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Prediction of business failure: a comparison of discriminant and logistic regression analyses

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Abstract

This paper investigates two predictive models of business failure and important financial variables detecting failure potential using the sample of 122 both publicly opened and closed firms from the period of 1999-2007. Discriminant and Logistic Regression Analyses are performed and their predictive accuracy are compared. The results demonstrate that most of the failed firms show the signs of financial distress long before the failure and no statistically significant difference between the prediction results and variable choice of the discriminant and logistic regression analyses.

Keywords: *Business Failure, Failure Prediction, Discriminant Analysis, Logistic Regression Analysis, Financial Distress.*

Finansal başarısızlığın tahmini: diskriminant ve lojistik regresyon analizlerinin karşılaştırılması

Özet

Bu çalışma; 1997-2007 döneminde halka açık ve halka kapalı toplam 122 işletmeden oluşan örneklem ile iki istatistiksel yöntem kullanarak işletmelerin finansal başarısızlığı bir ve iki yıl öncesinden tahmin etmeye ve finansal başarısızlığın öngörülmesinde yararlı olan finansal oranları ortaya çıkarmaya çalışmaktadır. Çalışmada Diskriminant ve Lojistik Regresyon Analizleri uygulanmış ve modellerin tahmin güçleri karşılaştırılmıştır. Sonuçlar; finansal başarısızlığa uğramış işletmelerin çoğunun finansal sıkıntı belirtilerini başarısızlıktan çok önce gösterdiklerine ve çalışmada kullanılan yöntemlerin arasında tahmin gücü ve değişken seçimi konusunda istatistiki açıdan önemli fark olmadığına işaret etmektedir.

Anahtar Kelimeler: *İşletmelerde Finansal Başarısızlık, Başarısızlık Tahmini, Diskriminant Analizi, Lojistik Regresyon Analizi, Finansal Sıkıntı.*

1. Introduction

Business failure is the situation that a firm can not pay lenders, suppliers, shareholders, etc., or a bill is overdrawn or the firm is bankrupt according to the law. All of these situations result in a discontinuity of the firm's operations. Business failure is a worldwide problem. The number of failing firms is important for the economy of a country and it can be considered as an index of the development and the robustness of the economy.

The ability to predict firm failure has drawn considerable attention from numerous researchers and practitioners. The importance of such efforts is obvious. Business failure is an indication of resource misallocaion which is undesirable from a social point of view. An early warning signal of probable failure will enable both management and investors to take preventive measures; operating policy change, reorganization of financial structure

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and even voluntary liquidation will usally shorten the lenght of time losses incurred and thereby improve both private and social resource allocation.

The development and use of models can be very important in two different ways. First, as "early warning systems" such models are very useful to managers, authorities… etc. That can act to prevent failure. These actions include the decision about merger of the distress firm, liquidation or reorganization type.[1] Second, such models can be usuful in aiding decision making of financial institutions in firms' evluation and selection. Decisions about credit-granting, investment etc., have to take into account the opportunity cost as well as the risk of failure.

The following secton briefly reviews some of the previous studies of business failure. Data and description of research design are explained in the third section. The fourth section presents the emprical results. Conclusions of the findings are given in the last section.

2. Literature Review

A large number of methodologies and models have been presented in business failure literature. The first studies, univariate ones, were about the usefullness of financial ratios and most of the analyses are viewed as descriptive statistics. Fitzpatrick [2] found that Net Income to Net Worth and Net Worth to Debt were the variables which are capable of predicting the risk of failure. Winakor and Smith [3] proposed Working Capital / Total Assets ratio as the best indicator of approaching failure. Merwin [4] observed three important ratios six years before failure: Working Capital / Total Assets, Net Worth / Total Debts and Current Assets / Current Liabilities. Beaver [5] introduced a univariate techniques for the classification of firms in two groups, using some financial ratios.The ratios providing the highest discrimination capability were Cash Flow / Total Debts, Net Income/ Total Assets and Total Debts/ Total Assets.

Altman [6] was the first to use multivariate analysis to analyze the ratios of various bankrupt and nonbankrupt groups and to examine the effect of using different combinations of financial ratios to predict business failure. Also in 1993, Altman devised a four-variable model that established different weights for the various ratios and new cut-off values to categorize firms as bankrupt and nonbankrupt.

