Probabilistic Prediction of Bank Failures with Financial Ratios: An Empirical Study on Turkish Banks

Gamze Özel
Department of Statistics
Hacettepe University Turkey
gamzeozl@hacettepe.edu.tr

Nihal Ata Tutkun
Department of Statistics
Hacettepe University Turkey
nihalata@hacettepe.edu.tr

Abstract

Banking risk management has become more important during the last 20 years in response to a worldwide increase in the number of bank failures. Turkey has experienced a series of economic and financial crisis since the declaration of Republic and banking system has the most affected sector from the results of these crises. This paper examines some bank failure prediction models using financial ratios. Survival, ordinary and conditional logistic regression models are employed in order to develop these prediction models. The empirical results indicate that the bank is more likely to go bankrupt if it is unprofitable, small, highly leveraged, and has liquidity problems and less financial flexibility to invest itself.

Keywords: Bank Failure, Conditional Logistic Regression, Cox Regression, Financial Ratio, Hazard, Ordinary Logistic Regression.

1. Introduction

Recent episodes of financial crises in emerging markets progressively highlighted the importance of a sound and well-functioning banking sector for macroeconomic stability and sustainable economic growth. There has been a great interest in constructing models to explain bank failure and in categorizing banks into failed or non-failed banks since the 1960s. The bank failure studies are important for two reasons: First, an understanding of the factors related to a bank's failure enables regulatory authorities to manage and supervise banks more efficiently. Second, the ability to differentiate between failed banks and non-failed ones could reduce the expected cost of bank failures. If examiners can detect problems early enough, regulatory actions can be taken either to prevent a bank from failing or minimize the costs to the public and thus taxpayers.

Since 1980s Turkish banking sector experienced a significant expansion and development in the number of banks, employment in the sector, diversification of services and technological infrastructure. Total assets of the banking sector increased from USD20.8bn (28.6% of GNP) in 1980 to USD58.2bn (38.2% of GNP) in 1990 and to USD155bn (76.9% of GNP) in 2000 (Alper, 2001). However, twin economic crises experienced by Turkey in 2000 and 2001 illustrated in a rather dramatic fashion the strong correspondence between a poorly functioning and under-regulated banking system, on the one hand, and the sudden outbreak of macroeconomic crises on the other.

Statistical techniques used in modeling bank failures include logistic models (Ohlson, 1980; Rose and Kolari, 1985; Pantolone and Platt, 1987) and survival models (Whalen, 1991; Henebry, 1996; Laviola et al., 1999). Apart from these techniques, a few number of studies conducted toward bank failure prediction in Turkey include univariate analysis Canbaş and Erol (1985) and Erol (1985), and multivariate regression analysis Çilli and Tuğrul (1988) and Ağaoğlu (1989). Some other articles aimed to the determination of the financial characteristics of the Turkish banking system include cluster analysis by Aydoğan (1990) and factor analysis by Karamustafa (1999). The efficiency and productivity of Turkish banks were measured for the period between 1999 and 2001 by employing data envelopment analysis in Atan (2003). Atan and Çatalbaş (2005) analyzed that the efficiency of Turkish banks according to capital structure by using data envelopment analysis.

The use of survival models to explain and predict failures of banks is relatively recent. Lane et al. (1986) represented the first article that proposed and empirically evaluated the application of a Cox regression model to predict bank failure. Henebry (1996) used this model to evaluate the predictive power of cash flow variables. Laviola et al. (1999) showed that the prediction of bank failure estimated via a Cox regression model outperformed logistic model for the Italian data. Due to the absence of previous work using a Cox regression model for the Turkish case, this paper priories the use of semi parametric methods, which allows to measure the effect of relevant variables that determine bank failures together with duration dependence effects, without the need of arbitrary and possibly not realistic assumptions.

After Turkey had experienced economic crises in 2001 and 2002, a new banking law was introduced which aimed to regulate and supervise of banking sector as a result of stand-by agreement with IMF. By this new law, it was prevented banks to benefit from high interest rates offered on public debt instruments and they got involved in classical bank activities. In this study, the financial statements of 70 banks in Turkey were analyzed in years 2000 through 2008 in order to see how those changes are beneficial in banking sector in the country. The Turkish data are potentially interesting, as this is a country with plenty of bank failures in the recent past. Although there have been some studies on bank failures in Turkey, these studies generally take into consideration Turkish commercial banks. However, in this study all of Turkish banks are considered to show more meaningful results with thirty-seven financial ratios suitable to CAMELS[1].

The rest of paper is organized as follows: In Section 2 methodology, sample data of the Turkish banks and determination of financial ratios are included. In Section 3, financial factors that affect the Turkish banks' failures after 2001 economic crisis are tried to be determined by survival models, ordinary and conditional logistic regression models.Finally, in Section 4 the conclusion is given and some future research perspectives are discussed.

[1]CAMELS refers to the six components of the bank supervision rating system developed in the United States of America: Capital adequacy, Assets quality, Management quality, Earnings ability, Liquidity and Sensitivity to the market conditions. CAMELS has been extensively used in the literature about bank ratings and failures.

2. Methodology

Suppose now that a bank begins to lose deposits, so all its efforts will be aimed at continue operating. Suppose now that after a week, the bank is still losing deposits and operating. A relevant question that managers, directors and control authorities would like to answer at that moment is what the failure probability is for the next week, period, or instant, considering that the bank is still operating. Another interesting question is what the estimated time is until its potential failure, given the bank's characteristics.

Survival models allow us to these in a parsimonious and informative way. Even though a detailed presentation of the survival models exceeds the scope of this paper, in this section we briefly discuss the particular aspects of this model that are pertinent for our analysis. This study also employs ordinary and conditional logistic regression models in order to analyze bank failures in Turkey.

2.1. Survival Analysis

Survival analysis deals with the occurrence and timing of events and survival models are used to investigate the relation between the survival time and some risk factors called covariates. Many statistical models such as Cox regression model and parametric regression models estimate their influences.

In general terms, the variable of interest in the survival analysis is the time it takes a system to change from one state to another one. Generally, such a change is associated with an event (finding a job, a bank's failure, the solution of a labor conflict, etc.), which indicates the ending of the an event whose duration we try to model. This random variable is called survival time (T), it takes positive values and have a continuous distribution with finite expectation. Probability density function f(t), survival function S(t) or hazard function h(t) characterize the distribution of T. Survival function gives the probability that failure will occur after time t and written as

$$S(t) = P(T > t) = \int_t^{\infty} f(x)dx , \qquad 0 < t < \infty \tag{1}$$

Many parametric (exponential, Weibull, log-logistic, log-normal, etc.) and non-parametric approximations are used to estimate survival function. Kaplan-Meier estimator is more often used and given by

$$\hat{S}(t) = \prod_{j=1} \left(\frac{n_j - d_j}{n_j} \right) \tag{2}$$

where t_j is the j^{th} ordered death time from $t_1 < \ldots < t_k$, n_j is the number of individuals still at risk at ordered time t_j and d_j is number of death at time t_j.

