0550 | 0.0676 | 0.0661 | 0.0594 | 0.0448 |
| Türkiye Garanti Bankası A.Ş. | 0.0654 | 0.0310 | 0.0184 | 0.0127 | 0.0177 | 0.0082 | 0.0231 | 0.0047 | 0.0227 |
| Türkiye İş Bankası A.Ş. | 0.0152 | 0.0059 | 0.0030 | 0.0018 | 0.0037 | 0.0035 | 0.0079 | 0.0037 | 0.0056 |
| Yapı ve Kredi Bankası A.Ş. | 0.0083 | 0.0399 | 0.0408 | **0.5207*** | 0.0728 | 0.0913 | 0.0572 | 0.0253 | 0.1070 |
| Arap Türk Bankası A.Ş. | 0.0057 | 0.0091 | 0.0324 | 0.0382 | 0.0365 | 0.0662 | 0.1024 | 0.0069 | 0.0372 |
| Citibank A.Ş. | 0.0033 | 0.0145 | 0.0162 | 0.0027 | 0.0067 | 0.0099 | 0.0388 | 0.0224 | 0.0143 |
| Denizbank A.Ş. | 0.0187 | 0.0105 | 0.0186 | 0.0177 | 0.0235 | 0.0901 | 0.0840 | 0.0243 | 0.0359 |
| Deutsche Bank A.Ş. | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0004 | 0.0027 | 0.0019 | 0.0000 | 0.0006 |
| Eurobank Tekfen A.Ş. | 0.0421 | 0.0479 | 0.0640 | 0.1025 | 0.0502 | 0.0912 | 0.1028 | 0.0593 | 0.0700 |
| Finans Bank A.Ş. | 0.0420 | 0.0409 | 0.0338 | 0.0252 | 0.0094 | 0.0484 | 0.0916 | 0.0289 | 0.0400 |
| Fortis Bank A.Ş. | 0.0127 | 0.0195 | 0.0303 | 0.0626 | 0.0619 | 0.0683 | 0.0785 | 0.0881 | 0.0527 |
| HSBC Bank A.Ş. | 0.0099 | 0.0105 | 0.0255 | 0.0215 | 0.0482 | 0.0419 | 0.0470 | 0.0249 | 0.0287 |
| ING Bank A.Ş. | 0.0910 | 0.1358 | 0.0706 | 0.0491 | 0.0739 | 0.1306 | 0.1127 | 0.1055 | 0.0962 |
| Millennium Bank A.Ş. | 0.0284 | 0.2800 | 0.3685 | 0.1883 | 0.3547 | 0.2332 | 0.2367 | 0.3451 | 0.2544 |
| Turkland Bank A.Ş. | 0.0151 | 0.0197 | 0.0192 | 0.0768 | 0.1562 | 0.2279 | 0.1680 | 0.0977 | 0.0976 |
| **Average** | **0.0574** | **0.0458** | **0.0712** | **0.0611** | **0.0496** | **0.0618** | **0.0705** | **0.0514** | **0.0586** |
| ** Represents misclassifications by the estimated logit model* | | | | | | | | | |