Deakin [7] modified the Altman model to include thr 14 best ratios identified by Beaver (1966) in his univariate study. He used the version of Multiple Discriminant Analysis (MDA) which assigns the probability of membership to the failed and nonfailed groups on the basis of its Z scores in previous years.

Edmister [8] developed and tested a number of methods of analyzing financial ratios to predict the failure of small businesses. He concluded that the predictive power of ratio analysis depends upon both the choice of analytical method and the selection of ratios. Unlike Altman and Beaver who found that one financial statement is sufficient for accurate classification, Edmister concluded that three consecutive statements are required for effective analysis of small businesses.

Blum [9] constructed an MDA to assess the probability of failure using twelve financial ratio and twelve nonfinancial indicators. The data were divided into twenty one ranges of at least three years and a discriminant function was fitted to half of the data in each range.

Moyer [10] pointed out that Altman's (1968) model had poor predicting ability and he had used a stepwise discriminant analysis to construct a model providing higher classification ability.

Altman, Haldeman and Narayanan [11] developed the revised version of Altman's original discriminant function which they refer to as "ZETA Model".This was done to base the estimation on larger companies, update the sample period and adopt the new accounting practices.

Casey and Bartczak [12] added cash flow variables to six acrual based variables in a discriminant model to see whether their inclusion improved the explanatory power of the model. Other researchers to focus on cash flow variables in MDA were Castanga and Matolcsy [13], Gombola, Haskins, Ketz and Williams [14], Aziz, Emmanuel and Lawson [15] and Aziz and Lawson [16].

Some of the other studies employing discriminant analysis for business failure prediction were Collongues [17], Conan Holder [18], Dmbolena and Khoury [19], Izan [20], Micha [21], Friedman et al. [22], Falbo [23], Laitinen [24] and Louma and Laitinen [25].

Multivariate conditional probability models (logit and probit analyses) were later introduced into failure prediction literature. Logit analysis for the prediction of business failure was firstly proposed by Ohlson [26]. Other researchers extended the basic techiques of logit analysis to obtain better classification accuracy.

Zavgren [27] developed a measure of information contained in a logistic function to assess the uncertainty of unexpected failure. Peel and Peel's[28] study involved British listed companies, the data was gathered for three years prior to bankruptcy and various multilogit models were generated. This enabled researchers to generate probabilities for a company failing one year ahead, two and three years ahead or remaining healty. Keasey, McGuiness and Short [29] developed a similar multilogit model to classify firms according to the time they are expected to fail.

Lau [30] defined five states in her study: non-failure, passing the dividend, default on a loan, debt reorganization and bankruptcy. Models were developed using ten explanatory variables from one, two and three year horizon. Generaly the models performed quite well, especially classifying the financially healty firms as non-failures. Subsequent studies adopted an identical approach, Bahson and Bartley [31], Ward [32], Ward and Foster [33] have reported similar results.

Gentry, Newbold and Whitford's [34] study complemented Casey and Bartzcak's [12] study which investigates the cash-based funds flow ratios can adequately classify failed and nonfailed firms. Their logit findings substantiated Casey and Bartzcak findings that cash flow from operations doesn't improve the classification results where as dividends fund flows was significant in distinguishing between failed and nonfailed companies.

Because of limitations of discriminant analysis, logit analysis was prefered by researchers. However, comparative studies between two methods (Press and Wilson [35], Collins and Green [36]) have not proved a higher classification accuracy for all cases and types of samples. Hamer [37] compared discriminant analysis to logit method for different data sets concluding that the models derived are of comparable ability to assess the probability of failure.

3. Data and Methodology

The purpose of this research is to construct bankruptcy prediction models, identify which financial ratios are of particular interest in predicting bankruptcy and to compare the prediction power of models. The sample consists of 169 manufacturing firms totally, 78 financially unsuccessful and 91 successful during the period 1997- 2007. Experiencing financial distress, defaulting on loan obligations, making an explicit agreement with creditors to reorganize debt structure and going bankruptcy are accepted as financial failure criteria of the study. Failing firms are randomly macthed with healty firms and on the basis of industry classification and the financial statement date. Ratios selected for this study have been promoted by theorists or have been found to be significant predictors of business failure in previous emprical researches. The year of failure for unsuccessful firms is selected as the year in which the firm undergoes financial distress. For publicly-opened firms, this information is gathered inspecting the "company news" section in the web site of Istanbul Stock Exchange (ISE), for publicly-closed firms, it is available in Dun& Bradstreet database.