Hazard function is defined by

$$h(t) = \lim_{\delta t \to 0} \frac{P(t \le T < t + \delta t / T \ge t)}{\delta t} \tag{3}$$

for $t > 0$ and represents the probability that an individual alive at t experiences the event in the next period δt.

2.1.1. Cox Regression Model

Cox regression model is widely used survival model which takes into account the effect of censored observations. The data based on a sample of size n, consists of (t_i, δ_i, x_i), $i = 1,\ldots,n$ where t_i is the time on study for the ith individual, δ_i is the event indicator ($\delta_i = 1$ if the event has occurred and $\delta_i = 0$ if the lifetime is censored) and $\mathbf{x}_i$ is the vector of covariates for the ith individual which may affect the survival distribution of T, the time to event. Hazard function for Cox regression model is given by

$$h_i(t) = h_0(t)\exp(\boldsymbol{\beta}'\mathbf{x_i}) \tag{4}$$

where $h_0(t)$ is the baseline hazard function and $\boldsymbol{\beta}$ is a px1 vector of unknown parameters.

Then, the likelihood for Cox regression model is given by

$$L(\beta) = \prod_{j=1}^{k} \frac{\exp(\boldsymbol{\beta}'\mathbf{x}_j)}{\sum_{\ell \in R(t_j)} \exp(\boldsymbol{\beta}'\mathbf{x}_\ell)} \tag{5}$$

where $\mathbf{x}_j$ is the vector of covariates for the individual who dies at the jth ordered death time, t_j. Coefficient vectors of the covariates are obtained by iteration using Newton-Raphson technique (Klein and Moescberger, 1997). The ordered death times are denoted by $t_1 < \ldots < t_k$, so that t_j is the jth ordered death time. The set of individuals who are at risk at time t_j are denoted by $R(t_j)$, so that $R(t_j)$ is the set of individuals who are alive and uncensored at a time just prior to t_j.

Although the model is based on proportional hazards assumption, no particular form of probability distribution is assumed for the survival times. The model is therefore referred to as a semi-parametric model (Cox, 1972). The semi parametric character of Cox proportional hazards model seems to provide a good balance between analytical simplicity and functional flexibility. The proportional hazards assumption implies that the effect of explanatory variables on the hazard function is constant over time and works by moving the baseline hazard rate up or down in a proportional way. Let $\mathbf{x}^* = (x_1{}^*, x_2{}^*, \ldots, x_p{}^*)$ and $\mathbf{x} = (x_1, x_2, \ldots, x_p)$ are the covariates of two individuals. Hazard ratio is given by

$$\exp\left[\sum_{i=1}^{p} \hat{\beta}_i \left(x_i{}^* - x_i\right)\right] \tag{6}$$

The proportional hazards assumption is satisfied when the value of the exponential expression for the estimated hazard ratio is constant. The assessment of proportional hazards assumption is done by several graphical or numerical approaches. In the violation of this assumption, different methods should be used to deal with non-proportional hazards.

Stratified Cox regression model is one of the survival models used in case of non-proportional hazards or when the data is evaluated according to one of the covariates (z) with k categories. There are two types of stratified Cox regression model: No-interaction model is defined by

$$h_g(t) = h_{0g}(t)\exp\left[\beta_1 x_1 + \beta_2 x_2 + ... + \beta_p x_p\right] \tag{7}$$

where g represents the strata. z is not implicitly included in the model whereas x's which are assumed to satisfy the proportional hazards assumption are included in the model. The baseline hazard function, $h_{0g}(t)$, is different for each strata. However, the coefficients $\beta_1,...,\beta_p$ are the same for each stratum. Since the coefficients of x's are same for each stratum, hazard ratios are same for each stratum. To obtain estimates of $\beta_1,...,\beta_p$ a likelihood function L that is obtained by multiplying together likelihood functions for each stratum is maximized (Kleinbaum and Klein, 2005). Interaction model is defined by

$$h_g(t) = h_{0g}(t)\exp[\beta_{1g} x_1 + \beta_{2g} x_2 + ... + \beta_{pg} x_p] \tag{8}$$

and the data set is stratified into k stratum according to the interested variable.

Stratified Cox regression model contains regression coefficients that do not vary over the strata. This property of the model is known as no-interaction assumption. If it is allowed for interaction, different coefficients for each of the strata are obtained. The test that is used to examine no-interaction assumption is likelihood ratio test statistics. For this test statistic, log likelihood functions of interaction and no-interaction models are used. Since interaction model contains product terms, it differs from no-interaction model. Thus, the null hypothesis is that the coefficients of product terms are equal zero. Likelihood ratio test statistic shows chi-square distribution with $p(k^* - 1)$ degrees of freedom under the null hypothesis (Kleinbaum and Klein, 2005).

2.1.2. Parametric Survival Models

In parametric regression models, the form of the baseline hazard function is assumed. Although Cox's semi-parametric model is the most employed regression tool, fully parametric models have some advantages. Nardi and Schemper (2003) showed that parametric models lead to more efficient parameter estimates than Cox regression model. Two approaches to the modelling of covariate effects on survival have become popular. In the first approach, natural logarithm of survival time $y = \log T$ is modelled and a linear model is assumed for y, namely

$$\mathbf{y} = \mu + \boldsymbol{\gamma}'\mathbf{x} + \sigma\boldsymbol{\varepsilon} \tag{9}$$

where **x** is a vector of covariates, $\boldsymbol{\gamma}' = (\gamma_1,...,\gamma_p)$ is a vector of regression coefficients, σ is a shape parameter and ε is a random error term (Klein and Moeschberger, 1997). The second approach to modelling the effects of covariates on survival is to model the conditional hazard rate as a function of covariates as

$$h(t) = h_0(t)\exp(\boldsymbol{\beta}'\mathbf{x}) \tag{10}$$

In Eq. (10), $h_0(t)$ has a specified parametric form or an arbitrary non-negative function. It is difficult to use a formal statistical test to discriminate between parametric models because the models are not nested. One way of selecting an appropriate parametric model is to use the Akaike's Information Criterion (AIC). Some graphical diagnostics such as Cox-Snell residuals versus time plots are used to provide a check of the overall fit of the model (Lee and Wang, 2003).

