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Financial statement indicators of financial failure: an empirical study on Turkish public companies during the November 2000 and February 2001 crisis

Abstract

The main aim of this study is to develop a financial failure prediction model that can be utilized by all actors in the economy. As a financial failure assumption, we consider Turkish Bankruptcy Law article 179 pursuant to Turkish Trade Law articles 324 and 434, and negative equity value. The study is conducted using 53 financial ratios extracted from financial statements of industrial companies listed on the ISE (Istanbul Stock Exchange) during economic crises between November 2000 and February 2001; and follows four main steps. In the first step one-way ANOVA test is conducted to financial ratios which are compiled from previous central studies and Turkish independent investment investigation company, to define how financial ratios differentiate between distressed and non-distressed firms. Then in the second step, discriminant analysis and logistic regression analysis are applied to those selected ratios. In the third step factor analysis is conducted to find out if the models measure different corporate characteristics, and in the conclusion both models are combined to construct an objective early warning system.

Keywords: failure prediction, factor analysis, discriminant analysis, logit analysis.
JEL Classification: C13, G32, G33.

Introduction

Nowadays, business enterprises operate in a rapid changing trade-economic, technological, psycho-social, and ecologic environment. This changing environment brings some sort of uncertainties. Under these uncertainties, sustaining operations and overcoming those uncertainties are an integral part of management. The crises that businesses encounter are inevitable and unpredictable; and preventing them requires special managerial attention and intervention. As a matter of fact, at the end of 20th century and at the beginning of the 21st century, the businesses not only in developing countries but also Western economies encountered economic crises.

November 2000 and February 2001 crisis had a great impact on Turkish economy. A large number of firms came to the point of bankruptcy, shut down of operations and the GDP contracted sharply. During the crisis, to rescue distressed firms, most of the banks and major finance companies constituted a moratorium, which was coordinated by The Turkish Banking and Regulation and Supervision Agency. This moratorium aimed to reconsolidate the debts of distressed firms via guarantee of government authorization, which is also known as "The Istanbul Approach". This approach was also supported by the World Bank and the IMF. Istanbul approach concerned 304 firms, 96 of which were medium-sized enterprises and restructuring agreements were concluded with 66 of medium-sized enterprises (OECD, 2004).

In the light of the brief information above, the recent bankruptcies of many companies have underlined the importance of failure prediction both in academia and industry. It now seems more necessary than ever to develop early warning systems that can help prevent or avert corporate default, and facilitate the selection of firms to collaborate with or invest in.

In bankruptcy prediction studies two main approaches can be distinguished: The first and the most often used one is the empirical search for predictors (financial ratios) that lead to lowest misclassification rates. The second approach concentrates on the search for statistical methods that would also lead to improved prediction accuracy (Back et al., 1996).

The pioneering study in the field of bankruptcy prediction was conducted by Beaver in 1966. Beaver made the first study in bankruptcies and estimating failure risk of companies. The only point where Beaver was mostly criticized was that his study was dependent on univariate analysis and considered certain groups (a limited number) of financial ratios. In 1968, Altman expanded this analysis to multivariate discriminant analysis. Until the 1980s DA (Discriminant Analysis) was the dominant method in failure prediction. Meyer and Pifer (1970) established a financial failure estimation model based on linear regression analysis in which 0 and 1 (y = 1; Failed) were taken as dependent variables. In 1972, Deakin tried to combine the studies of Beaver and Altman in a rationalist manner and utilized Beaver's 14 variables with application of series of multivariate discriminant models. In 1975, Libby tried to develop Deakin's model. Moyer (1977) brought forward the idea that the model developed by Altman (1968) had a poor foresight power and Moyer obtained higher classification success via utilizing stepwise DA. A number of other studies were conducted to develop DA to obtain better estimation results. Joy and Tofelson (1975) criticized the estimation power of DA, discriminating power of used variables and classification success. Taffler (1983) made some changes in DA and calculated performance scores for companies.

1. Two alternative prediction techniques

Discriminant analysis and logit analysis have different assumptions concerning the relationships between independent variables.

Discriminant analysis is a statistical technique used to classify an observation into one of several a priori groupings dependent on the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, which in our case are distressed and non-distressed firms (Altman, 1968; Altman et al., 1977; Altman, 2000). This is achieved by the statistical decision rule of maximizing the between group variance relative to the within group variance. This relationship is expressed as the ratio of between group variance to within group variance. DA in its most simple form attempts to derive a linear combination of individual characteristics (financial ratios) which best discriminates between groups from an equation that takes the following form:

$$Z = \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n,$$

where Z = discriminant score; β_i (i = 1, 2, ... , n) = coefficient (discriminant) weights; x_i (i = 1, 2, ... , n) = independent variables, the financial ratios.

Hence, each observation in our case firms receives a single composite discriminant score which is then compared to a cut-off value, which determines to which group the firm belongs to.