Previous studies have largely ignored publicly-closed firms because of the difficulty of obtaining data. But this research is the first one in Turkey incorporating publicly-closed firms into business failure analysis. The data of publicly-closed firms are gathered from Dun&Bradstreet regional office while that of publicly-opened firms are from Istanbul Stock Exchange. Of the 169 firms, 95 are publicly-closed and 74 are publicly-opened.

Because only two consecutive annual financial statements of publicly-closed firms are available prior to failure date, the prediction horizion is choosen as two years prior to failure and the "cash flow from the operation" components can be computed for only first year before failure.

Discriminant analysis is choosen as the first analysis in this research because of its pioneering characteristic in literature. Discriminant analysis imposes certain statistical requirements on predictors: multivariate normality of independent variables and equal variance-covariance matrices of groups. Because of these prerequisites, the distribution of financial ratios of 169 firms are examined and it is seen that the normality requirement is violated. The data is examined for the presence of outliers, thus the outlier analysis is performed. After extraction of outliers, it is observed that multinormality is provided and the sample size reduced to 122 firms, 51 unsuccessful and 71 successfull. Of these are 82 publicly-closed and 40 puclicly-opened firms.

In order to compare the predicting power of the models, it is continued to work with 122 firms although logistic regression analysis doesn't have strict assumptions like discriminant analysis.

Because of the large number of variables found to be significant indicators of corporate problems in past studies, a list of 30 potentally helpfull ratios is complied for evaluation. These ratios are classified into eight standart ratio categories. Table I presents 30 financial ratios used in the model.

Table 1: Independent Variables Of Models

FINANCIAL RATIOS	CATEGORY
Current Assets / Current Liabilities	Liquidity
(Current Assets – Inventories) / Current Liabilities	Liquidity
(Cash + Bank) / Current Liabilities	Liquidity
Sales / Accounts Receivable	Activity
Cost of Goods Sold / Inventories	Activity
Sales / Current Assets	Activity
Sales / Fixed Assets	Activity
Sales / Tangible Fixed Assets	Activity
Sales / Total Assets	Activity
Sales / Total Equity	Activity
Gross Profit / Sales	Profitability
Earnings Before Interest and Taxes / Sales	Profitability
Net Profit / Sales	Profitability
Net Profit / Total Equity	Profitability
Net Profit / Total Assets	Profitability
Total Debt / Total Assets	Financial Structure
Short Term Debt / Total Assets	Financial Structure
Long Term Debt / Total Assets	Financial Structure
Total Debt / Total Equity	Financial Structure
Total Equity / Total Assets	Asset Financing
Fixed Assets / Total Equity	Asset Financing
Fixed Assets / (Total Equity + Long Term Debt)	Asset Financing
Tangible Fixed Assets / Total Equity	Asset Financing
Current Assets / Total Assets	Asset Structure
Fixed Assets / Total Assets	Asset Structure
Tangible Fixed Assets / Total Assets	Asset Structure
Cash Flow From Operations / Interest Expense	Cash Flow
Net Sales	Size
Total Equity	Size
Total Assets	Size

Multicollinearity, usually found in financial data, was as high as might be expected. So, to eliminate multicollinearity, a different method of data reduction is applied in this study. The amount of variables to be included in the model is selected by correspondence analysis. First, the Kendall's coefficient of concordance is calculated for each ratio group. This coefficient is used to measure the degree of correspondence between two rankings and the assessing the significance of this correspondence [38]. In other words, it measures the strenght of associations between variables of a ratio group. If correspondence is significant, then, Spearman's rank correlation coefficient is calculated in order to choose representative ratio of each category.

From the original list of variables, for each category except for the asset structure, because the Kendall's coefficient of concordence can't not be found significant for this group, so all ratios of this group are added into the analysis, a ratio is selected as the representative for each category. Totally; 10 and 9 variables are selected as a result of correspondence analysis one and two year prior to failure respectively.Table 2 and Table 3 exhibits the representative ratios for each group.