2.2. Logistic Regression Analysis

In the logistic regression analysis, the values of dependent variable (Y_i) for bank i $(i = 1, 2, ..., n)$ are defined as 1, if the ith bank is failed or transffered to SDIF (Saving Deposit Insurance Fund of Turkey); 0, if the ith bank is non-failed. The logistic regression model is based on a cumulative logistic function and provides the probability of a bank belonging to one of the prescribed classes, which gives the financial characteristics of the bank. The posterior probability of failure is derived directly from the following logit specification

$$\log[P_{L_i}/(1-P_{L_i})] = a + b_1X_{i1} + b_2X_{i2} + ... + b_pX_{ip} \tag{11}$$

where a is the constant term, P_{L_i} is the probability of bank i's failure and $\mathbf{b} = (b_1,...,b_p)$ is a vector of regression coefficients for independent variables X_{ij}, $(i = 1,2,...,n;\ j = 1,2,..,p)$, i.e., financial ratios (Kolari et al., 2002).

From the logistic regression model, the estimated value of the dependent variable can be interpreted as the predicted probability of bank failure (P_{L_i}). By solving the P_{L_i} through Eq. (11), the predicted bank failure probability is described as

$$P_{L_i} = \frac{e^y}{(1+e^Y)} \tag{12}$$

where e is the base of the natural algorithm and y equals $a + b_1X_{i1} + b_2X_{i2} + ... + b_pX_{ip}$.

Logistic regression model generates coefficient estimates for each of the financial ratios and associated test statistics that indicate how well it discriminates between failed and non-failed banks. Based on that probability a bank is classified as failed or non-failed, using a cut-off probability, attempting to minimize the type I (failed banks classified as non-failed banks) and type II (non-failed banks classified as failed banks) errors (Mcleod, 2004).

To classify sample banks into a failed group or a non-failed group, the logit value of each sample bank is calculated based on the estimated model and then it is applied to the probability function, $P_{L_i} = e^y/(1+e^Y)$. In this study, banks with P_{L_i} values less than or equal to 0.5 are classified into the non-failed group and banks with P_{L_i} values more than 0.5 are classified into the failed or transferred to SDIF bank groups.

2.3. Conditional Logistic Regression Analysis

Conditional logistic regression analysis is often applied to matched case-control designs in which cases and controls are matched on variables that may be confounders (Rothman and Greenland, 1998). Early readable references on the application of the conditional logistic regression analysis to matched case-control designs are Breslow et al. (1978), Breslow and Day (1980) and Holford et al. (1978). This technique is also discussed by Hosmer and Lemeshow (2000) which gives a good introduction to the model.

Let (Y_{i1}, Y_{i2}), $i = 1,\dots,n$ denote the i^{th} pair of subjects where Y_{i1} stands for a case subject (1, if a bank is failed) and Y_{i2} is a control subject (0, otherwise). When the binary dependent variable has *p* explanatory variables for the matched case-control design, the conditional logistic regression model is given by

$$\operatorname{logit}\left[P(Y_{it} = 1)\right] = \alpha_i + \beta_1 x_{1it} + \beta_2 x_{2it} + \dots + \beta_p x_{pit}, \tag{13}$$

where x_{hit} denotes the value of independent variable *h* for subject *t* in pair *i*, $t = 1,2$ and $P(Y_{it} = 1)$ represents the probability for Y_{it} of being 1 and $\operatorname{logit}(\phi) = \log\left(\dfrac{\phi}{1-\phi}\right)$.

In matched case-control studies since the intercept terms $\{\alpha_i\}$ cause difficulties with inference about the primary parameters, it can be helpful to eliminate them from the model(Hirji,2006). With the conditional logistic regression analysis, we treat them as nuisance parameters and maximize the likelihood function for a conditional distribution that eliminates them to estimate $\{\beta_j\}$.

Let $\mathbf{x}_{it} = (x_{1it},\dots, x_{pit})'$ and $\boldsymbol{\beta} = (\beta_1,\dots,\beta_p)'$. To eliminate $\{\alpha_i\}$ in Eq. (11), we condition on their sufficient statistics, the pairwise success totals $\{S_i = y_{i1} + y_{i2}\}$. Given $S_i = 0$, $P(Y_{i1} = Y_{i2} = 0) = 1$, and given $S_i = 2$, $P(Y_{i1} = Y_{i2} = 1) = 1$. The distribution of (Y_{i1}, Y_{i2}) depends on $\boldsymbol{\beta}$ only when $S_i = 1$; that is, only the values of dependent variable differ from the two responses. Given $S_i = y_{i1} + y_{i2} = 1$, the conditional distribution is

$$P(Y_{i1} = y_{i1}, Y_{i2} = y_{i2} \mid S_i = 1) = \frac{P(Y_{i1} = y_{i1}, Y_{i2} = y_{i2})}{[P(Y_{i1} = 1, Y_{i2} = 0) + P(Y_{i1} = 0, Y_{i2} = 1)]}, \tag{14}$$

$$P(Y_{i1} = 0, Y_{i2} = 1 \mid S_i = 1) = \frac{\exp(\mathbf{x}'_{i2}\boldsymbol{\beta})}{[\exp(\mathbf{x}'_{i1}\boldsymbol{\beta}) + \exp(\mathbf{x}'_{i2}\boldsymbol{\beta})]},$$

$$P(Y_{i1} = 1, Y_{i2} = 0 \mid S_i = 1) = \frac{\exp(\mathbf{x}'_{i1}\boldsymbol{\beta})}{[\exp(\mathbf{x}'_{i1}\boldsymbol{\beta}) + \exp(\mathbf{x}'_{i2}\boldsymbol{\beta})]}.$$

Condition on $S_i = 1$, the joint distribution of the matched pairs is

$$\prod_{S_i = 1}\left(\frac{\exp(\mathbf{x}'_{i1}\boldsymbol{\beta})}{[\exp(\mathbf{x}'_{i1}\boldsymbol{\beta}) + \exp(\mathbf{x}'_{i2}\boldsymbol{\beta})]}\right)^{y_{i1}}\left(\frac{\exp(\mathbf{x}'_{i2}\boldsymbol{\beta})}{[\exp(\mathbf{x}'_{i1}\boldsymbol{\beta}) + \exp(\mathbf{x}'_{i2}\boldsymbol{\beta})]}\right)^{y_{i2}} \tag{15}$$

Differentiating the log of this conditional likelihood, equating to 0, and solving yields the conditional maximum likelihood estimator of $\boldsymbol{\beta}$ in Eq. (15) that can be obtained by an iterative procedure (Mehta et al., 2000).