Discriminant analysis performs better when variables follow multivariate normal distribution and the covariance matrices for every group are equal. However, empirical studies have shown that especially failing firms violate the normality condition (Back et al., 1996). Moreover, multicollinearity among independent variables is often a serious problem, especially when stepwise procedures are employed (Hair et al., 1998). However, empirical studies have proved that the problems connected with normality assumptions were not weakening DA's classification capability, but DA's prediction ability. In addition, Altman (2000) states that multicollinearity aspect is not serious in DA, it usually motivates careful selection of the predictive variables (ratios). It also has the advantage of potentially yielding a model with a relatively small number of selected measurements which convey a great deal of information. This information might very well indicate differences among groups, but whether or not these differences are significant and meaningful is a more important aspect of the analysis.

The two mostly used methods in deriving the discriminant models are the direct and stepwise methods. The direct method is based on model construction, so that the model is ex ante defined and then used in DA. In stepwise method, the procedure selects a subset of variables to produce a good discriminating model by a combination of forward selection and backward selection. This procedure starts with no variables in the model; variables are added as with the forward selection method and after each step, a backward elimination process is carried out to remove variables that are no longer judged to improve the model (Landau and Everitt, 2004). The stepwise method that is used in this study is built in function in the SPSS program.

To sum up, DA method can only provide the classification of the firms. Despite the importance of this classification, it can not provide information about failure risk of firms. Therefore, analysts recommend application of logit and probit econometrics models and comparison of the applied method with DA method (Canbas et al., 2005). To assess failure risk of firms, logit and probit econometrics models have been frequently used (Altas and Giray, 2005).

Logit analysis investigates the relationship between binary or ordinal response probability and explanatory variables. The parameters of the model are estimated by the method of maximum likelihood. Like DA this method weights the independent variables and assigns a Z score in a form of failure probability to each firm in the sample. The advantage of this method is that it relaxes the assumption of DA

The first practitioner of logit analysis in the failure prediction was Ohlson (1980). Most of the studies conducted after 1981 used logit analysis to relax the constraints of DA (Zavgren, 1985; Lau, 1987; Keasey and McGuinness, 1990; Tennyson et al., 1990).

Logit analysis uses the logistic cumulative probability function to predict failure. The result of the function is between 0 and 1 and probability of failure in logit analysis can be written as:

$$\text{Probability of failure} = \frac{1}{1+e^{-z}} = \frac{1}{1+e^{-(\beta_1+\beta_2 x_2+\ldots+\beta_n x_n)}} \text{ (Gujarati, 2003),}$$

where β_i (i = 1, 2, ... , n) = coefficient weights; x_i (i = 1, 2, ... , n) = independent variables, the financial ratios.

Logit analysis applies the same variable selection process as DA presented in previous paragraphs and in this study stepwise method is selected for model construction.

An empirical study is carried out by Microsoft Excel and SPSS 15 for windows.

2. Sample and variable selection

2.1. Sample selection. The initial sample is composed of 188 industrial firms listed on the ISE during the 2001 recession, of which 154 are non-distressed and 34 are financially distressed.

Financially distressed firms are defined by two criteria:

1. Turkish Bankruptcy Law article 179 pursuant to Turkish Trade Law articles 324 and 434; business enterprises incurring 2/3 loss in capital stock could be defined as bankrupt.

Bankruptcy is a legal procedure, even though those companies selected according to this criterion were not officially bankrupt, they could be classified as financially distressed.

2. Negative equity figures.

In this study, for the initial sample, the ratios are derived from financial statements dated one annual reporting period prior to financial distress occurrence. The data (financial statements) were derived from Istanbul Stock Exchange (www.imkb.gov.tr).

2.2. Variable selection. After the initial groups are defined and firms selected, balance sheet and income statement data are collected. 53 financial ratios have been found useful for this study. 26 financial ratios of variable set have been used in discriminant models of Beaver's (1966) univariate analysis and multivariate analysis of Altman (1968), Deakin (1972), Edminster (1972), Blum (1974), Altman et al. (1977), and El Hennawy and Moris (1983) which are representative examples of studies used multiple discriminant analysis technique. Moreover, additional 27 financial ratios from independent investment investigation company IBS Analysis (www. analiz.ibsyazilim.com) have been found useful for this study. These variables are classified into 6 standard ratio categories. In Table 1 aggregate financial ratios, their codes and ratio categories are presented.