Table 2: Representative Ratios for Each Ratio Category One Year Prior to Failure

CATEGORY	**REPRESENTATIVE RATIO**
Liquidity	Current Assets / Current Liabilities
Activity	Sales / Total Assets
Profitability	Net Profit / Total Assets
Financial Structure	Total Debt / Total Assets
Asset Financing	Fixed Assets / Total Equity
Size	Total Assets
Cash Flow	Cash Flow From Operations / Interest Expense
Asset Structure	Current Assets / Total Assets
	Fixed Assets / Total Assets
	Tangible Fixed Assets / Total Assets

Table 3: Representative Ratios for Each Ratio Category Two Year Prior to Failure

CATEGORY	**REPRESENTATIVE RATIO**
Liquidity	(Current Assets – Inventories) / Current Liabilities
Activity	Sales / Total Assets
Profitability	Net Profit / Total Assets
Financial Structure	Short Term Debt / Total Assets
Asset Financing	Fixed Assets / Total Equity
Size	Total Assets
Asset Structure	Current Assets / Total Assets
	Fixed Assets / Total Assets
	Tangible Fixed Assets / Total Assets

Discriminant and Logistic Regression analyses are conducted with the representative ratios one and two year prior to failure using SPSS program. To select the best set of discrminating ratios stepwise selection criteria is applied. The emprical results are explained in the next section.

4. Emprical Results

An important issue before conducting the models is to determine the individual discriminating ability of the variables, so F Test is performed. This test relates the difference between the average values of the ratios in each group to the variability of values within each group. In Table 1 and Table 2, the resulting F statistics are presented for one and two year prior the failure respectively.

Table 4: Test of Equality of Group Means One Year Prior to Failure

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
ca_cl	,872	17,663	1	120	,000
td_ta	,659	62,138	1	120	,000
fa_teq	,971	3,564	1	120	,061
sales_fa	,996	,524	1	120	,471
np_ta	,669	59,490	1	120	,000
tassets	,988	1,442	1	120	,232
cfo_int	,854	20,505	1	120	,000
tfa_ta	,962	4,735	1	120	,032
ca_ta	,988	1,437	1	120	,233
fa_ta	,988	1,437	1	120	,233

Table 5: Test of Equality of Group Means Two Year Prior to Failure

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
acidtest	,874	17,244	1	120	,000
np_ta	,810	28,118	1	120	,000
ta	,982	2,196	1	120	,141
sales_fa	,995	,579	1	120	,448
std_ta	,754	39,246	1	120	,000
fa_teq	,974	3,255	1	120	,074
tfa_ta	,931	8,854	1	120	,004
ca_ta	,969	3,894	1	120	,051
fa_ta	,969	3,894	1	120	,051

As it is seen in Table 1, one year prior to failure, Current Asset / Current Liabilities (ca _cl), Total Debt / Total Assets (td _ta) , Net Profit / Total Assets (np_ta) and Cash Flow From Operation / Interest Expense (cfo _int) ratios and In Table 2, two year prior to failure, (Current Assets – Inventories)/ Current Liabilities (Acidtest), Net Profit / Total Assets (np_ta), Short Term Debt / Total Assets (std_ta) ratios are all significant at 0,000 indicating extremely significant differences between failed and healty groups.

The aforementioned ratios are expected to be the large contributors to group seperation in conducted models.

4.1. Results for One Year Prior to Failure

4.1.1. Discriminant Model One Year Prior to Failure

Discriminant analysis identifies a set of variables that "best" discriminates between the two groups.The sensitivity of discriminant analysis is based on the validity of the assumptions [39].Besides the multivariate normality, the second distinctive assumption of discriminant analysis is the equality of variance covariance matrices across groups.

The hypothesis tesing of equality of covariance matrices is checked by Box's M test. As it is shown in Table 6, the null hypothesis of equal population covariance is accepted (Sig. 23,7 %).

Table 6: Box's M Test Results of Discriminant Model One Year Prior to Failure

Test Results

Box's M		8,241
F	Approx.	1,335
	df1	6
	df2	79519,470
	Sig.	,237

Tests null hypothesis of equal population covariance matrices.

Table 7: The Canonical Discriminant Coefficients of Discriminant Model 0ne Year Prior to Failure

Canonical Discriminant Function Coefficients

	Function
	1
td_ta	-2,856
np_ta	4,796
cfo_int	,188
(Constant)	,683

Unstandardized coefficients

Using the canonical discriminant function coefficients, the discriminant model one year prior to failure can be written as,

Z = 0,683 + 0,188 Cash Flow From Operations / Interest Expense + 4,796 Sales / Total Assets – 2,856 Total Debt / Total Assets

In the discriminant function, each weight represents the relative contribution of its associated variable to the function. The sign denotes that the variable makes either a positive or a negative cotribution it doesn't indicate the direction of the relationship [40].