For the conditional logistic regression models, the probabilities are predicted like ordinary logistic regression model. To calculate P_i from $\boldsymbol{\beta}$, the back transformation is

$$\hat{P}_{ij} = \frac{\exp(x_i'\boldsymbol{\beta}_j)}{1+\sum_{k\neq j}\exp(x_i'\boldsymbol{\beta}_k)} \qquad (16)$$

where $0 \leq \hat{P}_{ij} \leq 1$. If $\hat{P}_{ij} < 0.5$, then the subject is assigned to group 0. For $\hat{P}_{ij} \geq 0.5$, the subject is assigned to group 1.

3. Empirical Study Description

3.1. Sample Data of Turkish Banks and Financial Ratios

This section begins with the description of sample data for Turkish banks and continues with the definition and summary statistics of the financial ratios. The Turkish Banking System is a good example because it represents the most recent banking crisis in a developing economy. It has been subject to the following structural weaknesses in 2001: inadequate capital base, small and fragmented banking structure, dominance of state banks in total banking sector, weak asset quality, extreme exposure towards market risk, inadequate internal control systems, risk management, corporate governance and lack of transparency (Alper, 2001). Most of these banks failed to discharge their liabilities with their assets and some of them were mismanaged.

The sample of Turkish banks covered the period between 2000 and 2008 and contains forty-two financial ratios of seventy Turkish banks. Survival time (T) is defined as the time until the bank failed or transferred to SDIF. Non-failed banks and banks which are still not transferred to SDIF are treated as censored observations in the Cox regression model. For the ordinary and conditional logistic regression models, the definition and the values of the dependent variable are given by

$$Y = \begin{cases} 0, & \text{if the bank is nonfailed between 2000 and 2008} \\ 1, & \text{if the bank is failed or transferred to SDIF between 2000 and 2008.} \end{cases}$$

Banks Association of Turkey (BAT)published financial ratios of the failed and non-failed banks in its web site[2]. In this study financial ratios are used as independent variables for the Cox regression, ordinary and conditional logistic regression analyses.

Determination of financial ratios for bank failure prediction is a problem since multicollinearity can result in incorrect signs and magnitudes of the parameter estimates. Because of multicollinearity problem, high correlated financial ratios (C2, I10, L1, L3, C5) are removed and thirty-seven financial ratios believed to have effects on the Turkish

[2]See http://www.tbb.org.tr/english/bulten/yillik/2000/ratios.xls.

bank failures are chosen suitable to CAMELS. These financial ratios are collected into eight main groups as capital adequacy, assets quality, liquidity, profitability, income-expense structure, sector ratios, group ratios, and activity ratios. Definitions of financial ratios are presented in Table 1.

3.2. The Results of Survival Models

In the survival analysis, the interest is centered on an event that ends a length of time or duration. In this case, the survival time, is measured in eight-year periods and defined as the failure time until bank failure and transferred to SDIF. Turkish banks which are still alive at the end of the follow-up period are treated as censored observations. The data set consists of seventy Turkish banks, of which 48.57% are censored. The relationship between bank failures and financial ratios are modeled using the survival models.

The failure of Turkish banks is employed with Cox and stratified Cox regression models. Proportional hazards assumption is assessed by finding the correlation between Schoenfeld residuals for a particular covariate and the ranking of individual failure time for Cox regression model. It is found that all variables, except type of banks, hold proportional hazards assumption ($p < 0.05$). Therefore, stratified Cox regression model is described with no-interaction and interaction models and type of banks (commercial and non-commercial) is used as a strata variable. The results of Cox and stratified Cox regression models are obtained with stepwise selection. The values of AIC, –2logL, Wald statistics and significant variables are shown in Table 2.

Since the smallest AIC gives the best model, the results suggest that stratified Cox regression models are better than Cox regression model. For the stratified Cox regression model, no-interaction assumption is satisfied. The value (4.639) of test statistic is approximately chi-square with $df = 0$ under the null hypothesis. So, no-interaction model is preferred to interaction model.The result of no-interaction stratified Cox regression model is given in Table 3.

The reported coefficients in Table 3 have to be interpreted as the covariate effect on the hazard function or probability of bank failure. In this model, net income/average shareholders' equity (P2), (salaries and employee benefits+ res. for retirement)/number of personnel (AC2) and provisions tax included/total income (AC5) are found significant at a 5% significance level which affect the time of bank failure. P2 (net income/average shareholders' equity) presents a negative effect on the default risk (P2). AC2 ((salaries and employee benefits+ res. for retirement)/number of personnel) is significantly different from zero and with the expected sign. A marginal increase in its level increases the default risk in approximately 3.95%. AC6 (provisions tax included/total income) also has the correct sign. An instant increase in provisions tax included reduces the default risk in approximately 17.34%.

The results from the hazard model estimation are that banks with higher profitability and higher proportion of government bonds in their assets composition (higher liquidity) are less likely to fail. These results are consistent with Wheelock and Wilson (1995). They found that the banks with higher profitability and less loan their assets composition (higher liquidity) are in a lower risk of bank failure, using a hazard model in a sample of US banks.

Parametric regression models are tried to be used for Turkish bank failure. Anderson-Darling and Kolmogrov-Smirnov tests show that survival time does not exactly follow any known distribution; therefore parametric regression models cannot be performed.

3.3. The Results of Ordinary Logistic Regression Model

Logistic regression model is used in order to check the signs and significance of parameters of the variables in the model as to whether or not financial ratios are the most important predictors in explaining bank failure. Table 4 shows the results of logistic regression model.

Hosmer and Lemeshow's goodness of fit value, which is significant at the 5% significance level, reveals that the logistic model fits the data well because there is no significant discrepancy between observed and predicted classifications. According to Table 4, the observed significance level (0.00) associated with χ^2 for the model (30.217) is less than 1% significance level also indicating that the overall fitness of the logistic model is significant. These two goodness of fit measures show that the logistic regression model is significant that could identify potential bank failures with good accuracy. The coefficients of all variables are statistically significant at the 10% significance level. Based on the analysis of the intercept and the coefficients of the financial ratios, the logistic regression model for predicting the bank failure can be written as

$$\log\left[P_i/(1-P_i)\right] = 2.865 - 0.013\text{I2} - 0.015\text{I3} - 0.059\text{G1} - 0.004\text{C5} + 0.383\text{A1} \quad (17)$$

The results show that interest income/interest expenses, other operating income/other operating expenditure, total assets, foreign exchange position/shareholders' equity, and total loans/total assets are significant at a 10% significance level in explaining the bank failure probability. Not surprisingly, the signs of interest income/interest expenses, other operating income/other operating expenditure, total assets, and foreign exchange position/shareholders' equity are negative and the sign of total loans/total assets is positive. The negative signs of the parameter estimations in Table 4 provide the evidence that as the value of financial ratios increases the bank failure probability decreases. However, positive sign of the total loans/total assets equity indicates that an increase in this parameter estimate increases the bank failure probability. These results show that a bank with a higher capitalization, a higher investments return, and lower financial expenses is less probable to fail.