Table 1. Aggregate financial ratios found to be useful

Ratio category	Ratios	Ratio code	Analysts
Liquidity ratios	Current ratio	Lq1	B, D, A-H-N
Liquidity ratios	Quick ratio	Lq2	D
Liquidity ratios	Cash ratio	Lq3	E, D
Liquidity ratios	Working capital to total assets ratio	Lq4	B, A, D
Liquidity ratios	Current assets to total assets ratio	Lq5	D, E-M
Liquidity ratios	Quick assets to total assets ratio	Lq6	D, E-M
Liquidity ratios	Quick assets to inventory ratio	Lq7	B*
Liquidity ratios	Cash to total assets ratio	Lq8	D
Liquidity ratios	Cash flow to short-term debts ratio	Lq9	E
Liquidity ratios	Cash flow to total assets ratio	Lq10	E-M
Liquidity ratios	Cash flow to total debts ratio	Lq11	B*, B, D
Liquidity ratios	Working capital to equity ratio	Lq12	IBS
Leverage ratios	Total debts to total assets ratio	Lv1	B, D
Leverage ratios	Short-term debts to total assets ratio	Lv2	IBS
Leverage ratios	Short-term debts to total debts ratio	Lv3	IBS
Leverage ratios	Long-term debts to total assets ratio	Lv4	IBS
Leverage ratios	Financial debts to total assets ratio	Lv5	IBS
Leverage ratios	Interest coverage ratio	Lv6	A-H-N
Leverage ratios	Long-term debts to equity ratio	Lv7	E-M
Leverage ratios	Short-term debts to equity ratio	Lv8	E
Leverage ratios	Total debts to equity ratio	Lv9	IBS
Fiscal structure ratios	Tangible fixed assets to long-term debts ratio	Fs1	IBS
Fiscal structure ratios	Equity to fixed assets ratio	Fs2	IBS

Table 1 (cont.). Aggregate financial ratios found to be useful

Ratio category	Ratios	Ratio code	Analysts
Fiscal structure ratios	Fixed assets to long-term debts ratio	Fs3	IBS
Fiscal structure ratios	Financial fixed assets to fixed assets ratio	Fs4	IBS
Fiscal structure ratios	Financial fixed assets to long-term debts ratio	Fs5	IBS
Fiscal structure ratios	Retained earnings to total assets ratio	Fs6	A, A-H-N
Activity ratios	Account receivable turnover ratio	A1	IBS
Activity ratios	Inventory to net sales ratio	A2	E
Activity ratios	Payables turnover ratio	A3	IBS
Activity ratios	Net working capital to net sales ratio	A4	E, D
Activity ratios	Current assets to net sales ratio	A5	D
Activity ratios	Tangible fixed assets turnover ratio	A6	IBS
Activity ratios	Total assets turnover ratio	A7	A
Activity ratios	Long-term debt turnover ratio	A8	IBS
Activity ratios	Equity to net sales ratio	A9	E
Activity ratios	Quick assets to net sales ratio	A10	D
Activity ratios	Cash to net sales ratio	A11	D
Profitability ratios	Gross profit margin	P1	IBS
Profitability ratios	Net profit margin	P2	IBS
Profitability ratios	Operational profit margin	P3	IBS
Profitability ratios	Operating profit margin	P4	IBS
Profitability ratios	Ebit margin	P5	IBS
Profitability ratios	Taxes to net sales ratio	P6	IBS
Profitability ratios	Taxes to profit before taxes ratio	P7	IBS
Profitability ratios	Return on equity	P8	IBS
Profitability ratios	Return on long term debts	P9	IBS
Profitability ratios	Return on assets	P10	B, D
Profitability ratios	Financial expenses to inventories ratio	P11	IBS
Profitability ratios	Ebit to total assets ratio	P12	IBS
Profitability ratios	Operating income to total assets ratio	P13	A, A-H-N
Market value ratio	Market to book ratio	M1	IBS
Market value ratio	Mv of equity to book value of debts ratio	M2	A, A-H-N

Legend: A – Altman (1968); A-H-N – Altman, Haldeman and Narayanan (1977); B – Beaver (1966); B* – Blum (1974); D – Deakin (1972); E – Edminster (1972); E-M – El Hennawy and Morris (1983); IBS – IBS Analysis.

The sample selection method of this study follows the same pattern of financial failure studies in international literature. Those studies consider 3 or 5 annual periods prior to failure occurrence of each firm. Each annual period prior to failure occurrence can be represented as -1, -2, -3 and so on; for example, -1 is one annual period prior to failure; -2 is two annual period prior to failure. In this study an early warning system is developed according to financial ratios of one year prior to failure.

In the study to select the financial ratios that are to be used in the analysis, one-way ANOVA test is conducted. The aim is to define financial ratios of distressed and non-distressed groups that differentiate at 5% significance level.

In Table 2, mean, standard deviation, F-test and its significance level for distressed and non-distressed firms are presented. Small significance level indicates group mean differences. In our case the selected 35 financial ratios have significance level less than 5% that means one of the group differs from the other group. The ratios are sorted according to their significance level.