The classification results are given in Table 8 indicating that the discriminant model classifies 84,4 % of the firms correctly.

Table 8: The Classification Results Of Discriminant Model One Year Prior to Failure

Classification Results[a]

			Predicted Group Membership		
		state	,00	1,00	Total
Original	Count	,00	42	9	51
		1,00	10	61	71
	%	,00	82,4	17,6	100,0
		1,00	14,1	85,9	100,0

a. 84,4% of original grouped cases correctly classified.

Another objective of discriminant analysis is to classify future observations into one of the two groups. The proportional chance criterion is calculated in order to test the classification capability of discriminant function for future observations. If the percentage of correct classifications is higher than would be expected by chance it can be concluded that the discriminant model provides meaningfull information in classification.

Proportional chance criterion is calculated as; [41]

$C_{PRO} = p^2 + (1-p)^2$ where;

p = proportion of firms in group 1

1-p = proportion of firms in group 2

Using the groups proportions (71/122 healty and 51/122 failing) proportional chance criterion is calculated as 51,28 %. Therefore, the actual prediction rate of 84,4 % may be acceptable because it is above the proportional chance criterion. This means that when new companies are classified, the nature of the model is predictive.

4.1.2. Logistic Regression Model One Year Prior to Failure

Logistic regression is an attractive alternative to discriminant analysis.Its emprical results parallel those of multiple regression in terms of their interpretation and the casewise diagnostic measures available for examining residuals and it handles categorical independent variable easily whereas in discriminant analysis the use of dummy variables created problems with the variance covariance equalities. Logistic regression requires less restrictive statistical assumptions so the use of logit analysis esentially avoids all of the problems discussed with respect to discriminant analysis. Even if the assumptions are met, many researchers prefer logistic regression because it is similar to multiple regression. It has straightforward statistical tests, similar approaches to incorporating metric and nonmetric variables and nonlinear effects [42].

Before the estimation process begins, Hosmer and Lemeshow test is used to measure the overall fit of the model. This statistical test measures the correspondence of the actual and the predicted values of the dependent variable. The null and alternative hypotheses for assessing the overall model fit are;

H_0 : The hypothesized model fits the data.

H_A : The hypothesized model does not fit the data.

Table 9: Hosmer Lemeshow Test for Overall fit of Logistic Regression Model for One Year Prior to Failure

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7,249	8	,510
2	6,959	8	,541
3	10,326	8	,243

As it is seen in Table 9, In Step 3, the null hypothesis is accepted (Sig. 24,3 %). After the overall fit of the model has been assessed, using Table 10, the logistic regression model can be written as,

L = 1,403 + 0,351 Cash Flow From Operations / Interest Expense + 9,541 Sales / Total Assets – 4,418 Total Debt / Total Assets

Table 10: Variables of Logistic Regression Model One Year Prior to Failure

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	td_ta	-6,268	1,139	30,266	1	,000	,002
	Constant	3,839	,688	31,128	1	,000	46,477
Step 2[b]	td_ta	-4,144	1,262	10,787	1	,001	,016
	np_ta	11,192	3,242	11,918	1	,001	72525,949
	Constant	2,186	,807	7,331	1	,007	8,900
Step 3[c]	td_ta	-4,418	1,326	11,099	1	,001	,012
	np_ta	9,541	3,311	8,304	1	,004	13925,546
	cfo_int	,351	,164	4,587	1	,032	1,420
	Constant	1,403	,881	2,539	1	,111	4,068

a. Variable(s) entered on step 1: td_ta.

b. Variable(s) entered on step 2: np_ta.

c. Variable(s) entered on step 3: cfo_int.

The Wald statistic is used to assess statistical significance of coefficents. While Total Debt / Total Asset and Net Profit / Total Asset ratios are significant at an alpha level of 0,01, Cash Flow From Operations / Interest Expense ratio is significant at an alpha level of 0,05.

The sign of the original coefficients indicates the direction of relationship. A positive coefficient increases the probabiliy whereas the negative value decreases the prediced probability, because the original coefficients are expressed in terms of logit values.

