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Predicting bank failures in Turkey by Discrete Choice Models

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Abstract

This study investigates the factors that were important in the failure of banks in 1997-2006. The study uses cross-section time series data from 81 banks and employs limited dependent variable models. The major objectives are to examine the determinants of bank failures by explaining the contribution of both microeconomic and macroeconomic factors in the Turkish banking system and to estimate the likelihood of banking failure.

Keywords: Bank failures, Discrete choice model, Turkey.

JEL classification: G21, E44, E47.

1. Introduction

During the recent decades of trade and financial liberalization, the frequency of financial sector crises has risen both in developed and emerging market economies (Brown and Dinc, 2005). In Latin America, severe banking crises occurred in Chile and Colombia during the 1980s and in Mexico and Venezuela during the first half of the 1990s. The Turkish cases in 2000 and 2001 represent the most recent crises in an emerging market economy. The banking system problems that have occurred in Japan during the mid-1990s, in the UK in the early 1990s, in the US during the mid-1980s and early 1990s, and in the Nordic countries during the early 1990s have widely discussed in empirical literature.

The IMF (1998) report identifies several general categories of problems, which are frequently associated with financial crises (both banking and currency crises): unsustainable macroeconomic policies, weaknesses in financial structure, global financial conditions, exchange rate misalignments, and political instability. Moreover, Ozkan-Gunay and Tektas (2006) pointed out that poor banking practices, capital inadequacy, poor credit evaluation process, lack of revenue diversification, connected lending, maturity and currency mismatches, rapid increase in non-performing loans are the main causes of severe banking crises (Ozkan-Gunay and Tektas, 2006). Furthermore, for political reasons, preemptive actions regarding large bank failures are not taken by the governments at the periods just preceding the elections. This can be considered as one of the major reasons for severe banking crises, at least for emerging market economies (Brown and Dinc, 2005).

Both multinomial logit model and traditional binary model are applied to selected eigenvectors and variables based on principal component analysis in order to predict the probability of bank failures and determine the factors that affect bank failures. This study also analyzes econometrically the bank-specific and macroeconomic determinants of bank failures. In this study, the primary objective is to distinguish the state of problematic banks as failure and mergers/acquisition, using a multinomial logit model. Since a multinomial model discriminates between two failure outcomes and uses more information (i.e., failed banks versus mergers/acquisition), it is likely to be a better predictor of bank failures (Matthews and Whitfield, 2006). The other objectives are to examine the determinants of banking failures, to estimate the likelihood of banking failure, to analyze the contribution of microeconomic and macroeconomic factors in banking system problems in Turkey, and to identify leading indicators of banking failures in Turkey. This study is organized as follows: the next section provides a review of literature. Section 3 presents background of financial crisis in Turkey. Section 4 describes the data set used in the analysis and gives the results of principal component analysis and the descriptive statistics. Section 5 illustrates the estimation technique, the results of the estimated model and prediction. Section 6 concludes.

2. Literature review

The empirical literature on the determinants of bank failures and banking crises[1] is large. Mainly, the empirical literature can be divided into

[1] It is useful to distinguish between bank failures and banking crises. Banks, like other firms, are likely to encounter financial difficulties when the difference between the value of their assets and the value of their liabilities is negative (i.e. technical insolvency) (Demirguc-Kunt, 1989). A problem at a bank may be associated with the failure of other banks, if each bank is simultaneously affected by the same shock. This would suggest that banking system problems are more likely if the banks have similar fundamental characteristics. The banking crises in the Nordic countries (Finland, Norway and Sweden) during the early 1990s are an example of this (Bell and Pain, 2000).

three different approaches: microeconomic, macroeconomic, and mixed approaches. Microeconomic studies on bank failures are mainly based on the bank specific variables used in CAMEL rating categories[2], which are taken from the banks' financial statements. These studies use cross-section, micro-level data of specific countries' or regions' data. On the other hand, in the macroeconomic approach, the role of macroeconomic conditions on banking crises such as interest rates, inflation rates, Central Bank foreign exchange reserves, credit expansion, etc., as well as the role of institutional variables such as central bank independence, explicit deposit insurance, financial liberalization proxies etc., are examined (Gonzales-Hermosillo, 1999). These studies use cross-country and time-series macroeconomic data. Moreover, the mixed approach uses both bank-specific and macroeconomic variables.

Thomson (1991) estimated the logit model by using only financial statements of U.S. banks operating from 1982 to 1989 to predict the probability of bank failures. Thomson (1991) used CAMEL-motivated proxy variables to determine bank condition such as book equity capital, the loans to assets ratio, overhead to total assets ratio, deposits per branch, and size in terms of assets. Similarly, Logan (2001) also used a logit model to examine the balance sheet characteristics of small and medium-sized UK banks and identified leading indicators of bank failures over the period of 1989 and 1991. Logan (2001) found that the most important indicators in determining future failure were high dependence on net interest income, low profitability, low loan growth, and low short-term assets relative to liabilities.

Another thread of literature on banking crises used cross-country time-series macroeconomic data. In explaining cross-country comparisons in banking crises, Demirguc-Kunt and Detragiache (1999) and Hardy and Pazarbasioglu (1998) tried to utilize only macroeconomic variables to monitor banking sector fragility in a large sample of countries. Demirguc-Kunt and Detragiache (1999) emphasized that low GDP growth rate, high real interest rate, high inflation, high M2 to Central Bank foreign exchange reserves ratio, and high growth of real private credit significantly increase the likelihood of systemic problems. Along with an unstable macroeconomic environment, institutional characteristics had a role in systemic problems. Demirguc-Kunt and Detragiache (1999) also constructed a rating system for bank fragility using estimated crisis probabilities from a logit model. A similar study from Hardy and Pazarbasioglu (1998) suggested that systemic

[2] CAMEL is a rating system to evaluate the financial conditions of the banks for supervisory purposes. It has five categories: capital adequacy, asset quality, management quality, earnings and profitability, and liquidity. It was developed by US regulators. Variations of this framework are widely used by regulatory and supervisory agencies in a number of countries to evaluate the state of banks.

problems were related to a fall in real GDP growth, fluctuations in inflation, credit expansion, increase in real interest rates, decline in real exchange rates, and adverse trade shock.

Santor (2003) used a limited dependent variable model to examine contagion across banking systems in developed and developing countries (over 90 countries during 1975-1998) using only macroeconomic variables. Santor (2003) found that the probability of banking crises increases as countries have slow economic growth, high inflation, and high real interest rates. Besides, information contagion plays a significant role in predicting future banking crises. Hutchison and McDill (1999) also used a multivariate probit model to examine banking distress for a large sample of developed and developing countries (65 countries) in 1975-1997. Accordingly, they found a statistically significant association between the variables such as GDP growth rate, asset prices, and institutional factors such as Central Bank independence, explicit deposit insurance, financial liberalization, and the probability of banking sector distress in the sample countries and in Japan.

Gonzales-Hermosillo, et al. (1997) and Gonzales-Hermosillo (1999) used both bank-specific and macroeconomic variables to determine bank fragility and the factors of bank failures for Mexico, Columbia, and the US banking systems. Gonzales-Hermosillo (1999) found that the banking distress index tended to overstate the number of occurrences of banking problems. The results of this study showed that capital equity to total assets ratio and non-performing to total assets ratio, which was the proxy of fragility, were the main indicators of banking problems. The availability of quarterly data[3] in this study also improved the performance of the use of the limited dependent regression model so that it could give the possibility to monitor the evolution of the failure probability and to take preventive action before the failure (Gaytan and Johnson, 2002).