Table 2. ANOVA test statistics

Ratios	Non-distressed		Distressed		Test statistics	
	Mean	Std. D.	Mean	Std. D.	F	Sig.
Lv1	0,571	0,203	1,614	1,245	94,560	**0,000**
P10	-0,012	0,092	-0,578	0,689	93,894	**0,000**
P13	0,004	0,111	-0,539	0,696	82,706	**0,000**
Fs2	1,410	1,341	-1,090	2,096	79,951	**0,000**
Lv5	0,271	0,206	1,075	1,101	69,781	**0,000**
Lq4	0,170	0,181	-0,701	1,238	68,102	**0,000**
Lv2	0,441	0,185	1,217	1,112	65,519	**0,000**
Lq1	1,657	0,927	0,641	0,443	41,890	**0,000**
Lv4	0,131	0,112	0,397	0,476	38,156	**0,000**
Lq2	1,099	0,738	0,401	0,352	31,250	**0,000**
P12	0,135	0,104	0,002	0,239	25,828	**0,000**
Lq10	0,082	0,101	-0,039	0,240	21,685	**0,000**
Lq11	0,170	0,214	-0,003	0,153	21,475	**0,000**
Lq9	0,220	0,269	0,005	0,190	21,083	**0,000**
P9	0,200	5,402	-5,898	16,480	14,248	**0,000**
P5	0,288	0,350	-0,996	4,210	13,535	**0,000**
M2	2,305	2,550	0,717	1,330	13,386	**0,000**
Lq8	0,096	0,111	0,029	0,047	13,227	**0,000**
P3	0,112	0,257	-0,858	3,336	12,330	**0,001**
Lq3	0,341	0,571	0,042	0,088	10,034	**0,002**
A9	0,376	0,468	2,420	8,109	9,371	**0,003**
A4	0,379	0,983	-66,019	278,229	8,510	**0,004**
P8	-0,154	0,422	0,793	3,959	8,167	**0,005**
Lq6	0,400	0,160	0,312	0,204	7,948	**0,005**
P2	-0,029	0,277	-27,368	122,974	7,386	**0,007**
Lq5	0,611	0,169	0,516	0,261	7,305	**0,008**
P4	0,011	0,355	-27,024	122,641	7,262	**0,008**
A3	6,494	7,867	2,950	3,228	7,181	**0,008**
P6	0,034	0,080	0,000	0,000	6,499	**0,012**
Lv7	0,510	0,761	-0,819	6,193	6,485	**0,012**
A5	1,329	1,269	3,224	9,194	5,891	**0,016**
P7	0,230	0,584	0,000	0,000	5,712	**0,018**
A2	0,363	0,292	1,281	4,757	5,485	**0,020**
P11	1,156	2,510	9947,342	60477,586	4,042	**0,046**
Lq7	4,362	10,866	199,541	1196,698	3,974	**0,048**
A8	14,699	35,687	3,473	4,838	3,630	0,058
Fs6	0,074	0,066	0,049	0,097	3,492	0,063
A7	0,595	0,373	0,469	0,434	3,137	0,078
Lv9	2,184	2,289	-0,919	22,403	2,751	0,099
A1	2,613	1,637	3,210	4,134	1,904	0,169
P1	0,290	0,163	0,236	0,383	1,724	0,191
Fs4	0,106	0,164	0,148	0,239	1,571	0,212

Table 2 (cont.). ANOVA test statistics

Ratios	Non-distressed		Distressed		Test statistics	
	Mean	Std. D.	Mean	Std. D.	F	Sig.
Lv8	1,674	1,784	-0,100	16,954	1,566	0,212
A10	0,895	1,172	1,223	2,254	1,517	0,220
M1	0,961	0,804	0,786	1,314	1,045	0,308
Fs1	6,174	10,480	4,170	12,420	1,001	0,318
Fs3	7,380	12,060	5,285	14,961	0,806	0,370
Lv3	0,773	0,159	0,746	0,208	0,722	0,397
Lq12	3,739	3,640	1,493	32,029	0,698	0,404
A11	0,264	0,894	0,157	0,604	0,479	0,490
Lv6	401,854	4248,338	-5,653	35,442	0,339	0,561
A6	4,135	13,480	4,930	12,253	0,107	0,745
Fs5	0,956	2,577	0,821	2,457	0,083	0,774

3. Early warning models

3.1. Discriminant analysis model. The purpose of DA is to summarize the information contained by independent variables into an index value (dependent variable). The set of variables was chosen by stepwise selection method to enter or leave the model using the significance level 0,05 of an F-test from analysis of covariance. The variables of 1 annual period prior to failure constitute the model sample of this study and prediction ability of developed discriminant model of 1 annual period prior to failure would be tested through the variables of 2 and 3 annual period prior to failure.

In this analysis, the weights ($ß_i$), which discriminate best between distressed and non-distressed firms, are estimated. In this estimation the weights that maximize the proportion of between group sum of squares to within group sum of squares for discriminant scores are selected.

Linear discriminant function is in the form of:

$$Z_a = C + ß_1 Lq1 + ß_2 Lv7 + ß_3 Fs2 + ß_4 P10 + ß_5 P11.$$

In the function, Z_a stands for discriminant score of firm *a*; *C* stands for constant term; $ß_1$, $ß_2$, $ß_3$, $ß_4$, and $ß_5$ stand for estimated weights of current ratio, long-term debts to equity ratio, equity to fixed assets ratio, return on assets, and financial expenses to inventories ratio respectively. Briefly, these 5 financial ratios are the selected characteristics which best discriminate distressed firms from non-distressed ones.