Table 11: The Classification Results of Logistic Regression Model One Year Prior to Failure

Classification Table[a]

	Observed		Predicted state ,00	Predicted state 1,00	Predicted Percentage Correct
Step 1	state	,00	34	17	66,7
		1,00	12	59	83,1
	Overall Percentage				76,2
Step 2	state	,00	40	11	78,4
		1,00	8	63	88,7
	Overall Percentage				84,4
Step 3	state	,00	42	9	82,4
		1,00	10	61	85,9
	Overall Percentage				84,4

a. The cut value is ,500

The classification results show that before one year before the failure, logistic regression model predicted 84,4 % of the firms accurately.

It is seen that, both models selected the same ratios; the Cash Flow From Operations / Interest Expense which is the cash-based version of times interest earned ratio (Ebit / Interest) , Net Profit /Total Assets and Total Debt / Total Assets, as the best discriminator ratios between the failing and the healty firms one year prior to failure.

4.2. Results for Two Years Prior to failure

4.2.1. Discriminant Model Two Year Prior to Failure

The hypothesis tesing of equality of covariance matrices is done by Box's M test. As it is shown in Table 12, the null hypothesis of equal population covariance is accepted.(Sig. 42,6%)

Table 12: Box's M Test Results of Discriminant Model Two Year Prior to Failure

Test Results

Box's M		2,837
F	Approx.	,928
	df1	3
	df2	978423,0
	Sig.	,426

Tests null hypothesis of equal population covariance matrices.

Table 13: The Canonical Discriminant Coefficients of Discriminant Model for Two Year Prior to Failure

Canonical Discriminant Function Coefficients

	Function
	1
np_ta	-7,202
std_ta	3,399
(Constant)	-1,108

Unstandardized coefficients

The discriminant model can be written as;

Z = - 1,108 + 3,3999 Short Term Debt / Total Assets – 7,202 Sales / Total Assets

In Table 14, the classification results indicate that discriminant model classifies 84,5 % of the healty firms and % 74,5 of the failing firms correctly. The overall clssification accuracy of the model is 80,3 % .

Table 14: The Classification Results Of Discriminant Model Two Year Prior to Failure

Classification Results[a]

			Predicted Group Membership		
		state	,00	1,00	Total
Original	Count	,00	38	13	51
		1,00	11	60	71
	%	,00	74,5	25,5	100,0
		1,00	15,5	84,5	100,0

a. 80,3% of original grouped cases correctly classified.

The correct classification ratio (80,3 %) exceeds the proportional chance criterion (51,28 %) which proves that model's prediction ability is significantly better than chance.

4.2.2. Logistic Regression Model Two Year Prior to Failure

As seen in Table 15, the Hosmer Lemeshow test results show the significance level of 0,146 indicating that the model fit is acceptable.

Table 15: Hosmer Lemeshow Test for Overall fit of Logistic Regression Model Two Year Prior to Failure

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6,399	8	,603
2	12,115	8	,146

The logistic regression model can be written using Table 15 as,

L = 1,606 – 3,908 Short Term Debt / Total Assets + 10, 946 Sales / Total Assets

Table 16: Variables of Logistic Regression Model Two Year Prior to Failure

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	std_ta	-4,941	,993	24,765	1	,000	,007
	Constant	2,764	,542	26,012	1	,000	15,860
Step 2[b]	np_ta	10,946	3,607	9,207	1	,002	56734,965
	std_ta	-3,908	1,037	14,207	1	,000	,020
	Constant	1,606	,622	6,658	1	,010	4,983

a. Variable(s) entered on step 1: std_ta.

b. Variable(s) entered on step 2: np_ta.

The Logistic Regression model for two year prior to failure includes two variables; Short Term Debt / Total Assets and Net Profit / Total Assets, with logistic coefficients of -3,908 and 10,946 respectively and a constant of 1,606 (Table 16). Comparing these results to dicriminant model reveals almost identical results, as discriminant model included same variables / ratios.

The classification results demonstrate that the model has predictive accuracy of 78,4 % for failing, 84,5 % for healty and 82 % for overall. (These results are presented in Table 17) The logit model correctly classified 78,4 % of failing, 84,5 % of healty and 82 % of total firms.

Table 17: The Classification Results of Logistic Regression Model TwoYear Prior to Failure

Classification Table[a]

			Predicted		
			state		Percentage Correct
	Observed		,00	1,00	
Step 1	state	,00	30	21	58,8
		1,00	12	59	83,1
	Overall Percentage				73,0
Step 2	state	,00	40	11	78,4
		1,00	11	60	84,5
	Overall Percentage				82,0

a. The cut value is ,500

The accuracy of the models is also evaluated on the basis of Type I (predicting a failed firm not to fail) and Type II (predicting a healty firm to fail) errors. One year prior to failure, both discriminant and logistic models produce identical rates of Type I and Type II error, 7,3 % and 8,2 % respectively.