Bernhardsen (2001) has followed Gonzales-Hermosillo (1999) to predict the likelihood of bank failures and used a random-effects probit model to predict bankruptcies in Norway. Furthermore, Sales (2005) and Gonzales-Hermosillo et al. (1997) provide a financial fragility index for each bank, based on the probability of failure of banks. This index suggested that both Mexican and Brazilian banking systems showed signs of fragility before the crises.

While choosing either the microeconomic or the macroeconomic approach, a critical issue is to define bank failure and insolvency. Insolvency exists when the market value of the bank or the market value of the capital of the bank or institution turns out to be negative. Nevertheless, failure can be seen as the legal recognition of a bank's preexisting economic

[3] In banking crises studies, annual data was used commonly due to unavailability of quarterly or monthly data for less developed countries. Naturally, the performance of the model of the early warning of financial problems that uses annual data may be poor.

insolvency. As a matter of fact, it is a choice that supervisory or regulatory institution may put into operation or not (Demirguc-Kunt, 1989). As assessing the definition of bank failures, de jure failure takes place as economic insolvency is judged officially and the bank is closed or involuntarily merged out of existence, whereas de facto failure occurs when any regulatory authority cancels the bank's license (Demirguc-Kunt, 1989). As a result, the bank regulatory authority can be considered as the only determinant of both types of failure.

3. An overview of the Twin Financial Crisis in Turkey in 2000-2001

After financial liberalization[4], Turkey experienced three serious crises in April 1994, November 2000, and February 2001. The Turkish financial system suffered accordingly. Alper and Onis (2002) stated that macroeconomic imbalances, high and rising fiscal deficits, high inflation and real interest rates, the distortions created by state owned banks, full deposit insurance scheme, connected lending, high exposure concentrations, large foreign exchange positions, and weakness of regulation and supervision in the banking system are the major reasons of emerging market financial crises, especially in Turkey (Alper and Onis, 2002).

During the 1990s, the Turkish economy experienced high political instability. There were three elections and eleven governments. Brown and Dinc (2005) write that politicians had a motivation to take the costly action of postponement of severe regulatory intervention in bank failures until after the elections. This is because of the fact that failures of large banks may have an adverse effect on the economy at least in the short run (Rogoff and Sibert, 1988). Takeovers or closing of failing banks naturally necessitates large funds by taxpayers. Politicians will always choose not to handle such issues before the elections (Brown and Dinc, 2005). In the 1990s, the political instability in Turkey delayed the regulations in the banking sector as theory suggested.

Along with such political economy concerns regarding bank failures, there were high chronic inflation and high public sector borrowing because of the expansionary fiscal policies after the 1980s and loose monetary policies in the early 1990s. Furthermore, private commercial banks invested in government securities that issued short-term debt at high interest rates, by

[4] The Turkish banking sector has developed considerably in the liberalization era of the 1980s. Introducing uniform accounting principles, allowing to borrow directly from abroad by syndicated loans, establishing an interbank money market (Istanbul Stock Exchange and Capital Markets Board), starting T-bills and government bonds auctions and also technological and human resources improvements in the sector has helped the growth of the banking sector in Turkey (Ozkan-Gunay and Tektas, 2006).

opening longer-term foreign exchange (FX) positions. After the 1994 crisis[5], in Turkish banking system, there were three main problems related to the above distorted incentives: opening foreign exchange positions, a large number of weak banks providing connected lending, and banking supervision by the Treasury which had borrowing needs from banks (Rijckeghem and Ucer, 2005).

In December 1999, Turkey adopted an IMF stabilization program, which sought to ensure debt sustainability, to reduce chronic and high inflation with the use of foreign exchange as a nominal anchor, fiscal adjustment, and several structural measures. The 1999 IMF program also aimed to reform the banking sector by forming independent supervision and to rehabilitate state banks and improve the performance of the banking sector (Alper and Onis, 2002). Thus, the new banking law was enacted in the year of 1999, establishing the independent Banking Regulation and Supervision Agency (BRSA)[6] compatible with the regulation and supervision standards of the Basel committee, removing the distortions created by the state owned banks, setting the appropriate prudential requirements in line with international standards, and encouraging mergers of the banks to eliminate the weaknesses of the system.

However, the design of the 1999 IMF program did not provide measures on foreign exchange risks and liquidity risks in the banking sector. Although there was legislation about restrictions on open foreign exchange positions, widening open foreign exchange positions was ignored in order to meet large public sector borrowing requirements (Rijckeghem and Ucer, 2005). Despite liquidity risks, there were excessive restrictions on the Central Bank's ability to be the Lender of the Last Resort in the design of the program, since the IMF program eliminated the Central Bank's facility of implementing implicit insurance mechanism against systemic risks involving interbank deposits by specifying a ceiling on its Net Domestic Assets as a performance criteria (Alper and Onis, 2002). Furthermore, the number of weak banks in the banking sector was underestimated, though five private banks were taken under the Saving Deposit Insurance Fund at the beginning of the IMF program (Ertugrul and Selcuk, 2001). The last issue is that the short-term borrowing and lending operations of state banks related to the so-called 'mission' losses were also neglected in the design of the IMF program, creating vulnerability to the shocks in the banking system.

5 At the beginning of 1994, the Central Bank increased the interest rates and the Turkish lira was devalued by 60%. The overnight interest rates peaked to 1000%, resulting in panic in the financial system (Ozkan-Gunay and Tektas, 2006). With liquidity problems of the banks in conjunction with the depositor runs in the spring of 1994, the currency crisis resulted in the withdrawal of permission for carrying out banking operations of three medium-sized banks. In April 1994, the stabilization, structural adjustment policies, and full coverage of insurance scheme for bank deposits were introduced (Ertugrul and Selcuk, 2001).

6 BRSA was in full operation by September 2000.

Along with these effects, in February 2001, the currency peg had to be abandoned and replaced by free-floating regime. Therefore, the Turkish economy and its banking system were hit hard by the crises of 2000 and 2001. The size of the banking system in terms of assets contracted by 17% of GDP and 35% of banks were eliminated from the system. The resulting output loss of the twin crises was substantial and the economy contracted by over 9% in 2001, which was the nation's most severe recession since 1945 (Alper and Onis, 2002).

To recapitulate, the following factors led the Turkish financial system to experience a crisis in November 2000: First, there were the problematic issues in sustaining capital inflows. Second, despite the existence of an exchange rate risk and the financial need of the Treasury, there was not sufficient support by the IMF. Third, as a result of widening open foreign exchange positions, large amounts of duty losses of state banks, connected lending of weak banks under the full deposit insurance scheme, weak implementation of supervision by the Treasury due to conflicts of interest, a large number of weak banks, and unfavorable external conditions, the banking system was highly fragile.

The crises of November 2000 and February 2001 stemmed primarily from the fragility of the banking sector. The Turkish experience shows that both public and private banks contributed significantly to the outbreak of the economic crises. In retrospect, it can be expressed that private commercial banks played an instrumental role in November 2000, while public banks emerged as the central actors in the context of the subsequent crisis of February 2001 (Alper and Onis, 2002). As discussed throughout this section, all distorted incentives in the Turkish banking sector such as opening foreign exchange positions, liquidity problems, poor asset quality, and capital inadequacy due to the weakness of regulation and supervision in the banking system is analyzed in conjunction with the empirical specification in the next section.