Table 3. Discriminant model weights

Characteristics	Weights
Lq1	0,631
Lv7	0,192
Fs2	0,465
P10	5,142
P11	0,0000263
(Constant)	0,618

Table 3 presents the estimated weights of the discriminant function. Discriminant model is obtained by putting the estimated weights into related places and the outcome of the model takes the form below.

$$Z_a = 0{,}618 + 0{,}631 Lq1_a + 0{,}192 Lv7_a + 0{,}465 Fs2_a + $$
$$+ 5{,}142 P10_a + 0{,}0000263 P11_a.$$

All of the discriminant coefficients are positive; hence, increases in selected characteristics (ratios) of a firm reduce its probability of failure.

Table 4. Test statistics of estimated discriminant function

Eigenvalue	Canonical correlation	Wilks' lambda	Chi-square	df	Sig.
0,765	0,658	0,567	101,955	5	0,000

Table 4 presents the test statistics of estimated discriminant function. Eigenvalue is the ratio of the between group sum of squares to the within group sum of squares for the discriminant scores. The largest eigenvalue corresponds to the eigenvector in the direction of the maximum spread of the group means, in other words, largest eigenvalue indicates efficiency of discriminant function. Eigenvalue of estimated discriminant function is quite large.

Canonical correlation measures the association between the discriminant scores and the groups. Canonical correlation coefficient is the square root of the ratio of between groups sum of squares to the total sum of squares, values close to 1 indicate a strong correlation between discriminant scores and the groups.

Wilks' lambda is the proportion of total variance in the discriminant scores not explained by differences among the groups. Values close to 0 indicate the group means are different. The value of Wilks' lambda is transformed into Chi-square to be used along with degrees of freedom to determine significance. Significance level of estimated discriminant function is 0,000; this indicates that the group means differ.

To classify an individual firm between distressed and non-distressed firms, optimum cut-off score (Z) is calculated according to group means and group sizes.

$$Z = \frac{N_D Z_D + N_{ND} Z_{ND}}{N_D + N_{ND}} = 0{,}000005 \cong 0,$$

where Z – cut-off score; N_D – number of distressed firms; N_{ND} – number of non-distressed firms; Z_D – discriminant scores mean of distressed firms; Z_{ND} – discriminant scores mean of non-distressed firms.

Therefore:

If $Z_a > Z$, firm a is classified as non-distressed;

If $Z_a < Z$, firm a is classified as distressed.

High classification accuracy of DA proves that this model can be used in failure prediction studies. Even though this model provides a classification score for each firm, it does not provide the failure probability of firms. In the following part logit analysis is conducted to classify firms with regard to their failure probabilities.

3.2. Logit analysis model. As it is mentioned above, logit analysis does not assume multivariate normality and equal covariance matrices as discriminant analysis does. In this regard, logit model is superior to the discriminant model.

For the logit analysis variables are selected using the logistic regression procedures available in SPSS 15. In logistic regression dependent variable (Y) gets the value "1" for distressed firms and "0" for the non-distressed firms. Therefore, if $P_a \geq 0{,}50$ the model classifies firm a as distressed. As in discriminant analysis model, stepwise (forward conditional) selection method is used and the same significance level 0,05 has been set for variables to enter or leave the model. The variables of 1 annual period prior to failure constitute the model sample of this study and prediction ability of developed logit model of 1 annual period prior to failure would be tested through the variables of 2 and 3 annual period prior to the failure.

Table 5. Estimated variables and their coefficients for logit model

	B	S.E.	Wald	df	Sig.	Exp(B)
Lq2	6,763	2,249	9,045	1	0,003	865,262
Fs2	-17,979	5,309	11,467	1	0,001	0,000*
P9	-0,809	0,292	7,696	1	0,006	0,445

Table 5 presents estimated variables and their coefficients and other test statistics for logit model. B is the estimated coefficient with standard error S.E., Wald statistics is equal to square of the ratio of B to S.E., if the Wald statistics is significant (less than 0,05) then the parameter is useful to the model. All of the parameters are useful to the model with their respective significance levels. Exp(B) is the predicted change in odds for a unit increase in the predictor (ratio). When Exp(B) is less than 1, increasing values of the variable correspond to decreasing odds of the event occurrence and vice versa when Exp(B) is greater than 1. Therefore, a unit increase in Lq2 could be interpreted as increase in failure probability and a unit increase in Fs2 and P9 could be interpreted as decrease in failure probability.

If the estimated coefficients are put into related places in cumulative probability function, then the cumulative probability function takes the form below:

$$P_i = \frac{1}{1 + e^{-(6{,}763Lq2 - 17{,}979Fs2 - 0{,}809P9)}}.$$

3.3. Factor analysis. To study further whether or not the DA and Logit models really measure different corporate characteristics, principal component factor analysis is applied using all variables of one annual period prior to failure. The reason is to find out if the variables in two alternative models portray different financial dimensions so that selection of one variable into the model is not only a consequence of extremely small differences in the values of test statistics.