Two years prior te failure, the Type I error of discriminant model proves to be 11 % while the Type II error is even better at 9 %. The logit model has identical rate, 9 %, of Type I and Type II error.

5. Summary and Conclusion

This study develops and empirically tests two business failure prediction models. Both linear multiple discriminant and logistic regression analyses are conducted one and two years prior to failure. Stepwise procedure is applied in order to avoid multicollinearity while systematically selecting variables. Besides publicly opend firms, the study also incorporates the publicly closed firms into the sample which is not done until today in our country because of many important problems pertaining to the development of their data.

The time period studied here spanned two years. One year prior to failure, the results indicate that three ratios which are statistically significant for the purpose of assessing the probability of failure. These are (i) total asset profitability, (ii) the financial structure as reflected by a measure of leverage (iii)some measure of current liquidity (Cash Flow from Operations / Interest Expense). Two year prior to failure, the models identified two significant variables that help discriminating between two groups of firms (i) a measure of profitability (ii) a measure of leverage.

In both years and in both models, the "Net Profit / Total Asset" variable which has the highest coefficient, provided the most significant information in classifying failed and healty firms. The leverage ratio ranks in second in its contribution to the overall prediction and classification ability of the models. CFO, operating cash flow measure contributed information to improve the classification accuracy of the models for the first year before failure and this component improved the classification rate of failed and healty companies.

The Cash Flow From Operations component can not be computed for the second year before failure lacking of financial statements of puclicy–closed firms for three years before the failure. So the impact of cash flow ratio in discrimination of the firms two years prior to failure can not be assessed.

The profitability ratio offers a reasonable measure of management effectiveness; the leverage ratios represent historical reasons to business failure, reasons that are directly related to the excessive or unwise use of leverage and the cash flow ratio constitutes a necessary measure of solvency.

Predictive accuracy of discriminant model amounts to 84,4 % at the first year and 80,1 % at the second year before the failure. The misclassification rate of failed firms (Type I error) is smaller than the misclassification rate of healty firms (Type II error) one year prior to failure but the reverse is true for the second year before failure.

Logistic regression model achieves 84,4 % at the first year and 82 % at the second year before the failure. The misclassification rate of failed firms (Type I error) is less than the misclassification rate of healty firms (Type II error) in the first year like discriminant model, and equal rates of both types of errors are observed in the second year before the failure.

The classification results show that no statistically significant difference between the results for each of the two years before bankruptcy, regardless of whether the logit or the discriminant model is used.

As a summary;

- The profitability ratio prevailed as the most significant indicators in both years,
- The degree of leverage was found to be important in both years,
- Although acid test ratio is expected to be a significant indicator two years prior to failure, existence of high correlation (59,6 %) between this ratio and leverage ratio lead the stepwise procedure choose the other one.
- The activity ratio is not significantly different for failing and healty firms,
- The asset structure doesn't make any meaningful contribution to classification of firms
- Asset financing ratio is not distinguishing variable in failure prediction.

The constructed models are relatively simple to apply and may be of use in practical applications. The findings of this research are consistent with the findings of previous studies (Kaplan and Urwitz [43], Ohlson[26] and Gentry, Newbold and Withford [34]) which have found that both discriminant and logistic regression analyses generate similar results, despite of the assumed advantages of latter.

References

[1] M.Casey, V. McGee, C. Stinkey, Discriminating Between Reorganized and Liquidated Firms in Bankruptcy, The Accounting Review, 249- 262, April 1986

[2] P.J.Fitz Patrick, A Comparison of Ratios of Successful Industrial Enterprises with Those of Failed Firms, Certified Public Accountant,656- 662, December 1932.

[3] R.F.Smith, H.A.Winakor, Changes in the Financial Structure of Unsuccessful Industrial Corporations**"**, The Accounting Review, Vol. 11,No.1, 87- 88, March 1936.

[4] C.Merwin, Financing Small Corporations in Five Manufacturing Industries, National Bureau of Economic Research,1926- 36, 1942.