In the empirical part of the paper, high levels of liquidity, asset quality, and good management of banks are found to be the major determinants of bank survival, as expected. Furthermore, as a supervisory tool, the estimated degree of fragility of individual banks and the overall banking system may serve as a leading indicator of coming difficulties. These findings may help institutions like the Banks Association of Turkey and the Banking Supervision and Regulation Agency to devise or fine-tune their procedures in detecting banking sector fragilities. The main drivers of the failures in Turkey, which are discussed in this paper, are analyzed econometrically. For this, discrete choice models, a duration model, and a dynamic panel data model are used.

4. Data

The quarterly data for bank-specific variables are drawn from the balance sheet and income statements, which are used to compute financial ratios for 36 failed banks, of which 8 are mergers and acquisitions, and 45[7] non-failed banks. These financial statements are collected from the quarterly reports of The Banks Association of Turkey[8] over the period of December 1997- June 2006[9]. Moreover, the quarterly macroeconomic data are obtained from IMF International Financial Statistics (IFS[10]) for the same period.

Microeconomic variables are mainly based on CAMEL rating categories (capital adequacy, asset quality, management quality, earnings and profitability and liquidity), which are taken from the banks' financial statements. Besides, by using macroeconomic variables, the role of macroeconomic conditions on banking crises such as interest rates, inflation rates, Central Bank foreign exchange reserves and credit expansion etc,, are examined (Gonzales-Hermosillo, 1999). Both microeconomic and macroeconomic variables that appear in previous studies, with few exceptions, have been identified as good indicators of failures.

4.1. Principal component analysis

Principal component analysis is a multivariate statistical technique. Principal components are linear combinations of the variables that explain variance-covariance properties of the variables. Direct uses of principal component analysis are the identification of groups of inter-related variables, the reduction of number of variables, and a method of transformation of data (Anderson, 2003). Principal component analysis is a technique of categorizing patterns in data and expressing the data in such a way to highlight their similarities and differences. The main advantage of principal component analysis is to compress the data by reducing the dimension without loss of information (Anderson, 2003).

From the point of view of statistical theory, Anderson (2003) argued that the set of principal components yields a convenient set of coordinates, and the accompanying variances of the components characterize their statistical properties. In statistical practice, the method of principal

[7] The total number of banks in the banking system (except participation banks) is 46, excluding the Birleşik Fon Bankası which is in the group of banks in the Saving Deposit Insurance Fund as of June 2006. Moreover, 89.34% of paid-in capital of Türk Dış Ticaret Bankası A.Ş. was transferred to Fortis Bank in July 2005. However, Fortis Bank was not included in the sample due to its lack of data.

[8] http://www.tbb.org.tr/net/donemsel/default.aspx?dil=EN

[9] In this period, there is a difference between the date of the last financial statements issued and the date of failure for some of the failed banks. Therefore, in the estimation process, the date of the last financial statements is taken as the date of failure, as in Molina (2002).

[10] http://ifs.apdi.net/imf/ifsbrowser.aspx?branch=ROOT

components is used to find linear combinations with large variance (Anderson, 2003). Therefore, principal component analysis yields orthogonal explanatory variables and eigenvectors, and removes collinearity in the estimation.

The motivation in using principal component analysis is to identify highly correlated variables. This is done so that later econometric analysis will suffer less in accuracy and reliability. It is more likely to have highly correlated subsets of variables when there are a large number of variables in the database, as is the case here. The objective of principal component analysis is to reduce the dimensionality (number of variables) of the dataset but retain most of the original variability in the data (Anderson, 2003). The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

Both microeconomic variables and macroeconomic variables are separately subjected to principal component analysis. As the first step, the factors whose eigenvalues are greater than one should be retained for both microeconomic and macroeconomic variables separately. The first principal component is the eigenvector with the highest eigenvalue. If the eigenvalues are small, the loss of information will be less. Next,, the first p eigenvectors having eigenvalues greater than one are classified based on CAMEL categories and macroeconomic conditions. Principal component analysis is utilized to classify eigenvectors and to determine proxy variables and corresponding eigenvectors for each CAMEL category from the pool of independent variables, which summarizes the financial information of the banks and macroeconomic conditions. Furthermore, the Bartlett's test for sphericity for the presence of correlation and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy are used before the principal component analysis, Both the Bartlett test of sphericity and the KMO confirm that the principal component analysis is appropriate[11].

Table 4.1 presents the eigenvalues of factors for both microeconomic and macroeconomic variables. Based on the results of the principal component analysis, the first eight eigenvectors whose eigenvalues are greater than one for microeconomic variables and the first three eigenvectors whose eigenvalues are greater than one for macroeconomic variables are chosen.

[11] The Bartlett test of sphericity for microeconomic and macroeconomic variables equal 31101.5 and 20101.4 (p=0.00), respectively, so the model is statistically significant. Furthermore, the KMO measure of sampling adequacy for microeconomic and macroeconomic variables are equal to 0.65 and 0.75, respectively, and they are above the accepted level of 0.50 for both microeconomic and macroeconomic variables.

Table 4.1
Eigenvalues of Factors for Microeconomic and Macroeconomic Variables

Components	Eigenvalues	Proportion of Explained Variance	Cumulative Explained Variance
1	3.81	0.20	0.20
2	2.75	0.14	0.35
3	2.07	0.11	0.45
4	1.81	0.10	0.55
5	1.69	0.09	0.64
6	1.51	0.08	0.72
7	1.02	0.05	0.77
8	1.00	0.05	0.82
1	4.98	0.50	0.50
2	2.54	0.25	0.75
3	1.04	0.10	0.86

The first eight eigenvectors for microeconomic variables explain 82 percent of total variance and the first three eigenvectors for macroeconomic variables explain 86 percent of total variance (see Table 4.1). Tables A.1 and A.2 in the Appendix section present the variables that have the highest factor scores related to these eigenvectors. The classifications of eigenvectors are based on these scores. However, there are very close scores in a single eigenvector. Principal component analysis is again applied to those variables that have close eigenvalues to determine the selected variables in such a situation.

Based on the classification of eigenvectors, the first eigenvector is named as the size category for share in sector in terms of assets.[12] The classifications of the other seven eigenvectors are named as earning category for the ratio of income before tax to total assets, liquidity category for the ratio of liquid assets to total assets[13], asset quality category for the ratio of permanent assets to total assets[14], earnings category for the ratio of net

[12] The share in sector in terms of loans has a greater factor score than that of the share in sector in terms of assets. In the second application of the principal component analysis with four variables—share in sector in terms of loans, assets, deposits and logarithmic value of assets—the share in sector in terms of assets has the greatest score with 0.53.

[13] Although the ratio of total loans to total assets has the greatest score in the first step, in the second application of the principal component analysis with four variables—the ratio of loans to assets, the ratio of liquid assets to assets, the ratio of FX liquid assets to FX liabilities, the ratio of total deposits to number of branchesshare in the sector in terms of assets has the greatest score with 0.61.

[14] In the second application of the principal component analysis with four variables—the ratio of permanent assets to total assets, the ratio of FX deposits to number of branches, the ratio of

income to shareholder equity, management category for the ratio of total deposits to number of branches[15], liquidity category for the ratio of foreign exchange liquid assets to foreign exchange liabilities, and asset quality category for the ratio of total loans to net working capital, respectively.

The variables and eigenvectors selection procedure based on principal component analysis is also applied to ten macroeconomic variables in table A.2 in the Appendix section, covering the macroeconomic conditions of the country. Among the macroeconomic variables, the first three eigenvectors can be named as credit channel category for credit growth[16], real costs category for real interest rate variable, and real effect category for GDP growth.