Principal component analysis is a factor extraction method used to form uncorrelated linear combinations of the observed variables like linear discriminant analysis. However, principal component analysis provides a method to identify alternative dimensions among the set of variables. The first component (factor) has the maximum variance. Successive components explain progressively smaller portions of the variance and are all uncorrelated with each other.

The criterion based on eigenvalues higher than 1 yielded an eight factor solution. The results of Varimax rotated factor patterns for one annual period prior to failure are presented in Table 6.

Table 6. Varimax rotated factor pattern

Ratios	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Lq1	0,0503	0,0993	**0,7839**	0,2893	0,1687	0,0213	0,0778	0,1944
Lq2	0,0331	0,0802	**0,8482**	0,2379	0,1549	0,1395	0,0293	0,1404
Lq3	0,0158	0,0206	**0,9358**	0,0656	0,1011	-0,0083	-0,0006	-0,0924
Lq4	0,5056	0,4054	0,2083	**0,6154**	0,1964	0,1705	0,0723	0,0438
Lq5	0,1376	0,1066	0,0359	0,1710	0,1814	**0,8865**	0,1412	0,0110
Lq6	0,0605	0,1226	0,2158	0,1568	0,1742	**0,8834**	0,0377	-0,0010
Lq7	**-0,9705**	-0,0215	0,0015	-0,2200	0,0017	-0,0388	0,0025	0,0007
Lq8	0,0103	0,0342	**0,7598**	0,1130	0,1093	0,2451	0,0197	-0,2004
Lq9	0,0241	0,0616	0,4172	0,0979	**0,8381**	-0,0312	0,0091	0,0995
Lq10	-0,0002	0,0719	0,0079	0,2357	**0,9160**	0,1776	0,0365	-0,0118
Lq11	0,0137	0,0643	0,4053	0,0929	**0,8581**	0,0237	-0,0006	0,0666
Lv1	-0,4182	-0,3161	-0,2178	**-0,7985**	-0,1515	0,0185	-0,0408	-0,0552
Lv2	-0,5154	-0,4145	-0,2190	**-0,6262**	-0,1592	0,0953	-0,0348	-0,0449
Lv4	0,0503	0,0967	-0,0904	**-0,7489**	-0,0466	-0,1734	-0,0316	-0,0480
Lv5	-0,4116	-0,0216	-0,1816	**-0,8616**	-0,1179	-0,0265	-0,0184	-0,0297
Lv7	0,0022	-0,0024	0,0188	0,0438	-0,0258	0,0127	**0,9295**	-0,0058
Fs2	0,0957	0,1444	0,3926	**0,6907**	0,0724	0,3210	0,0031	0,0364
A2	0,0479	**-0,9819**	-0,0620	-0,0113	0,0110	-0,0832	0,0123	-0,0171
A3	0,0464	0,0241	**0,6963**	0,0523	0,1011	0,0517	-0,0174	0,2760
A4	**0,7815**	0,5839	0,0288	0,1853	-0,0142	0,0721	-0,0002	0,0036
A5	-0,1936	**-0,9541**	0,0958	-0,0709	0,0181	0,0013	-0,0005	-0,0394
A9	-0,4484	**-0,8706**	0,0026	-0,1177	-0,0034	-0,1028	-0,0214	-0,0088
P2	**0,9093**	0,3359	0,0213	0,2224	-0,0048	0,0630	-0,0009	0,0013
P3	0,5619	**0,7777**	-0,0459	0,2207	0,0689	0,0548	0,0185	0,0132
P4	**0,9124**	0,3270	0,0221	0,2233	-0,0064	0,0618	-0,0017	0,0010
P5	0,4278	**0,8427**	0,0947	0,1420	0,1250	0,1224	0,0159	-0,0071
P6	0,0151	-0,0248	**0,8129**	0,0461	0,0846	0,0930	-0,0587	-0,0624
P7	0,0007	0,0220	0,1279	0,0997	0,0836	0,0053	-0,0172	**0,9287**
P8	-0,0018	-0,0068	0,0003	-0,0586	-0,0826	-0,1358	**-0,9125**	0,0113
P9	-0,0262	**0,8348**	0,2388	0,0827	0,2407	0,0093	-0,0132	-0,0257
P10	0,3536	0,1572	0,1551	**0,8235**	0,3297	0,0576	0,0520	0,0040
P11	**-0,9705**	-0,0208	-0,0091	-0,2198	0,0024	-0,0439	0,0036	0,0018
P12	0,0070	0,0967	0,0822	0,2735	**0,8707**	0,2798	0,0352	0,0017
P13	0,3541	0,1540	0,1905	**0,8443**	0,2221	0,0320	0,0306	0,0111
M2	-0,0016	0,0497	**0,7538**	0,2172	0,0793	-0,1588	0,0205	0,0401
% of variance	17,2905	16,5485	15,3938	15,2341	10,1635	5,83312	4,99079	3,08465
Cumulative %	17,2905	33,839	49,2328	64,4669	74,6304	80,4635	85,4543	88,5389