As a result of the logistic regression model, we find that the banks with low earnings, low liquidity, or risky asset portfolios are more likely to fail than the other banks. The results are consistent with Logan (2001), using a logistic regression model finds that pure profitability and illiquidity are common among UK bank failures in the 1990s.

The in-sample banks are classified into a failed/transferred to SDIF bank group or a non-failed bank group by the logistic regression model. The logit value of each sample bank is calculated based on Eq. (17) and then it is applied to the probability function in Eq. (12)

to obtain the predicted probability for being a bank failure. P_{L_i}, which is the predicted probability of a bank failure and lies between 0 and 1, is shown for each of the in-sample banks in Appendix. To determine the bank's predicted status, P_{L_i} is compared to the cut-off probability of 0.5. Banks with P_{L_i} values equal to or below 0.5 are classified into the non-failed group (Group 0), whereas banks with P_{L_i} values exceeding 0.5 are classified into the failed group (Group 1). One can evaluate the predictive accuracy by looking at the percent, which is shown in Table 5.

Table 5 shows that the percentage of correctly predicted statistics is 80 percent. This result suggests that the logistic regression model performs well within sample. Appendix also shows that among seventy in-sample banks, fourteen banks are misclassified.

3.4. The Results of Conditional Logistic Regression Model

The conditional logistic regression model is empirically developed to explain variables affecting the bank failure. For this aim, cases ($n = 36$) are defined as banks which are failed or transferred to SDIF after 2001 financial crisis and controls ($n = 34$) are defined as banks which survived after 2001 financial crisis (non-failed). More than one control per case used in order to increase the precision of the odds ratio estimates. Cases and controls are matched on type of Turkish banks (commercial or non-commercial) to account for these potential confounders. All the coefficients of the model are tested based on the Wald statistic and following stepwise process for variable inclusion. The estimation results for the final conditional logistic regression model are reported in Table 6.

As seen in Table 6, conditional logistic regression model is statistically significant at 95% confidence level. Based on the analysis of the coefficients of the financial ratios, the conditional logistic model for predicting the bank failure can be written as

$$\log\left[P_i/(1-P_i)\right] = -0.213\text{P1} + 0.00003\text{I4} - 0.239\text{AC5} \tag{18}$$

The results show that the models containing net income/average total assets (P1), total income/total expenditure (I4),provisions tax excluded/total income (AC5) are significant at a 95% confidence level in explaining the probability of bank failure in Turkey. The coefficient of P1 (net income/average total assets), is negative and significant at the 95% confidence level. This implies that, other things equal, profitable banks have a lower probability to fail, as expected. The results for the total income/total expenditure (I4) confirm it has a positive statistically coefficient in the conditional logistic regression model. Provisions tax excluded/total income (AC5) is negative and significant, implying that banks with higher level of capital have a higher probability to survive. Overall, the picture is that well capitalized banks exhibit a lower failure probability because the capital buffer is sufficient to absorb unexpected losses. To summarize, a bank is more likely to go bankrupt if it is unprofitable, high leveraged, and has liquidity problems, negative equity situation, and less flexibility to invest itself. Consistent with previous studies (Kuznetsov, 2003; Peresetsky et al. 2011), the results of the conditional logistic regression model indicates that the probability for a bank to be confronted with a license revocation due to failure is higher for unprofitable, illiquid and undercapitalized banks.

The in-sample banks are classified into a failed/transferred to SDIF bank groups or a non-failed bank group by the conditional logistic model. The conditional logistic value of each sample bank is calculated based on Eq. (18) and then it is applied to the probability function in Eq. (16) to obtain the predicted probability for being a bank failure. P_{CL_i} is compared to the cut-off probability of 0.5 in the Appendix and classification summary is given in Table 7.

According to Table 7, twenty-four banks are misclassified among seventy in-sample banks. The results show that the conditional logistic regression model is able to classify in-sample banks into failed or non-failed groups with 65.7% accuracy rate.

4. Discussion

Turkish Banking System has gone through some major developments during the last decade. Previous studies on the Turkish banking crisis have focused on the general factors that surrounded the defaults of multiple banks. These descriptive studies showed the macroeconomic environment and the general financial situation of the banks before the crisis. Although looking at the general picture is useful, previous literature does not consider the significance of individual financial factors that are common to both failed/transferred banks to SDIF and non-failed banks.

The aim of this paper is to find out the important financial ratios related to the financial structure and performance of a bank, which could separate out failing banks prior to the failure. These financial ratios, then, can be used to make a statistical model of bank failures after 2001 economic crisis in Turkey. This is also a kind of analysis that investigates the general characteristics of a bank that is likely to go bankrupt.

Our empirical analysis reveals that no-interaction stratified Cox regresssion model significantly outperforms other survival and logistic regression models. Therefore, no-interaction stratified Cox regression model is the best model for explaining the Turkish bank failures.Net income/average shareholders' equity, (salaries and employee benefits+res. for retirement)/number of personnel and provisions tax included/total income have effects on the Turkish bank failure. Our empirical results indicate that low earnings and liquidity, and risky asset portfolios have played a key role in determining a bank's failure. According to the logistic regression model, the most important financial ratios influencing a bank's failure are the ratios grouped by capital adequacy, assets quality, liquidity, and group ratios. These models suggest that bank regulators may derive substantial benefits from the use of simple ratios, possibly as a supplementary requirement, even when more complex measures such as risk-weighted ratios are used to formulate the primary requirements.

Although Pamukbank, Adabank and Şekerbank seem to misclassify according to logistic regression model, the latest advances supports our classification results. Firstly, Pamukbank, which is misclassified as non-failed, claims that according to general conditions it was inequitable to transfer the bank to the SDIF (BRSA, 2003). Council of State opposed this transfer since the Pamukbank's demand of being transferred to Yapı Kredi Bank was refused by BRSA without inspecting the situation enough. Istanbul

Chamber of Commerce denoted that it was impossible to understand the sudden transfer of Pamukbank to SDIF, since there was a possibility of uniting the bank with Yapı Kredi Bank, which was in the same group with Pamukbank. The results of our predictions about Adabank showed that this bank had to be failed but it was not failed in fact. One reason may be that the owner of Adabank and Imarbank is same. Adabank had been seized by the BRSA in July 2003 as part of the Imarbank *i*nvestigations (BRSA, 2003).