4.2. Descriptive Statistics

The selection of the explanatory eigenvectors depends on both bank-specific and macroeconomic variables to predict bank failures that have been mentioned in the previous section. As a preliminary check, a test of mean differences is done as in Hutchison and McDill (1999). This can describe different movements in microeconomic variables for the failed/merged banks and non-failed banks separately. For failed/merged banks, one quarter before the failure was excluded from the data in order to assess the pattern of explanatory variables for failed banks before the crisis. Therefore, this test reports differences between the failed/merged banks and the non-failed banks during non-failure periods.

The mean differences of the microeconomic eigenvalues and variables for both non-failed and failed banks are given in table 4.2. In the first and second column, the mean values for both failed and non-failed banks are shown[17] and the last column illustrates the p-value of mean difference tests[18]. According to the mean difference test, all variables are found significantly higher in non-failed banks than in failed banks. If mean values for non-failed banks are higher (lower) than that of failed banks then the sign of estimated coefficients can be expected to be negative (positive) in line with t-test results.

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total deposits to number of branches, and the ratio of permanent assets to liquid assets—the ratio of permanent assets to total assets has the greatest score with 0.66.

15 In the second application of the principal component analysis with three variables—the ratio of total deposits to number of branches, the ratio of permanent assets to liquid assets and the ratio of FX deposits to number of branches—the ratio of total deposits to number of branches has the greatest score with 0.69.

16 In the second application of the principal component analysis with four variables—credit growth, the ratio of credit to private sector to GDP, the ratio of domestic credit to GDP and inflation rate—credit growth has the greatest score with 0.51.

17 The standard deviations are shown in parentheses.

18 The two-sample t-test is used to determine if the two population means are equal.

Table 4.2
Mean Difference Test[19] for Selected Eigenvectors and Variables

Variables / Eigenvectors	Mean Values For Non-failed Banks	Mean Values For Failed Banks	Differences in Mean Values (P > |t|)
Share in Sector (T. Assets)	1.93 (3.68)	0.88 (1.14)	0.00
Size Category	0.10 (2.11)	-0.28 (1.40)	0.00
Income Before Tax/T. Assets	3.43 (8.88)	-0.03 (25.54)	0.00
Earnings Category	0.13 (1.33)	-0.37 (2.29)	0.00
Liquid Assets/T. Assets	44.53 (23.12)	45.81 (22.98)	0.27
Liquidity Category	-0.01 (1.47)	0.00 (1.34)	0.97
Permanent Assets/T. Assets	12.88 (12.75)	15.04 (14.48)	0.86
Asset Quality Category	0.14 (1.20)	-0.38 (1.64)	0.00
Net Income/S. Equity	0.10 (1.00)	0.06 (2.77)	0.05
Earnings Category	0.05 (0.74)	-0.14 (2.19)	0.00
T. Deposits/No. of Branches	16.14 (35.87)	18.37 (31.44)	0.20
Management Category	-0.02 (1.08)	0.07 (1.56)	0.14
FX Liquid Assets/FX	47.80 (54.76)	36.65 (24.86)	0.00
Liquidity Category	0.01 (0.91)	-0.01 (1.23)	0.03
T. Loans/Net Working Capital	-0.07 (2.22)	0.01 (0.30)	0.38
Asset Quality Category	-0.01 (1.16)	0.01 (0.22)	0.69

The share in sector in terms of total assets, the size of banks in terms of assets can be negatively related to the likelihood of failure since relatively large banks may diversify risks subject to small banks. Besides “too large to fail” policies can help decrease the failure probability for relatively large banks (Gonzales-Hermosillo et al., 1997). The ratio of foreign exchange liquid assets to foreign exchange liabilities reflects the liquidity structure and foreign exchange exposure risk. Again, the ratio is expected to be negatively related to the probability of bank failure. The expected signs of these selected eigenvectors and related variables based on t-tests are consistent with the theoretical view.

From the income-expenditure side of the banks, the ratio of total deposits to the number of branches can be assessed in terms of efficiency. It is assumed that managerial ability can be measured to the extent that it can be a sign of explicit managerial decisions. Within the same context, the ratio of income before tax to total assets and the ratio of net income to shareholders’ equity reflect the earnings condition of the banks.

As expected, the earnings and management quality proxy variables are negatively related to the probability of bank failure. However, the sign of the earnings proxy may be positive since riskier investments are more profitable

[19] Ho: Mean (Exp. var. for failed banks) – Mean (Exp. var. for non-failed banks) = 0

depending on the condition of the banks. Furthermore, the ratio of total loans to net working capital and the ratio of permanent assets to total assets can be assessed in the asset quality category. Banks that failed during the sample period had a higher ratio of total loans to net working capital and ratio of permanent assets to total assets. The interpretation of this is straightforward: A high level of the ratio of total loans to net working capital indicates a high level of credit risk of the banks.

Based on the t-test results, except for the eigenvectors related to the liquidity category, management category, and asset quality category, the eigenvectors related to other CAMEL categories including size category are significant at the one percent significance level. Similarly, except for the ratio of liquid assets to total assets, the ratio of permanent assets to total assets, the ratio of total deposits to number of branches and the ratio of total loans to net working capital, other variables are again significant at the one percent significance level, based on mean difference test results. Therefore, the mean values of selected explanatory variables and eigenvectors for non-failed banks are different from those for failed banks. This provides preliminary evidence that motivates further analysis.

We have thus prepared a set of eigenvectors and variables based in principal component analysis that will be utilized in the empirical specification; the discrete choice model. Multinomial and binary logit models are used by comparing the predictive accuracy of the models in order to capture the different outcomes of failure with the same selected eigenvectors and related variables, separately.

5. Discrete choice model

Both a multinomial logit model and a traditional binary model are applied to the selected eigenvectors based on principal component analysis in order to predict the probability of bank failures and determine the factors of bank failures. The traditional logit model for panel data is used to explain the probability of bank failure. In each quarter, the bank is either experiencing a failure or not. Accordingly, the dependent variable is a binary outcome taking the values of 0 when the bank fails or 1 when it survives. Let i = 1, 2,.., 81 denote the banks and t = 1, 2,…, 35 denote the quarters for the i^{th} bank. The conventional function, which indicates the cumulative standard logistic probability distribution function, is described as follows:

$$\text{Prob}\,(\text{Failure}_{it} = 1) = \exp\,(X_{it}\beta) / (1+ X_{it}\beta\,) \qquad (5.1)$$

Equation (5.1) is estimated using maximum likelihood procedure. Moreover, the probability of bank failures that will occur at a particular time in a particular bank is hypothesized to be a function of a vector of n explanatory variables X_{it} and β is a vector of n unknown coefficients[20] (Greene, 1997).

[20] See Greene (1997) for a full exposition of the derivations.

A multinomial logit model, which is used to differentiate between bank failures, mergers/acquisitions, and non-failed outcomes, is estimated by maximum likelihood. Again, let i = 1, 2,.., 81 denote the banks and t = 1, 2,…, 35 denote the quarters for the i^{th} bank. The conventional function is described as follows:

$$\text{Prob}\ (Y_{it} = j) = \exp\ (X_{it}\beta_j)\ /\ (\sum_{k=0}^{2} X_{it}\beta_k) \quad \text{for } j= 0,1 \text{ or } 2 \qquad (5.2)$$

where Y_{it} is a random variable indicating the state of the banks in each quarter. This can take a value of j = 0, 1 or 2, which represents non-failed, failure, and mergers/acquisition, respectively. The vector X_{it} represents a set of exogenous variables and β represents regression parameters to be estimated. The estimated equations above provide a set of probabilities for the j + 1 choices for an individual with characteristics X_{it} (Greene, 1997). Equation (5.2) is estimated again using the maximum likelihood procedure. Moreover, the multinomial logit model assumes independence of odd ratios of different alternatives; therefore, the model requires that the assumption of ‘independence of irrelevant alternatives (IIA)’ be satisfied (Greene 1997). In order to validate this assumption, the Hausman specification test as well as the Small-Hsiao IIA test is presented in table A.3 in the Appendix section.