## Figure1: Average probability of failures by years

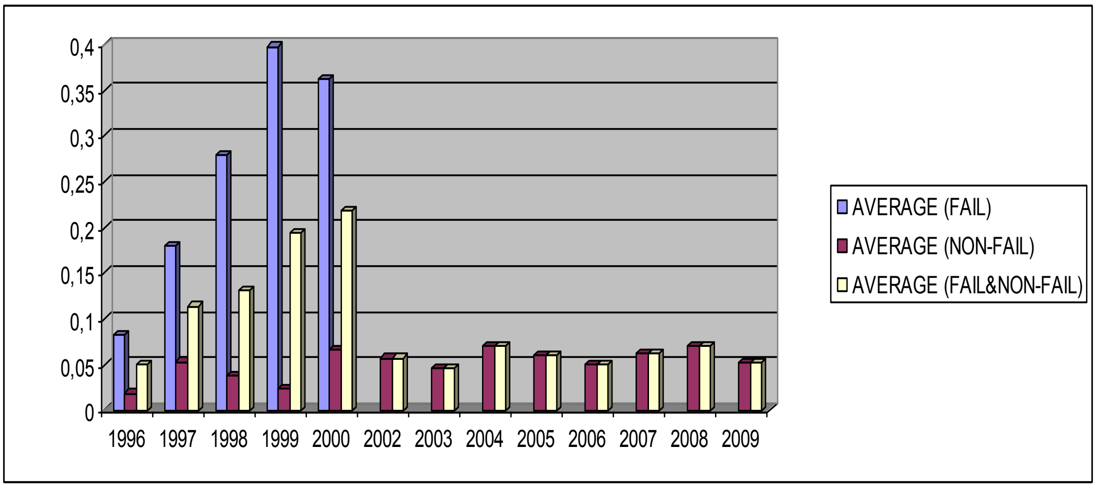



Figure 1 above, based on the last rows of Tables 6 and 9, and illustrates the average probability of failures predicted by the logit model for all the commercial banks in Turkey since 1996. The economic and financial measures that were undertaken after the 2001 crisis, which in part were designed to better scrutinize the financial system and specifically banks, seem to be working. Despite the deterioration of macroeconomic conditions in Turkey, in terms of growth, unemployment, inflation, difficulties in the export markets, a global financial crisis shaking the world, and a relatively unstable political environment in recent years, the Turkish commercial banks appear to be quite far from the risk of failure.

### 3. Concluding Remarks

Results of this study show that if decision makers monitor banks over time, they can capture a significant amount of information about the changes in the financial conditions of banks. Using uncorrelated financial factors provides more refined and enhanced information to decision makers than using financial ratios directly. As such, they can become part of the early warning toolkit available to internal management and outside bank supervising agencies.

Economic conditions also appear to affect the probability of bank failures. Banking crises happen when the macroeconomic environment is weak, particularly when growth is low and inflation is high. In addition, high real interest rates are in general associated with systemic problems of the banking sector (Demirgüç-Kunt and Detragiache, 1998). The moral hazard problem (financial liberalization combined with explicit deposit insurance and weak law enforcement) also increases the failure probabilities (Hutchison and McDill, 1999).

All of the above macroeconomic problems were observed in Turkey during the period of 1992-2009, contributing to the failure of 26 banks between 1994 and 2003. There is no doubt that the adverse macroeconomic conditions contributed to bank failures in Turkey. However, no banks have failed in Turkey since 2003, despite the global financial crises and the failures experienced by some of the prominent players in the global financial system. It could be argued that the adverse macroeconomic conditions and the unfavorable global financial environment have increased the probability of bank failures. Nevertheless, the non-failed banks in Turkey have survived in contrast to the group that failed under the same adverse macroeconomic conditions and financial environment. Hence, despite the adverse effects of worsening macroeconomic conditions on bank failures, this study underlines two important factors unequivocally contributing to bank failures: 1) internal conditions resulting from a bank's own mismanagement and misguided policies; and 2) the failure of monitoring agencies to warn and to take under close examination the banks with high potential to fail.

A cursory examination of recent bank failures in the United States suggests that similar factors may have played a role in the wave of fresh bank failures there. Future research can determine whether these findings hold true for other countries, and if the world can learn from the Turkish experience. Our gut feelings are that they can.

## 4. Early Warning System

In order to use the early warning system developed in this paper for bank failures in a future period *t*, we explain the process step-by-step below.

*4.1. Select the significant ratios for bank failures*

Select the significant original ratios for the banks via ANOVA. These are the ratios whose means differ significantly between failed and non-failed banks. Then, calculate the means and standard deviations for each of these ratios. The means and standard deviations of the significant ratios calculated for the model sample of 1996-2000 are given in Table 10.