Finally, there are also supporting ideas for Şekerbank case, which makes the misclassification of being failed more understandable. That is, according to the BRSA report (2006), Şekerbank who agreed with the Netherlands's Rabobank but was rejected by the court was in the way of reaching an agreement with Kazakhstan. Moreover, in contradiction to Pamukbank case, the capital increase of Şekerbank was granted by BRSA in 2004. Now, Şekerbanksold a 34 percent stake to Kazakhstan's Bank TuranAlem. As a conclusion, all of these opinions about these banks show that although the classification predictions seem to be faulty in real, some unnatural manipulations took roles in those three banks' cases.

References

1. Ağaoğlu, E. A. (1989). *Türkiye' de banka işletmelerinin ekonomik analizi ve gelişme eğilimleri*. Yayımlanmamış Doktora Tezi, ODTÜ, Ankara.
2. Alper, C. (2001). The Turkish liquidity crisis of 2000: What went wrong? *Russian and East European Finance and Trade*, 37(6), 51-71.
3. Atan, M. (2003). Türkiye bankacılık sektöründe veri zarflama analizi ile bilançoya dayalı mali etkinlik ve verimlilik analizi. *Ekonomik Yaklaşım*, 48(14), 71 – 86.
4. Atan, M., Catalbas G. (2005). The effects of capital adequacy on efficiency of banks. *Journal of Business and Finance,* 237, 49-62.
5. Aydoğan, K. (1990). *An investigation of performance and operational efficiency in Turkish banking industry*. T.C. Merkez Bankası, Tartışma Tebliği.
6. BAT, (2000). The Turkish Banking System Report, Available at http://www.tbb.org.tr/english/v12/research.htm.
7. Breslow, N. E., Day, N. E., Halvorsen, K. T., Prentice, R. L., Sabai, C. (1978). Estimation of multiple relative risk functions in matched case-control studies. *American Journal of Epidemiology,* 108, 299-307.
8. Breslow, N. E. and Day, N. E. (1980). Statistical Methods in Cancer Research. The Analysis of Case-Control Studies. *International Agency for Research on Cancer, Lyon, France,* 1, 248–279.
9. BRSA Report of Turkey, 2003, www.bddk.org.tr (accessed on July 5, 2011).
10. BRSA Report of Turkey, 2006, www.bddk.org.tr (accessed on July 5, 2011).
11. Canbaş, S. and Erol, C. (1985). *Türkiye'de ticaret bankları sorunlarının saptanması: Erken uyarı sistemine giriş*, Türkiye Ekonomisi ve Türk Ekonomiİlmi, 1, Marmara Üniversitesi Türkiye Ekonomi Araştırma Merkezi.
12. Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society,* 34, 187-220.

13. Çilli, H. and Tuğrul, T., (1988). *Türk bankacılık sistemi için bir erken uyarı modeli*. T. C. Merkez Bankası, Tartışma Tebliği.
14. Erol, C. (1985). İşletmelerin finansal güçlüklerinin önceden saptanmasında ayrıştırma analiz tekniğinin ticari banka işletmelerinde denenmesi. *Anadolu Üniv. İktisadi ve İdari Bilimler Fak. Dergisi*, 3(2).
15. Henebry, K. L. (1996). Do cash flow variables improve the predictive accuracy of a Cox proportional hazards models for bank failure? *The Quarterly Review of Economi cs and Finance*, 36 (3).
16. Hirji, K. F. (2006). *Exact Analysis of Discrete Data, Florida*: Chapman & Hall.
17. Holford, T. R., White, C., Kelsey, J. L. (1978). Multivariate analysis for matched case-control studies, *American Journal of Epidemiology*, 107, 245-256.
18. Hosmer, D. W. and Lemeshow, S. (2000). *Applied logistic regression,* New York: John Wiley & Sons, 223–43.
19. Karamustafa, O. (1999). Bankalarda temel finansal karakteristikler: 1990-1997 sektör üzerinde amprik bir çalışma. *İMKB Dergisi*, 3(9).
20. Klein, J. P. and Moeschberger, M. L. (1997). *Survival analysis techniques for censored and truncated data*, New York: Springer.
21. Kleinbaum, D. G. And Klein, M. (2005). *Survival analysis: A self-learning text,* New York: Springer.
22. Kolari, J., Glenon, D., Shin, H. and Caputo, M. (2002). Predicting large U.S. commercial bank failures. *Journal of Economics and Business,* 54, 361-387.
23. Kuznetsov, A. (2003), Crisis of 1998 and determinants of stable development of a bank, working paper # BSP/2003/062 E. – Moscow: New Economic School.
24. Lane, W. R., Looney, S. W. and Wansley, J. W. (1986). An application of the Cox proportional hazards model to bank failure. *Journal of Banking & Finance* 10(4), 511-531.
25. Laviola, S., Marullo-Reedtz, P. and Trapanese, M. (1999). The evidence from Italy. In: G. Kaufman Ed. *Research in Financial Services: Private and Public Policy*, JAI Press, 1.
26. Lee, E. T. and Wang, J. W. (2003). *Statistical methods for survival data analysis*. 3rd ed. Hoboken, NJ: Wiley.
27. Logan, A. (2001). The United Kingdoms small banks' crisis of the early 1990s. What were the leading indicators of failure? , *Bank of England Working Paper*, 139.
28. Mcleod, R. (2004). Dealing with Bank System Failure: Indonesia, 1997-2003, *Bulletin of Indonesian Economic Studies*, 40(1), 95-116.
29. Mehta, C. R., Patel, N. and Senchaudhuri, P. (2000). Efficient Monte Carlo methods for conditional logistic regression. *Journal of the American Statistical Association,* 95(449), 99-108.
30. Nardi, A. and Schemper, M. (2003). Comparing Cox and parametric models in clinical studies. *Statistics in Medicine,* 22, 3597-3610.
31. Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bank Failure. *Journal of Accounting Research,* 18(1), 109-131.