The variables of the two alternative models are loaded on five factors, i.e. on the first, second, third, fourth and seventh factors. Variables in DA model are representing first, third, fourth and seventh factors, on the other hand, variables in logit model are representing second, third and fourth factors. The names of the factors are based on the ratios with highest loading on the factors. Factor one can be named as inventory factor, this factor is represented in DA model. The second factor can be named as turnover factor, this factor is represented in logit model. The third factor can be named as cash factor, and the fourth factor can be named as leverage and profit factor, these two factors are represented in both DA and logit models. The seventh factor can be named as equity factor, this factor is represented in DA model. Factor five can be named as cash flow factor; the sixth factor can be named as dynamic assets factor and the eighth factor has only one high loading on variable "taxes to profit before taxes ratio". These three factors are not represented in DA and logit model.

The analysis may indicate that logit model uses less information than DA model. In the logit model there are smaller numbers of variables and dimensions than in DA model.

3.4. Evaluation of models. To sum up, the numbers of variables included into models as well as the information content of the models are affected by the model's selection method. Moreover, related to alternative prediction methods, namely DA and logit, they also lead to different number of Type I errors and Type II errors and total prediction accuracies.

In previous parts DA and logit models and each technique are presented. It is noticed that the underlying assumptions of DA and logit model concerning the relationships among independent variables affect the model selection process in an outstanding way. The two alternative models use different information. To find out if there are differences in their prediction ability, the models are tested through one, two and three annual period prior to failure data. Table 7 presents the prediction accuracy results for each technique.

Table 7. Prediction results for DA and logit analyses

Model	Annual periods prior to failure		
Discriminant analysis	-1 (%)	-2 (%)	-3 (%)
Type I error	29,7	40,5	83,8
Type II error	0,7	0,7	0,7
Total error	6,5	8,7	17,4
Overall prediction accuracy	93,5	91,3	82,6
Logit analysis			
Type I error	10,8	13,5	35,1
Type II error	0	3,4	4,1
Total error	2,2	5,4	16,3
Overall prediction accuracy	97,8	94,6	83,7

In one annual period prior to failure, logit model performs better than DA model. It produces only 10,8% type I errors and 0% type II errors (classifying the firm as distressed when it is non-distressed), while DA model produces 29,7% type I errors and 0,7% type II errors. The overall errors amount 2,2% for logit model and 6,5% for DA model, the overall prediction accuracy amounts to 97,8% for logit model and 93,5% for DA model.

In two annual periods prior to failure, both models are superior to each other in produced type I and type II errors, the fewest type I errors are constructed by logit model and the fewest type II errors are constructed by DA model. Logit model produces 13,5% and 3,4% type I errors and type II errors respectively and DA model produces 40,5% and 0,7% type I and type II errors respectively. The overall errors amount to 5,4% for logit model and 8,7% for DA model, the overall prediction accuracy amounts to 94,6% for logit model, and 91,3% for DA model.

In three annual periods prior to failure, both models perform nearly the same in overall errors and prediction accuracy. The overall errors amount to 16,3% for logit model and 17,4% for DA model, the overall prediction accuracy amounts to 83,7% for logit model and 82,6% for DA model. Logit model produces fewest type I errors amounting to 35,1% than 83,8% of DA model, on the contrary, DA model produces fewest type II errors amounting to 0,7% than 4,1% of logit model.

As a result, in overall errors and prediction accuracy logit model performs better than DA model. On the other hand, it is noticed that DA model performs better in regards to type II errors which remained constant at 0,7% for three periods. Type II errors of logit model have a tendency to decrease while approaching to the the failure occurrence period.

Increase in produced type I errors could be interpreted as the financial structures of putative financially distressed firms were better in the periods before financial crisis period. While approaching to the crisis period the financial structure of the putative distressed firms had a tendency to change for the worse and for this reason these firms fell into distress. While approaching to the crisis period, profitability of putative distressed firms had a tendency to decrease and their liquidity structure deteriorated.

Conclusion

Companies should be considered like living organisms. Throughout their life cycle they could also become ill and the terrible disease for them is financial distress. The best method to cure this disease is defining the symptoms and taking remedial actions. As Ackoff (1999) initiates, a symptom indicates the presence of a threat or an opportunity; variables used as symptoms are properties of the behavior of the organization or its environment. Such variables can also be used dynamically as presymptoms or omens, as indicators of future opportunities or problems.

The targets of the prediction models could be summarized as letting analyst or any of the stakeholders act due to the results of the model and pre-intervene to the variables in order to affect the prediction results. In this sense, combining multivariate statistical analyses and models and considering them as a whole, it is possible to construct a multidimensional and objective early warning system that let analyst take course of action according to the results and pre-intervene to the balance sheet and income statement variables to assess organizational strategies.