**Table 10: Mean and the standard deviation of the original ratios**

| Code | Name of ratios | Mean ( $r_i$ ) | Std. Deviation ( $r_i$ ) |
|---|---|---|---|
| *R2* | Loans under follow-up (net) / Total Loans | 27.8311 | 147.7170 |
| *R3* | Permanent Assets / Total Assets | 9.9451 | 10.2954 |
| *R4* | Liquid Assets / Total Assets | 42.9643 | 18.1115 |
| *R5* | Liquid Assets / (Deposits + Non-Deposit Funds) | 53.3474 | 28.9007 |
| *R6* | FC Liquid Assets / FC Liabilities | 42.6753 | 21.8244 |
| *R7* | Net Profit (Losses) / Total Assets | -1.5724 | 21.1828 |
| *R8* | Net Profit (Losses) / Total Shareholders' Equity | -31.7799 | 961.1210 |
| *R9* | Income Before Taxes / Total Assets | -0.4058 | 21.6515 |
| *R10* | Interest Income / Total Expenses | 94.8643 | 101.8308 |
| *R11* | Interest Income / Interest Expenses | 221.8283 | 323.1240 |
| *R12* | Non-Interest Income / Non-Interest Expenses | -7.0459 | 122.7749 |
| *R13* | Total Income / Total Expense | 122.8556 | 45.5298 |
| *R14* | Total Assets (Share in Sector, %) | 2.0823 | 3.1751 |
| *R15* | Total Loans (Share in Sector, %) | 2.0410 | 3.1954 |
| *R17* | Total Assets (Share in Group, %) | 7.2436 | 11.4202 |
| *R18* | Total Loans (Share in Group, %) | 8.1306 | 15.6838 |
| *R26* | Net Income / No. of Branches | 1.3323 | 17.7110 |
| *R29* | (Personnel Expenses + Reserve for Employee Termination Benefit) / Total Assets | 2.6997 | 2.1204 |

*4.2. Compute the standardized values of the ratios selected*

Compute the standardized values of the ratios selected in section 4.1 by using the original values and the mean and standard deviation of each ratio given in table 10.

$$z_{ibt} = z_{in} = \frac{r_{in} - \overline{r_i}}{s_i}$$

Here $z_{in}$ is the standard value of ratio *i* for observation *n* (bank *b* in period *t*). $\bar{r}_i$ and $s_i$ are the mean and standard deviation of ratio *i* for all the banks and years in the model sample given in table 10. Hence, the original ratios are standardized so that the mean and the standard deviation of the standardized ratios are zero and one, respectively. Thus, the matrix of standardized ratios is

$$Z_{Nxm} = \begin{bmatrix} z_{21} & z_{31} & \cdots & z_{M1} \\ z_{22} & z_{32} & & \\ \vdots & & \ddots & \\ z_{2N} & & & z_{MN} \end{bmatrix}.$$

Here *N* is the number of observations (number of banks in each year added for the period of interest, 200 for our test sample). Each observation can be used for risk evaluation of a particular bank in a particular future period, *t*. Note that the matrix $Z_{Nxm}$ starts with the first observation of ratio two, $r_2$ since the first ratio, $r_1$, turns out to be insignificant in the ANOVA test along with $r_{16}$, $r_{19} - r_{25}$ and $r_{27} - r_{28}$. Thus, the index *M* refers to the last significant ratio, $r_{29}$, while index *m* indicates the number of significant ratios in the ANOVA test (*m =18*) in Table 11.

*4.3. Compute the factor scores matrix*

Multiply the standardized ratios matrix ($Z_{Nxm}$) obtained in step 2 by the component score coefficients matrix ($L_{mxk}$) given in Table 11, to obtain the factor scores matrix, ($F_{Nxk}$). Each row of $F_{Nxk}$ shows the significant factor scores used in the LOGIT analysis for a particular bank *b* in period *t*.

**Table 11: Component score coefficient matrix ($L_{mxk}$)**

| | F1 | F3 | F4 | F5 |
|---|---|---|---|---|
| **Z2** | -0.244 | 0.033 | 0.152 | -0.008 |
| **Z3** | -0.023 | -0.183 | 0.241 | 0.220 |
| **Z4** | -0.067 | 0.349 | -0.042 | -0.092 |
| **Z5** | -0.021 | 0.33 | 0.036 | 0.006 |
| **Z6** | -0.030 | 0.387 | -0.068 | 0.156 |
| **Z7** | 0.274 | -0.039 | -0.025 | 0.007 |
| **Z8** | -0.078 | -0.020 | 0.085 | 0.118 |
| **Z9** | 0.268 | -0.034 | -0.004 | 0.010 |
| **Z10** | 0.093 | 0.034 | -0.065 | -0.488 |
| **Z11** | -0.105 | -0.043 | 0.699 | -0.041 |
| **Z12** | 0.078 | 0.072 | -0.094 | 0.584 |
| **Z13** | 0.103 | -0.066 | 0.438 | 0.055 |
| **Z14** | 0.006 | 0.038 | -0.014 | 0.134 |
| **Z15** | 0.015 | 0.013 | -0.002 | 0.140 |
| **Z17** | -0.063 | 0.069 | 0.059 | -0.128 |
| **Z18** | -0.055 | 0.056 | 0.063 | -0.214 |
| **Z26** | 0.211 | -0.020 | -0.066 | 0.005 |
| **Z29** | -0.128 | 0.187 | 0.043 | 0.018 |