5.1. Estimation results

This section presents both multinomial logit models, which jointly determine failure, merger/acquisition, and non-failure, and standard binary logit models, in which merger/acquisition and failure outcomes are pooled. Tables 5.1-5.4 illustrate the specifications for the binary and multinomial logit models. The first three columns for each model illustrate the estimated coefficients, the relevant statistics of significance (z) and the p-value, respectively. The first model specification includes only bank-specific eigenvectors and variables and the second one combines both microeconomic and macroeconomic eigenvectors and variables for both models.

The results[21] of the binary model in table 5.1 show that all bank-specific eigenvectors, except for the size category, liquidity categories, and one of the asset quality categories, are significant at the one percent significance level. Moreover, for the joint-significance of variables, the Wald and LR[22] tests are applied and in both model specifications, the null hypothesis of zero coefficients of explanatory variables is rejected at the one percent significance level (see table 5.1).

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[21] These results based on panel data in which the observations responding from the failure quarter onwards are excluded for both models.

[22] LR test statistics is equal to the difference between log likelihood values of the model in the first iteration and the last iteration, which is multiplied by minus 2 (Gonzales-Hermosillo, 1999).

Table 5.1
Estimation Results of Binary Logit Model for Selected Eigenvectors[23]

Variables / Models	Model 1			Model 2		
	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables						
Size Category	-0.24	-0.89	0.38	-0.13	-0.72	0.47
Earnings Category	-0.80	-4.64	0.00	-0.49	-4.93	0.00
Liquidity Category	-0.37	-1.44	0.15	-0.15	-0.97	0.33
Asset Quality Category	-0.51	-2.87	0.00	-0.47	-3.73	0.00
Earnings Category	-0.40	-2.48	0.01	-0.28	-2.43	0.02
Management Category	0.37	2.00	0.05	0.16	1.26	0.21
Liquidity Category	0.32	1.11	0.27	0.25	0.94	0.35
Asset Quality Category	0.02	0.04	0.97	0.03	0.10	0.92
Intercept Dummy	2.09	2.26	0.02	2.26	3.54	0.00
Constant	-6.94	-5.70	0.00	-6.13	-12.1	0.00
Macroeconomic Variables						
Credit Channel	-	-	-	0.41	2.68	0.01
Real Cost	-	-	-	0.27	2.44	0.02
Real Effect	-	-	-	-0.05	-0.27	0.79
Model Fit						
AIC	234.50			217.90		
Pseudo R^2	0.233			0.247		
Diagnostic Test of Validity of Regressors						
LR	100.38			136.95		
Wald	31.91			72.34		

Table 5.2 reports that all selected bank-specific variables except for the share in sector in terms of assets, the ratio of liquid asset to asset, the ratio of net income to equity, deposits per branch, and the ratio of loans to net working capital are significant at the one percent significance level. These results are consistent with the results of the binary logit model with selected eigenvectors. Moreover, for joint-significance of variables, the Wald and LR[24] tests are applied and in both model specifications, and the null hypothesis of zero coefficients of explanatory variables is rejected at one percent significance level (see tables 5.1 and 5.2).

[23] The eigenvector selection procedure based on principal component analysis is explained in detail in section 4.1.

[24] LR test statistics is equal to the difference between log likelihood values of the model in the first iteration and the last iteration, which is multiplied by minus 2 (Gonzales-Hermosillo, 1999).

Tables 5.1 and 5.2 also show the overall model selection criteria with Akaike's information criteria (AIC)[25] and Pseudo R^2[26]. According to both criteria, the estimates in the full model specification, which use both microeconomic and macroeconomic variables, provide higher Pseudo R^2 and lower AIC values than that of the former one, which uses only microeconomic variables.

Table 5.2

Estimation Results of Binary Logit Model for Selected Variables[27]

Variables / Models	Model 1			Model 2		
	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables						
Share in Sector (T. Assets)	-0.21	-1.16	0.25	-0.13	-0.99	0.32
Income Before Tax/T. Assets	-0.05	-5.52	0.00	-0.05	-6.07	0.00
Liquid Assets/T. Assets	0.01	0.62	0.53	0.01	1.25	0.21
Permanent Assets/T. Assets	0.03	2.42	0.02	0.01	1.19	0.24
Net Income/S. Equity	0.05	0.68	0.50	0.02	0.28	0.78
T. Deposits/No. of Branches	0.00	0.03	0.98	0.00	0.64	0.52
FX Liquid Assets/FX Liabilities	-0.04	-2.86	0.00	-0.03	-3.05	0.00
T. Loans/Net Working Capital	0.07	0.23	0.82	0.05	0.18	0.85
Intercept Dummy	1.97	2.48	0.01	3.58	4.14	0.00
Constant	-5.36	-5.87	0.00	-3.93	-5.68	0.00
Macroeconomic Variables						
Credit Growth	-	-	-	-0.04	-2.75	0.01
Real Interest Rate	-	-	-	0.02	2.52	0.01
GDP Growth	-	-	-	-0.06	-2.03	0.04
Model Fit						
AIC	248.29			222.34		
Pseudo R^2	0.215			0.254		
Diagnostic Test of Validity of Regressors						
LR	96.07			116.03		
Wald	43.49			76.72		

[25] AIC can be used for the model having different number of variables. It can be defined as the sum of log likelihood value and the number of explanatory variables, which is multiplied by minus 2.

[26] Pseudo R^2 can be used for comparing the fit of different models for the same dependent variable. It is equal to one minus the ratio of the log likelihood value of the model in the first iteration to the log likelihood value in the last iteration (Gonzales-Hermosillo, 1999).

[27] The variable selection procedure based on principal component analysis is explained in detail in section 4.1.

For the second quarter of 2001, a crisis dummy variable[28] is included in both model specifications for each model and it is found positive and statistically significant. From tables 5.1 and 5.2, the full specification of the models, earning categories and asset quality category are found negative and statistically significant, as expected (see table 5.1). This means that the said categories are negatively related to bank failures. As in the estimation with variables, the ratio of income before tax to total assets and the ratio of foreign exchange liquid assets to foreign exchange liabilities are negative, as expected. They have a negative effect on the probability of failure (see table 5.2). The results of the two different estimations have consistency in terms of significance of the independent variables.

From the macroeconomic perspective, in most studies, there is evidence that if there is a credit expansion in the economy, banking sector problems can be expected (Demirguc-Kunt and Detragiache, 1997). In this study, credit growth is likely to be positively associated with the likelihood of failure. Lower GDP growth rate or adverse developments in the real side of the economy can be a main source of banking sector problems (Demirguc-Kunt and Detragiache, 1997). The real interest rate is likely to be related to the proxy of macroeconomic mismanagement, which adversely affects the economy and the banking system through various channels. Therefore, the sign of the estimated coefficient of real interest rate turns out to be positive. In this study, except for the credit growth variable, other macroeconomic variables have the expected signs. Only the eigenvector related to macroeconomic real effect is statistically insignificant. There is no additional proper information on banking failure in the estimation with eigenvectors. This is because of the fact that ingredients of the said eigenvector have the composition of the other variables (see Section 4).