32. Pantolone, C. and Platt, M. B. (1987). Predicting commercial bank failure since deregulation. *New England Economic Review*, 32, 37-47.
33. Peresetsky A., Karminsky A. and Golovan S., (2011). Probability of default models of Russian banks, *Economic Change and Restructuring*, 1-38.
34. Rose, P. S. and Kolari, J. W. (1985). Early warning systems as a monitoring device for bank condition. *Quarterly Journal of Business and Economics,* 24, 43-60.
35. Rothman, K. J. and Greenland, S. (1998*). Modern epidemiology*. Philadelphia: Lippincott-Raven Publishers, 147–161.
36. Vierkant, R. A., Therneau, T. M., Kosanke, J. L. and Naessens, J. M. (2000). *MCSTRAT: A SAS macro to analyze data from a matched or finely stratified case–control design*. Technical Report Series (Number 65). Department of Health Sciences Research, MayoClinic, Rochester, MN.
37. Wheelock, D. and Wilson, P. (1995). Why do banks disappear? The determinants of U.S. bank failures and acquisitions. *Federal Reserve Bank of Saint Louis, Working Paper*, 950133, August.
38. Whalen, G. A. (1991). A proportional hazard model of bank failure: An examination of its usefulness as an early warning tool. Federal Reserve Bank of Cleveland. *Economic Review,* 1, 21-31.

Table 1:Definitions of financial ratios

Code	*Financial Ratios*
	Capital Adequacy
C1	Shareholders' Equity+Total Income /Total Assets
C2	Shareholders' Equity+T. Income /Dep.+Non-deposit Funds
C3	Net Working Capital/Total Assets
C4	Sharehold.' Equity+T. Income /T. Assets+Non-cash Loans
C5	Foreign ExchangePosition /Shareholders' Equity
C6	Foreign Exchange Position/ Shareholders' Equity
	Assets Quality
A1	Total Loans/Total Assets
A2	Non-Performing Loans/Total Loans
A3	Permanent Assets/Total Assets
A4	Fx Assets/Fx Liabilities
	Liquidity
L1	Liquid Assets/Total Assets
L2	LiquidAssets/(Deposits+Non-DepositsFunds)
L3	Fx LiquidAssets/Fx Liabilities
	Profitability
P1	Net Income/Average Total Assets
P2	Net Income/Average Shareholdes' Equity
P3	Net Income/Average Share in Capital
P4	Income Before Tax/Total Asstes
P5	Provision for Non-Performing Loans/Total Loans
P6	Provision for Non-Performing Loans/Total Assets
	Income-Expense Structure
I1	Net Interest Income After Non-Performing Loans/Average Total Assets
I2	Interest Income/Interest Expenses
I3	Other Operating Income/Other Operating Expenditure
I4	Total Income/Total Expenditure
I5	Interest Income/Average Income Assets
I6	Interest Expenditure/Average Expenditure Assets
I7	Interest Expenditure/Average Income Assets
I8	Interest Income/Total Income
I9	Other Operating Income/Total Income
I10	Interest Expenditure/Total Expenditure
I11	Other Operatşng Expenditure/Total Expenditure
	Sector Ratios
S1	Total Assets (sector)
S2	Total Loans (sector)
S3	Total Deposits (sector)
	Group Ratios
G1	Total Assets (group)
G2	Total Loans (group)
G3	Total Deposits (group)
	Activity Ratios
AC1	(Salaries and Emp'eeBenefits+Res.for Ret.)/Total Assets
AC2	(Salaries and Emp'eeBenefits+Res.for Ret.)/Number of Personnel (Billion TL)
AC3	Res. For Ret./Number of Personnel (Billion TL)
AC4	Operating Expenses/Total Assets
AC5	Provisions Tax Excluded/Total Income
AC6	Provisions Tax Included/Total Income

Table 2:The Results of Semi Parametric Regression Models

Model			-2logL	AIC	Wald	Significant Variables
Cox Regression			112.838	116.838	19.931	I4, AC2
Stratified Cox Regression	No-interaction		101.064	107.064	20.944	P2,AC2,AC6
	Interaction	Strata 1	81.386	87.386	16.152	P2,AC2,AC6
		Strata 2	19.474	21.474	4.996	-

Table 3: Analysis of Maximum Likelihood Estimates for No-interaction Stratified Cox Regression Model

Variable	Parameter Estimate	Std. Error	Chi-Sq.	Pr > Chi-Sq.	Hazard Ratio	95% Hazard Ratio Confidence Limits	
						Lower	Upper
P2	-0.0093	0.0028	10.955	0.0009	0.991	0.985	0.996
AC2	0.0395	0.0156	6.422	0.0113	1.040	1.009	1.073
AC6	-0.1734	0.0749	5.352	0.0207	0.841	0.726	0.974

Table 4: The Results of the Logistic Model Estimation

Overall Model Fit						**Value**
-2 log likelihood (-2LL)						63.134
Cox & Snell R^2						0.351
Omnibus Test of Model Coefficients			χ^2	**df**	**Sig.**	
Step			30.217	5	0.000	
Block			30.217	5	0.000	
Model			30.217	5	0.000	
Hosmer&Lemeshow Goodness of Fit Test			13.373	8	0.099	
Variable in the Equation	**b**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp (b)**
C5	-0.004	0.002	2.783	1	0.095*	0.997
A1	0.383	0.183	4.389	1	0.036	1.466
I2	-0.013	0.005	7.833	1	0.005	0.987
I3	-0.015	0.007	4.997	1	0.002	0.985
G1	-0.059	0.035	2.889	1	0.089*	0.942
Intercept	2.865	1.281	4.999	1	0.025	

* Significant at 10% level

Table 5: Classification Summary Matrix for the In-Sample Banks

Actual Group	Predicted Group	
	Group 0	Group 1
Group 0	19	8
Group 1	6	37

Note: Overall percentage of observations classified correctly: $80\% = [(19+37)/70]$
Group 0: Non-failed banks, Group 1: Failed banks.

Table 6: The Results of Conditional Logistic Regression Model

Variable	Parameter Estimate	Std. Error	Chi-Square	Pr > Chi-Sq.	Odds Ratio
P1	-0.213	0.056	14.771	0.0001	0.808
I4	0.00003	0.00001	9.011	0.003	1.000
AC5	-0.239	0.108	4.894	0.027	0.787
Model Fit Statistics		**Testing Global Null Hypothesis: Beta=0**			
-2logL	**AIC**	**Likelihood Ratio**		**Wald Statitics**	
152.264	154.264	**Chi-Square**	**Pr>Chi-Sq.**	**Chi-Square**	**Pr>Chi-Sq.**
		6.444	0.011	8.414	0.0037

Table 7: Classification Summary Matrix for the In-Sample Banks

Actual Group	Predicted Group	
	Group 0	Group 1
Group 0	29	0
Group 1	24	17

Note: Overall percentage of observations classified correctly: $65.7\% = [(29+17)/70]$

Group 0: Non-failed banks, Group 1: Failed banks.