$$F_{Nxk} = Z_{Nxm} L_{mxk}$$

$$F_{Nxk} = \begin{bmatrix} z_{21} & z_{31} & \cdots & z_{M1} \\ z_{22} & z_{32} & & \\ \vdots & & \ddots & \\ z_{2N} & & & z_{MN} \end{bmatrix} \begin{bmatrix} l_{11} & l_{31} & l_{41} & l_{51} \\ l_{12} & l_{32} & l_{42} & l_{52} \\ \vdots & & \ddots & \\ l_{1N} & l_{3N} & l_{4N} & l_{5N} \end{bmatrix} = \begin{bmatrix} f_{11} & f_{31} & f_{41} & f_{51} \\ f_{12} & f_{32} & f_{42} & f_{52} \\ \vdots & & \ddots & \\ f_{1N} & f_{3N} & f_{4N} & f_{5N} \end{bmatrix}$$

Here *N* is the number of banks that are selected for evaluation in some future period *t*, and *k* is the number of significant factors (*k*=4) given in Table 11.

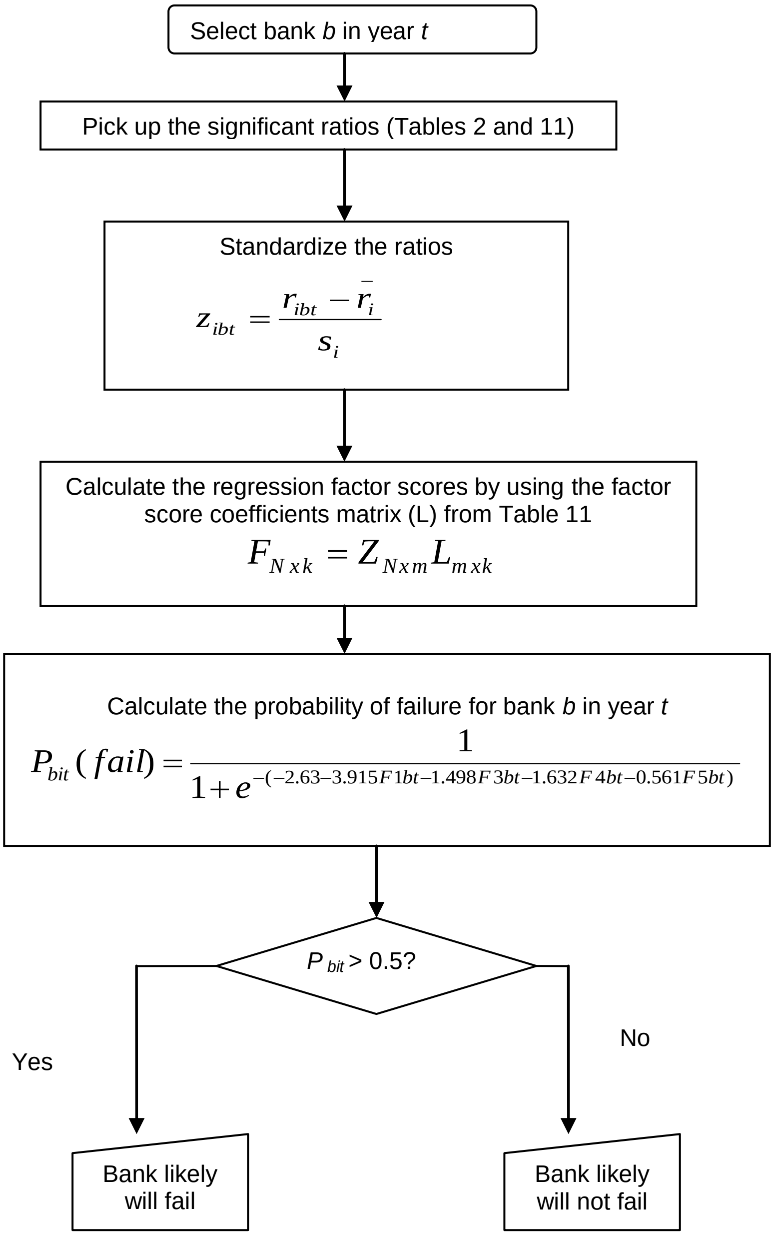
### *4. 4. Calculate the failure probabilities*