Tables 5.3 and 5.4 report the results of the re-estimation of two specifications of both selected eigenvectors and variables using a multinomial logit model. Again, all banks and all periods are included in the pooled sample. The coefficients that affect the probability of merger/acquisition positively also affect the probability of failure positively and vice versa. The coefficients differ largely across the probabilities of merger/acquisition and failure in both specifications of the multinomial logit model. However, the estimated coefficients in both binary and multinomial logit models are close to each other for the failed banks. Moreover, the dummy variable is found statistically insignificant which is different from that of binary logit model. There is no effect of financial crisis on the probability of merger/acquisition.

[28] The effect of the crisis that occurred in February 2001 can be seen from the financial reports of the banks, which were published in the second quarter of 2001. Therefore, a dummy variable is included to both model specifications per model. It takes the value 1 from 2001.q2 to 2006.q2 but 0 elsewhere.

In table 5.4, the sign of the coefficient on the variable "net income / shareholders' equity" is positive. This may be unexpected. However, the sign of the earnings proxy is not clear "a priori". Although profitability can signal a well-functioning bank, excessively risky projects can be very profitable for a while before the failure. In this study, the profitability proxy variable has a positive impact on hazard rate. In other words, the profitability of the banks has a negative impact on the survival of the banks.

It is also tested that whether the binary models are valid restrictions of the multinomial models. Table 5.2 reports the likelihood based on Pseudo R^2 statistics and a statistical test that discriminates formally between the binary and multinomial specifications. With regard to the former one, the estimates in the multinomial logit model provide higher pseudo R^2 values than the binary model in each specification.

Furthermore, table A.3 in the Appendix section indicates that both model specifications with selected eigenvectors and variables confirm the validity of the IIA assumption based on both Hausman and Small-Hsiao specification tests. Moreover, in Wald tests for combining outcomes, the null hypothesis—namely, that the categories can be collapsed—is strongly rejected for both specifications in the multinomial logit model[29].

5.3. Prediction

Thomson (1991) pointed out that the discrete choice models order a bank as failed if the predicted value of the dependent variable exceeds an exogenously set cut-off probability. The cut-off probability is typically set at 0.5. However, as unsatisfactory results are obtained using a cut-off probability of 0.5, it is suggested that the cut-off probabilities should be corrected by using the mean of predicted values of the dependent variable. In addition, if a type I error[30] is regarded to be more costly than a type II error, a lower value for the cut-off probability can be adjusted (Thomson, 1991).

In examining both the binary and the multinomial logit models from tables A.4-A.7 in the Appendix section, the prediction results for the cut-off

[29] For the first model specification with selected eigenvectors, which uses only microeconomic variables, test statistics for all categories of failed–merger/acquisition, failed–non-failed, and merger/acquisition–non-failed are 46.97 (sign level 0.00), 40.60 (sign level 0.00), and 69.08 (sign level 0.00) with 9 degrees of freedom, respectively. For the full specification with selected eigenvectors, test statistics are 38.70 (sign level 0.00), 57.18 (sign level 0.00), and 64.94 (sign level 0.00) with 12 degrees of freedom, respectively. For the first specification with selected variables, test statistics are 69.83 (sign level 0.00), 48.03 (sign level 0.00), and 66.19 (sign level 0.00) with 9 degrees of freedom, respectively. Lastly, for the full specification with selected variables, test statistics are 47.72 (sign level 0.00), 63.56 (sign level 0.00), and 75.66 (sign level 0.00) with 12 degrees of freedom, respectively.

[30] Type I error occurs when a failed bank is incorrectly classified as a non-failed bank and type II error occurs when a non-failed bank is incorrectly classified as a failed bank (Thomson, 1991).

probability of 0.5 are not satisfactory. Accordingly, only 9 banks for the binary logit model estimated with both selected eigenvectors and related variables out of all failed banks are correctly classified as failed banks in any quarters of the sample period. Moreover, only 7 and 9 banks for the multinomial logit model estimated with both selected eigenvectors and related variables out of all failed banks are correctly classified as failed banks in any quarters of the sample period, respectively. Based on the mean predicted values, the predictive accuracy jumped from 20% to 75% in the category of predicted as a failure in the quarter of failure in both the binary and the multinomial logit model estimated with both selected eigenvectors and related variables. Further, for the other categories, the results are more satisfactory than that of former one (see tables A.4-A.7 in the Appendix section).

In the last column of tables A.4-A.7, the third alternative of cut-off probability is given. It reports that the calculated percentage of predictive accuracy is based on different cut-off probabilities for each quarter; that is, they vary with the mean of the predicted values of the dependent variable quarter by quarter. In the binary models, with different cut-off probabilities, the overall prediction varies between 89% and 45% for estimated with eigenvectors, and 92% and 34% for estimated with variables, respectively. In the multinomial models, giving almost the same result, the overall prediction varies between 89% and 44% for estimated with eigenvectors, and 94% and 33% for estimated with variables, respectively. Naturally, models with higher cut-off probabilities present more accurate results in non-failed observations correctly classified than in failed observations correctly classified. This adjustment provides the minimization of failure costs.

Detailed prediction results of failed banks for both models that are given in tables 5.5 and 5.6 are constructed based on different cut-off probabilities for each quarter. Binary logit models correctly classify 88% of all the failures in any quarter for estimated with eigenvectors and 92% of all the failures in any quarter for estimated with variables; in the quarter of failure, 83% of the failures for estimated with eigenvectors and 78% of the failures for estimated with variables and at least four quarters before the failure 89% of the failures for estimated with eigenvectors and variables.

Moreover, the multinomial logit model gives almost the same results with the binary logit model. Accordingly, in tables 5.7 and 5.8, it correctly classifies 89% of the failed banks as a failure in any quarter for estimated with eigenvectors and 94% of all the failures in any quarter for estimated with variables. The rates in the quarter of failure are 81% of the failures for estimated with eigenvectors and 79% of the failures for estimated with variables. The rates in the category of at least four quarters before the failure are 89% of the cases for estimated with eigenvectors and 92% of the cases for

Table 5.5
Prediction Results for Binary Logit Model for Selected Eigenvectors

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	YES	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	YES	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	YES	YES
Ak Uluslararası Bankası A.Ş.	NO	YES	YES
Credit Lyonnais Turkey	NO	YES	YES
Credit Suisse First Boston	NO	YES	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	YES
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	YES	NO	NO
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	YES	NO	NO
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	NO	NO	YES
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	NO	YES
Rabobank Nederland	YES	NO	NO
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	NO	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	YES	YES
Yurt Ticaret ve Kredi Bankası	NO	YES	YES
Number of incorrectly classified	4	6	4
Percentage of incorrectly classified	11.11	16.67	11.11

Table 5.6
Prediction Results for Binary Logit Model for Selected Variables

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	YES	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	NO	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	YES	YES
Ak Uluslararası Bankası A.Ş.	NO	NO	YES
Credit Lyonnais Turkey	YES	NO	NO
Credit Suisse First Boston	NO	NO	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	NO
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	NO	YES	YES
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	NO	NO	YES
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	YES	NO	NO
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	NO	YES
Yurt Ticaret ve Kredi Bankası	NO	YES	YES
Number of incorrectly classified	3	8	4
Percentage of incorrectly classified	8.33	22.22	11.11

Table 5.7
Prediction Results for Multinomial Logit Model for Selected Eigenvectors

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	YES	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	YES	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	NO	YES
Ak Uluslararası Bankası A.Ş.	NO	NO	YES
Credit Lyonnais Turkey	NO	YES	YES
Credit Suisse First Boston	NO	NO	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	YES
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	YES	NO	NO
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	YES	NO	NO
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	YES	NO	NO
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	YES	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	YES
Number of incorrectly classified	4	7	4
Percentage of incorrectly classified	11.11	19.44	11.11

Table 5.8
Prediction Results for Multinomial Logit Model for Selected Variables

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	NO	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	NO	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	NO	YES
Ak Uluslararası Bankası A.Ş.	NO	NO	YES
Credit Lyonnais Turkey	NO	YES	YES
Credit Suisse First Boston	NO	NO	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	NO
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	NO	YES	YES
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	NO	YES	YES
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	YES	NO	NO
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	NO	YES
Yurt Ticaret ve Kredi Bankası	NO	YES	YES
Number of incorrectly classified	2	8	3
Percentage of incorrectly classified	5.56	22.22	8.33

estimated with variables. These results suggest that the elements that contribute to banking failure may be in place for four quarters or more before the failure. According to both models, banks in difficulties one year before the failure should have failed; however, political reasons or the weakness in regulation and supervision can delay the failure process.