APPENDIX. Classification Results Based on the Cut-off Probability (0.5) for the In-Sample Banks

Code			Ordinary Logistic Regression		Conditional Logistic Regression	
	State-owned Commercial Banks	**Actual Group**	**Classified Group**	P_{L_i}	**Classified Group**	P_{CL_i}
B1	Etibank A.Ş.	1	1	0.961	1	0.940
B2	TürkiyeCumhuriyetiZiraatBankası	0	0	0.308	0	0.340
B3	TürkiyeEmlakBankası A.Ş.	1	1	0.724	1	0.587
B4	TürkiyeHalkBankası A.Ş.	0	0	0.392	0	0.375
B5	TürkiyeVakıflarBankası T.A.O.	0	1*	0.612	0	0.210
	Privately-owned Commercial Banks					
B6	Adabank A.Ş.	0	1*	0.872	0	0.440
B7	Akbank T.A.Ş.	0	0	0.170	0	0.181
B8	Alternatif Bank A.Ş.	0	1*	0.500	0	0.370
B9	Anadolubank A.Ş.	0	0	0.346	0	0.235
B10	Bank Ekspres A.Ş.	1	1	0.984	1	0.982
B11	Bayındırbank A.Ş.	1	1	0.889	0*	0.396
B12	BirleşikTürkKörfezBankası A.Ş.	1	1	0.579	0*	0.360
B13	Demirbank T.A.Ş.	1	1	0.702	1	0.571
B14	Denizbank A.Ş.	0	1*	0.533	0	0.206
B15	Egebank A.Ş.	1	1	0.999	1	0.699
B16	EgeGiyimSanayicileriBankası A.Ş.	1	1	0.875	1	0.699
B17	EskişehirBankası T.A.Ş.	1	1	0.991	1	0.990
B18	Fiba Bank A.Ş.	1	1	0.859	0*	0.327
B19	Finans Bank A.Ş.	0	0	0.429	0	0.247
B20	İktisat Bankası T.A.Ş.	1	1	0.993	1	1.000
B21	Interbank	1	1	0.997	1	0.995
B22	Kentbank A.Ş.	1	1	0.679	0*	0.432
B23	Koçbank A.Ş.	1	1	0.529	0*	0.402
B24	Milli Aydın Bankası T.A.Ş.	1	1	0.984	1	0.790
B25	MNG Bank A.Ş.	1	1	0.958	0*	0.435
B26	Oyak Bank A.Ş.	1	1	0.937	1	0.557
B27	Pamukbank T.A.Ş.	1	0*	0.465	0*	0.247
B28	Sitebank A.Ş.	1	1	0.958	1	0.863
B29	Şekerbank T.A.Ş.	0	1*	0.811	0	0.236
B30	Sümerbank A.Ş.	1	1	0.993	1	0.991
B31	TekstilBankası A.Ş.	0	0	0.489	0	0.246
B32	Toprakbank A.Ş.	1	1	0.839	0*	0.454
B33	Turkish Bank A.Ş.	0	1*	0.868	0	0.153
B34	TürkDışTicaretBankası A.Ş.	1	1	0.601	1	0.600
B35	Türk Ekonomi Bankası A.Ş.	0	1*	0.558	0	0.315
B36	TürkTicaretBankası A.Ş.	1	1	0.947	1	0.945
B37	Türkiye Garanti Bankası A.Ş.	0	0	0.312	0	0.235
B38	Türkiyeİmarbankası T.A.Ş.	1	1	0.612	0*	0.471
B39	TürkiyeİşBankası A.Ş.	0	0	0.348	0	0.154
B40	TürkiyeTütüncülerBankası	1	1	0.997	1	0.994
B41	Yapı ve Kredi Bankası A.Ş.	0	0	0.286	0	0.149

Code	State-owned Commercial Banks	Actual Group	Ordinary Logistic Regression		Conditional Logistic Regression	
			Classified Group	P_{L_i}	Classified Group	P_{CL_i}
	Foreign Banks					
	Foreign Banks Founded in Turkey					
B42	Arap Türk Bankası A.Ş.	0	1*	0.514	0	0.341
B43	Bnp - Ak Dresdner Bank A.Ş.	1	1	0.613	0*	0.304
B44	HSBC Bank A.Ş.	0	0	0.097	0	0.382
B45	OsmanlıBankası A.Ş.	1	0*	0.177	0*	0.316
B46	Ulusal Bank T.A.Ş.	1	1	0.979	1	0.986
	Foreign Banks Having Branches in Turkey					
B47	Abn Amro Bank N.V.	0	0	0.172	0	0.033
B48	Banca di Roma S.P.A.	1	1	0.667	0*	0.206
B49	Bank Mellat	0	0	0.496	0	0.201
B50	Citibank N.A.	1	0*	0.179	0*	0.211
B51	Credit LyonnaisTurkey	1	1	0.896	0*	0.169
B52	Habib Bank Limited	0	0	0.042	0	0.059
B53	ING Bank N.V.	1	0*	0.269	0*	0.099
B54	Rabobank Nederland	1	0*	0.377	0*	0.452
B55	SociétéGénérale (SA)	0	0	0.359	0	0.251
B56	The Chase Manhattan Bank N.A.	1	1	0.628	0*	0.089
	Development and Investment Banks					
	State-owned Development and Investment Banks					
B57	İllerBankası	0	0	0.147	0	0.119
B58	TürkEximbank	0	0	0.107	0	0.133
B59	TürkiyeKalkınmaBankası A.Ş.	0	0	0.135	0	0.007
	Privately-owned Development and Investment Banks					
B60	Atlas YatırımBankası A.Ş.	1	1	0.541	0*	0.185
B61	GSD YatırımBankası A.Ş.	0	0	0.280	0	0.062
B62	NurolYatırımBankası A.Ş.	0	0	0.341	0	0.013
B63	OkanYatırımBankası A.Ş.	1	1	0.847	0*	0.352
B64	Sınai YatırımBankası A.Ş.	1	1	0.525	0*	0.279
B65	Tat YatırımBankası A.Ş.	1	1	0.999	0*	0.476
B66	Tekfen Yatırım ve Finansman Bankası A.Ş.	1	1	0.960	0*	0.326
B67	ToprakYatırımBankası A.Ş.	1	1	0.914	0*	0.058
B68	Türkiye Sınai KalkınmaBankası A.Ş.	0	1*	0.525	0	0.269
	Foreign Development and Investment Banks					
B69	CréditAgricole Indosuez Türk Bank A.Ş.	1	1	0.904	0*	0.352
B70	Deutsche Bank A.Ş.	0	0	0.311	0	0.255

Note: * represents misclassified banks.