On the other hand, the efficiency of the early warning system is dependent on preparation of financial statements in accordance with accounting standards consistent with legal regulations. In other terms, the efficiency of the early warning system increases with the transparency of the financial statements. Consequently, early warning system is a worthwhile technique in prediction financial failure, perfection of the system is dependent on proper work of accounting and auditing firms in economic system.

This study included in its scope production industry companies quoted to ISE for the crisis period of November 2000 and February 2001. It further applied the discriminant analysis and logit analysis to data of one, two and three annual periods prior to failure. The study shows that the use of DA and logit analysis leads to different failure prediction models with different amount of variables, also different methods lead to the selection of different financial ratios except for Fs2 (equity to fixed assets ratio) which is the unique common variable in both models. Despite the selection method used, liquidity and profitability seem to be important factors in failure prediction. The reason could be interpreted as liquidity and profitability failure is more common failure type in Turkey that stresses the significance of these factors in the models.

The group of original variables was formed by selecting 26 of those variables from previous central studies in which good predictors of failure were found and 27 of those variables from the independent investment investigation of IBS company. These variables were divided into six categories, namely liquidity, leverage, fiscal structure, activity, profitability and market value. To analyze further the constructed models, factor analysis was conducted. Factor analysis indicated that the two alternative models had different information content.

Furthermore, the prediction accuracy of constructed models was tested through each three annual periods prior to failure data. The results indicated that logit model performed better than DA model.

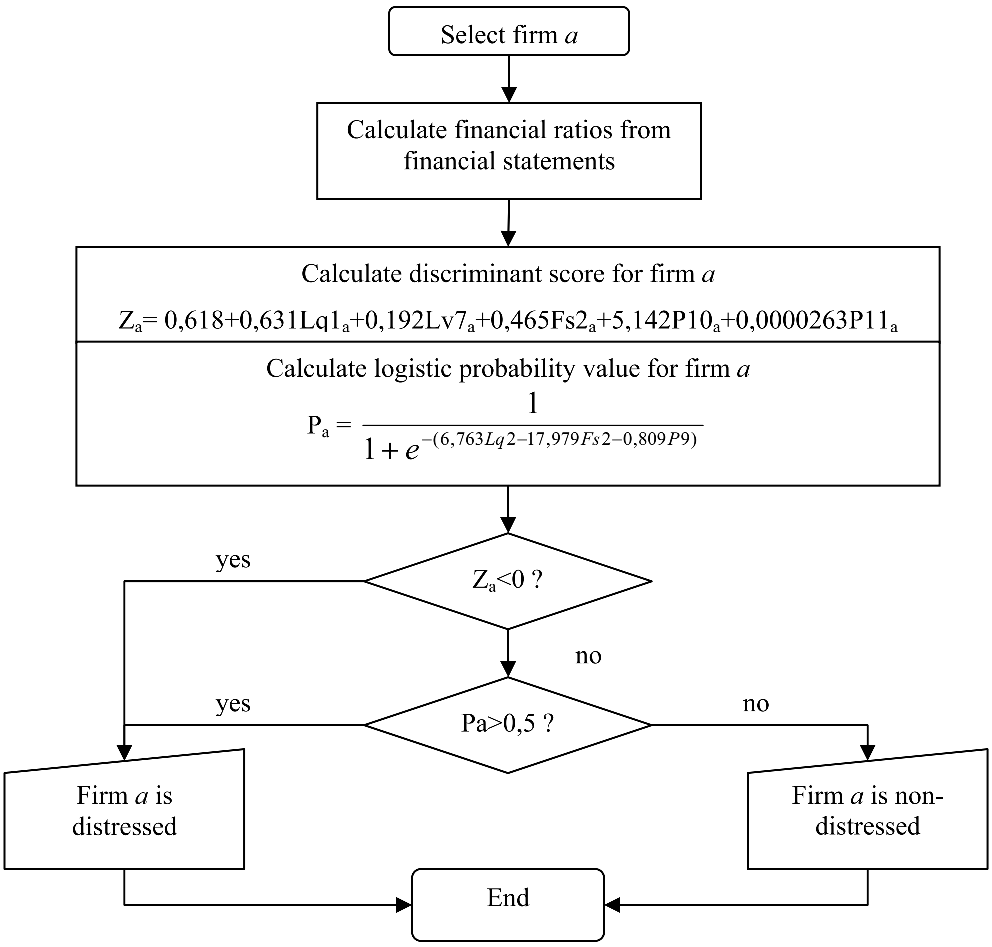

Fig. 1. General flow diagram of early warning system

To sum up, the differences between alternative methods affect the number of variables to be selected and information contents of the models differ due to the variables measuring different corporate characteristics. Therefore, combining multivariate statistical analyses and models and considering them as a whole, it is possible to construct a multidimensional and objective early warning system. This system is summarized in Figure 1, which represents a general flow diagram of constructed models to be used as an early warning system.

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