6. Conclusion

This study attempted to estimate the probability of individual bank failures, which is a function of both bank-specific and macroeconomic eigenvectors and corresponding variables. We estimated both binary and multinomial models. Banks with a strong liquidity state in terms of foreign exchange, higher earnings, and asset quality have a role to decrease the likelihood of banking failures.

From the macroeconomic perspective, higher credit growth and real interest rates are associated with a higher probability of banking failures. The results are consistent with the findings of Wheelock and Wilson (2000), Logan (2001), and Molina (2002) in samples of US, UK, and Venezuelan banks, respectively. The significance of macroeconomic variables is also consistent with the studies of Demirguc-Kunt and Detragiache (1997) and Hutchison and McDill (1999).

However, the aim of this study is not to construct a manual for bank failures for supervisory institutions. The findings can be interpreted as the microeconomic and macroeconomic determinants of the failure probabilities of the Turkish banking system with different models. According to prediction results, the multinomial logit model with estimated variables gives slightly more accurate results than that of the other three specifications.

The findings in this study may help decision makers in supervisory institutions in terms of the determinants of bank failures in the Turkish banking system. Moreover, it can provide a motivation for developing a duration model for the determination and prediction of timing of failures since the discrete choice models do not use information concerning how long banks survive.

7. Appendix

Table A.2

The Scores of the First Three Factors with Macroeconomic Variables

Variable	Factor 1	Factor 2	Factor 3
GDP Growth	-0.228	-0.248	**0.603**
Depreciation	0.233	0.364	0.349
Real Interest Rate	-0.062	**0.556**	0.362
M2/CB Foreign Reserves	-0.243	0.373	-0.473
Credit Growth	**0.399**	0.105	-0.268
Credit to Private Sector/GDP	-0.398	0.027	0.041
Domestic Credit/GDP	-0.419	0.035	-0.044
Bank Liquid Assets/Bank Reserves	0.257	-0.407	0.176
Interbank Interest Rate	0.306	0.405	0.212
Inflation	0.423	-0.124	-0.087

Table A.3

Tests of the Independent Irrelevant Alternative (IIA) Assumption[31]

Models	Model 1	Model 2
Tests of IIA for the Model with Selected Eigenvectors		
Hausman Tests of IIA assumption	omitted 1 $\chi^2(10) = 0.023$ (1.000)	omitted 1 $\chi^2(13) = 0.005$ (1.000)
	omitted 2 $\chi^2(10) = 0.002$ (1.000)	omitted 2 $\chi^2(13) = 0.052$ (1.000)
Small-Hsiao Tests of IIA assumption	omitted 1 $\chi^2(10) = 15.120$ (0.128)	omitted 1 $\chi^2(13) = 15.229$ (0.293)
	omitted 2 $\chi^2(10) = 13.185$ (0.213)	omitted 2 $\chi^2(13) = 12.202$ (0.511)
Tests of IIA for the Model with Selected Variables		
Hausman Tests of IIA assumption	omitted 1 $\chi^2(10) = 0.001$ (1.000)	omitted 1 $\chi^2(13) = 0.001$ (1.000)
	omitted 2 $\chi^2(10) = 0.003$ (1.000)	omitted 2 $\chi^2(13) = 0.003$ (1.000)
Small-Hsiao Tests of IIA assumption	omitted 1 $\chi^2(10) = 17.269$ (0.069)	omitted 1 $\chi^2(13) = 21.620$ (0.062)
	omitted 2 $\chi^2(10) = 8.947$ (0.537)	omitted 2 $\chi^2(13) = 9.684$ (0.720)

[31] In the table, the dummy variable d represents the state of the banks (takes on values of 0, 1, or 2); non-failed, failed and mergers/acquisitions banks, respectively.

Table A.4
Predictive Accuracy for the Binary Logit Model with Selected Eigenvectors[32]

Classification	Cut-off 0.50	Cut-off 0.017	Variation in Cut-off
Predicted as a failure (in any quarter) correctly	25.00	86.11	88.89
Predicted as a failure in the quarter of failure correctly	25.00	69.44	83.33
The percentage of non-failed observations that are correctly classified	100.00	85.87	68.12
The percentage of failed observations that are correctly classified (included all quarters before the failure)	2.03	16.21	44.57

Table A.5
Predictive Accuracy for the Binary Logit Model with Selected Variables

Classification	Cut-off 0.50	Cut-off 0.018	Variation in Cut-off
Predicted as a failure (in any quarter) correctly	22.22	97.22	91.67
Predicted as a failure in the quarter of failure correctly	19.44	75.00	77.78
The percentage of non-failed observations that are correctly classified	100.00	83.23	70.36
The percentage of failed observations that are correctly classified (included all quarters before the failure)	1.66	20.44	34.44

[32] The cut-off probability in the second column is the mean of predictive values, 0.017, and in the third column it is the mean of predicted values of dependent variable quarter by quarter.

Table A.6
Predictive Accuracy for the Multinomial Logit Model with Selected Eigenvectors

Classification	Cut-off 0.50	Cut-off 0.014	Variation in Cut-off
Predicted as a failure (in any quarter) correctly	25.00	86.11	88.89
Predicted as a failure in the quarter of failure correctly	25.00	69.44	80.56
The percentage of non-failed observations that are correctly classified	100.00	88.05	66.73
The percentage of failed observations that are correctly classified (included all quarters before the failure)	2.03	15.84	44.20

Table A.7
Predictive Accuracy for the Multinomial Logit Model with Selected Variables

Classification	Cut-off 0.50	Cut-off 0.014	Variation in Cut-off
Predicted as a failure (in any quarter) correctly	27.78	97.22	94.44
Predicted as a failure in the quarter of failure correctly	25.00	69.44	77.78
The percentage of non-failed observations that are correctly classified	100.00	87.06	70.23
The percentage of failed observations that are correctly classified (included all quarters before the failure)	2.03	19.15	32.97

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Özet

Türkiye'de banka batışlarının kesikli seçim modelleri ile kestirimi

Bu çalışma, 1997-2006 yılları arasında Türkiye'de banka batışlarına ilişkin etmenleri incelemektedir. Çalışma, 81 bankanın akış kesiti zaman serisi verlerini kullanarak limitli bağımlı değişken modeli ile incelemektedir. Bu çalışmada amaç banka batışlarını belirleyen etmenlerden mikroekonomik ve makroekonomik değişkenlerin katkılarını açıklamak ve banka batış olasılıklarını tahmin etmektir.

Anahtar kelimeler: Banka batışları, Kesikli seçim modeli, Türkiye.

JEL kodları: G21, E44, E47.