Finally, calculate the failure probabilities for each bank, *b*, in year *t* using the factor scores ( $F_{Nxk}$ ) obtained in section 4.3 as independent variables in the logit model.

$$p(y_{bt} = 1) = \frac{1}{1 + e^{-(-2.63 - 3.915 F1_{bt} - 1.498 F3_{bt} - 1.632 F4_{bt} - 0.561 F5_{bt})}}$$

To summarize, we provide the steps of the early warning system in Figure 2 below.

**Figure 2: Flow diagram of early warning system**



**References**

Alam, P., Booth, L.K. and Thordarson, T., 2000. The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: an experimental study. Expert Systems with Applications 18, 185-199.

Banking Regulation and Supervision Agency (BRSA) Banking Sector Restructuring Program: Progress Report, 23, October, 2003.

Canbaş, S., Çabuk, A. and Kılıç, S.B. 2005. Prediction of commercial bank failure via multivariate statistical analysis of financial structures: The Turkish case. European Journal of Operational Research 166 (2), 528-546.

Cole, R., A. and Gunther, J.W. 1998. Predicting bank failures: A comparison of on-and off-site monitoring systems. Journal of Financial Services Research 13 (2), 103-117.

Demirgüç-Kunt, A. and Detragiache, E. 1998. The determinants of banking crises in developing and developed countries. IMF Staff Papers 45 (1).

Hutchison, M. and McDill, K. 1999. Are all banking crises alike? The Japanese experience in international comparison. NBER Working Paper 7253.

Jo, H. and Han, I. 1996. Integration of case-based forecasting, neural network, and discriminant analysis for bankruptcy prediction. Expert Systems with Applications 11, 415-422.

Keasey, K. and McGuinness, P. 1990. The failure of UK industrial firms for the period 1976-1984, logistic analysis and entropy measures. Journal of Business Finance and Accounting 17 (1), 119-135.

Kılıç, S.B. 2003. "Mali başarısızlık tahmininde çok değişkenli istatistiksel yöntemlerin ve çok kriterli analize dayali bir modelin kullanılması: Türk bankacılık sisteminde bir uygulama (Using multivariate statistical methods and a model of multicriteria analysis in predicting financial failure: An application in the Turkish banking sector)", Unpublished Ph.D. Thesis, Çukurova University, Institute of Social Sciences, Adana, Turkey.

Kolari, J., Glennon, D., Shin, H. and Caputo, M. 2002. Predicting large US commercial bank failures. Journal of Economics & Business 54, 361-387.

Lam, K.F. and Moy, J.W. 2002. Combining discriminant methods in solving classification problems in two-group discriminant analysis. European Journal of Operational Research 138, 294-301.

Meyer, P.A. and Piffer, H.W. 1970. Prediction of bank failures. Journal of Finance 25, 853-868.

Pantolone, C. and Platt, M.B. 1987. Predicting commercial bank failure since deregulation. New England Economic Review, 37-47.

Rose, P.S. and Kolari, J.W. 1985. Early warning systems as a monitoring device for bank conditions. Quarterly Journal of Business and Economics 24(1), 43-60.

Shannon, C.E., Weaver W., 1949. The Mathematical Theory of Communication. Chicago and London: University of Illinois Press.

Shin, S.W. and Kılıç, S.B., 2006. Using PCA-based neural network committee model for early warning of bank failure. Lecture Notes in Computer Science Book Series; Advances in Natural Computation 4221/2006, 289-292.

Shin, S.W., Lee, K.C. and Kılıç, S.B., 2006. Ensemble prediction of commercial bank failure through diversification of input features. Lecture Notes in Computer Science Book Series; Advances in Artificial Intelligence 4304/2006, 887-896.

Sinkey, J. 1975. A multivariate statistical analysis of the characteristics of problem banks. Journal of Finance 30(1), 21-38.

Tam, K.Y. and Kiang, M.Y. 1992. Managerial applications of neural networks: The case of bank failure predictions. Management Science 38(7), 926-947.

Zavgren, C.V. 1985. Assessing the vulnerability to failure of American industrial firms. A logistic analysis. Journal of Business Finance and Accounting 12 (1), 19-45.