Table 5.3

Estimation Results of Multinomial Logit Model for Selected Eigenvectors[33]

Variables / Models	1 (Failed)			2 (Merger/Acquisition)			1 (Failed)			2 (Merger/Acquisition)		
	Coef.	z	P>z	Coef.	z	P>z	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables												
Size Category	-0.05	-0.40	0.69	-0.07	-0.18	0.86	-0.08	-0.56	0.58	-0.13	-0.32	0.75
Earnings Category	-0.64	-5.22	0.00	-0.46	-3.84	0.00	-0.54	-3.73	0.00	-0.30	-2.38	0.02
Liquidity Category	-0.05	-0.29	0.78	-0.34	-1.21	0.23	-0.09	-0.50	0.61	-0.32	-1.16	0.25
Asset Quality Category	-0.35	-2.70	0.01	-0.22	-1.59	0.11	-0.43	-3.02	0.00	-0.33	-2.36	0.02
Earnings Category	-0.23	-2.59	0.01	-0.06	-0.42	0.67	-0.25	-2.87	0.00	-0.08	-0.56	0.58
Management Category	0.01	0.08	0.94	0.63	2.76	0.01	-0.05	-0.27	0.79	0.53	2.49	0.01
Liquidity Category	0.47	3.06	0.00	-0.01	-0.06	0.95	0.35	2.12	0.03	-0.06	-0.35	0.72
Asset Quality Category	0.03	0.80	0.42	0.28	1.95	0.05	0.00	0.03	0.98	0.30	1.79	0.07
Intercept Dummy	0.68	1.48	0.14	1.77	1.65	0.10	2.26	2.41	0.02	3.08	1.49	0.14
Constant	-5.42	-13.48	0.00	-7.61	-7.47	0.00	-6.37	-9.01	0.00	-8.86	-5.52	0.00
Macroeconomic Variables												
Credit Channel	-	-	-	-	-	-	0.47	2.23	0.03	0.19	0.52	0.60
Real Cost	-	-	-	-	-	-	0.22	2.03	0.04	0.61	1.97	0.05
Real Effect	-	-	-	-	-	-	0.07	0.44	0.66	-0.39	-0.74	0.46
Model Fit												
AIC	259.86						237.58					
Pseudo R2	0.284						0.326					
Diagnostic Test of Validity of Regressors												

[33] Eigenvectors (also used in binary models) selection procedure based on principal component analysis is explained in detail in section 4.1.

LR	110.06	126.33
Wald	106.29	121.52

Table 5.4
Estimation Results of Multinomial Logit Model for Selected Variables[34]

Variables / Models	1 (Failed)			2 (Merger/Acquisition)			1 (Failed)			2 (Merger/Acquisition)		
	Coef.	**z**	**P>z**	**Coef.**	**z**	**P>z**	**Coef.**	**z**	**P>z**	**Coef.**	**z**	**P>z**
Microeconomic Variables												
Share in Sector (T. Assets)	-0.13	-1.24	0.22	-0.04	-0.37	0.71	-0.16	-1.45	0.15	-0.05	-0.36	0.72
Income Before Tax/T. Assets	-0.06	-4.99	0.00	0.03	2.66	0.01	-0.06	-4.61	0.00	0.02	2.08	0.04
Liquid Assets/T. Assets	0.01	0.88	0.38	0.02	0.63	0.53	0.01	1.04	0.30	0.01	0.51	0.61
Permanent Assets/T. Assets	0.02	1.81	0.07	0.04	3.36	0.00	0.01	0.78	0.43	0.03	2.08	0.04
Net Income/S. Equity	0.07	2.96	0.00	-0.16	-2.62	0.01	0.05	2.08	0.04	-0.11	-1.55	0.12
T. Deposits/No. of Branches	0.00	0.62	0.54	0.00	0.34	0.73	0.00	0.22	0.83	0.01	1.20	0.23
FX Liquid Assets/FX Liabilities	-0.03	-2.28	0.02	-0.03	-1.40	0.16	-0.03	-2.46	0.01	-0.03	-1.64	0.10
T. Loans/Net Working Capital	0.00	0.20	0.84	0.17	2.38	0.02	-0.01	-0.24	0.81	0.19	2.26	0.02
Intercept Dummy	0.78	1.71	0.09	2.07	1.87	0.06	3.91	3.01	0.00	3.64	1.27	0.21
Constant	-4.79	-7.19	0.00	-7.74	-4.41	0.00	-3.90	-5.98	0.00	-7.19	-4.25	0.00
Macroeconomic Variables												
Credit Growth	-	-	-	-	-	-	-0.06	-2.17	0.03	-0.02	-0.51	0.61

[34] Variables (also used in binary models) selection procedure based on principal component analysis is explained in detail in section 4.1.

Real Interest Rate	-	-	-	-	-	-	0.03	2.31	0.02	0.02	1.46	0.15
GDP Growth	-	-	-	-	-	-	-0.03	-0.83	0.40	-0.11	-1.67	0.10
Model Fit												
AIC	268.18						238.60					
Pseudo R2	0.285						0.344					
Diagnostic Test of Validity of Regressors												
LR	114.18						137.76					
Wald	120.66						134.66					

Table A.1
The Scores of the First Eight Factors with Microeconomic Variables

Variable+	Classification	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Net Working Capital/ T. Assets	Capital Adequacy	-0.215	0.336	-0.092	0.256	0.132	-0.089	-0.056	0.020
S. Equity/FX Position	Capital Adequacy	-0.078	0.106	0.338	0.102	0.214	-0.250	-0.015	0.005
Permanent Assets/T. Assets	Asset Quality	0.014	-0.376	0.005	**0.324**	0.064	0.466	-0.007	0.011
T. Loans/T. Assets	Asset Quality	0.203	0.084	-0.514	-0.136	-0.219	0.020	0.042	0.017
T. Loans/S. Equity	Asset Quality	0.110	0.008	-0.245	-0.277	0.583	0.063	0.010	-0.008
T. Loans/Net Working Capital	Asset Quality	-0.020	0.000	0.008	-0.021	0.002	0.006	-0.119	**0.992**
Permanent Assets/Liquid Assets	Asset Quality	-0.073	-0.336	0.160	0.348	0.156	0.365	-0.055	-0.007
Net Income/No. of Branches	Management	-0.047	0.274	-0.185	0.007	-0.121	0.244	-0.175	-0.039
FX Deposits/No. of Branches	Management	-0.036	0.201	0.231	-0.362	-0.113	0.502	-0.002	-0.009
T. Deposits/No. of Branches	Management	-0.009	0.173	0.344	-0.416	-0.080	**0.349**	-0.011	-0.006

Income Before Tax/T. Assets	Earnings	-0.130
Net Income/T. Assets	Earnings	-0.088
Net Income/S. Equity	Earnings	-0.032
Liquid Assets/T. Assets	Liquidity	-0.256
FX Liquid Assets/FX Liabilities	Liquidity	0.015
Share in Sector in terms of T. Assets	Size	**0.453**
Share in Sector in terms of T. Loans	Size	0.455
Share in Sector in terms of T. Deposits	Size	0.443
Log (T. Assets)	Size	0.430

0.455	-0.077	0.282	0.107	0.208	0.094	0.009
0.439	-0.107	0.284	0.104	0.161	0.114	0.013
0.057	0.161	0.232	**-0.651**	-0.083	0.043	0.006
0.129	**0.422**	-0.091	0.153	-0.244	-0.058	-0.027
-0.033	0.058	-0.025	0.021	0.013	**0.958**	0.112
0.116	0.196	0.165	0.076	0.005	-0.028	0.004
0.126	0.096	0.131	0.034	0.025	-0.035	0.011
0.100	0.217	0.158	0.083	-0.007	-0.019	0.003
0.102	0.038	-0.077	-0.047	-0.074	-0.013	0.011