[5] W.H. Beaver, Financial Ratios as Predictors of Failure, Emprical Research in Accounting-Selected Studies, Journal of Accounting Research, 71- 111, 1967.

[6] E.I. Altman, "Financial Ratios, Discriminant Analysis and Prediction of Corporate Failure", Journal of Finance, Vol.23, No:4,589- 609, September 1968.

[7] E.Deakin, A Discriminant Analysis of Predictors of Business Failure, Journal of Accounting Research, Vol. 10, No.1,167- 179, Spring 1972.

[8] R.O.Edmister, An Emprical Test of Financial Ratio Analysis for Small Business Failure Prediction", Journal of Financial and Quantitative Analysis, Vol. 7, No.2,1477- 1493,March 1972.

[9] M. Blum, Failing Company Discriminant Analysis, Journal of Accounting Research, Vol.12,No.1,1- 25, Spring 1974.

[10] R.C.Moyer, Forecasting Financial Failure: Reexamination, Financial Management, Spring, 11- 17,1977.

[11] E. Altman, R. Haldeman, P.Narayanan, ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations", Journal of Banking and Finance,29- 54, June 1977.

[12] C. Casey, N. Bartczak, Using Operating Cash Flow Data to Predict Financial Distress: Some Extensions", Journal of Accounting Researh, Vol.23,No.1,384- 401,Spring 1985

[13] A.D.Castanga, Z.P. Matolcsy, Using Operating Cash Flow Data to Predict Financial Distress: Some Extensions, Journal of Accounting Research,384- 401, 1985.

[14] M.J. Gombola, M.E. Haskins, J.E.Ketz, D.D.Williams, Cash Flow in Bankruptcy Prediction, Financial Management, 55- 65, 1987.

[15] A.Aziz, D.C.Emmanuel and G.H. Lawson, Bankruptcy Prediction-An Investigation of Cash-Flow Based Models", Journal of Management Studies, c.25,No:5,419- 437,September 1988.

[16] A.Aziz, G.H. Lawson, Cash Flow Reporting and Financial Distress Models: Testing of Hypotheses, Financal Management, 55- 63, 1989.

[17] Y.Collongues, Ratios Financiers et Prevision Des Faillites Des Petites et Moyennes Enterprises, Revue Bank, No.365,963- 970, 1977.

[18] J.Conan, M.Holder, Variables Explicatives de Performances et Controle de Gestion Dans Les PMI, These d'Etat, Universite de Paris Dauphine, Paris,1979.

[19] I.G.Dambolena,., S.J Khoury, "Ratio Stability and Corporate Failure", Journal of Finance,1017- 1026, September 1980.

[20] H.Y.Izan, Corporate Distress in Australia, Journal of Banking and Finance 8,303- 320, 1984.

[21] B.Micha, analysis of Business Failures in France, Journal of Banking and Finance 8, 281- 291, 1984.

[22] H.Friedman, E.I.Altman, D-L.Kao, Introducing Recursive Partitioning for Financial Classification: The Case of Financial Distress, The Journal of Finance, Vol. XL, No. 1, 269-291, 1985.

[23] P.Falbo, Credit Scoring by Enlarged Discriminant Analysis, Omega, Vol.13,No.4, 275- 289, 1991.

[24] E.K.Laitinen, Financial Ratios and Different Failure Processes, Journal of Business Finance and Accounting, 18(5),649- 673, 1991.

[25] M.Louma, E.K.Laitinen, Survival Analysis as a Tool for Company Failure Prediction, Omega, Vol.19,No.6,673- 678, 1991.

[26] J.A. Ohlson, Financial Ratios and the Probabilistic Prediction of Bankruptcy", Journal of Accounting Research, Vo. 18, No.1,109- 131, Spring 1980.

[27] C.V.Zavgren, Assessing the Vulnerability to Failure American Industrial Firms, A Logistic Analysis, Journal of Business Finance and Acounting, 12(1),19- 45,1985.

[28] M.J. Peel, D.A.Peel, A ultilogit Approach to Predicting Corporate Failure: Some Evidene for the UK Corporate Sector, Omega,309- 318, 1988.

[29] K.Keasey, P.McGuiness and H.Short, Multilogit Approach to Predict Corporate Failure, Further Analysis and The Issue of Signal Consistency Omega, Vol.18, No.1,85-94, 1990.

[30] A.H.L.Lau, A Five-State Financial Distress Prediction Model, Journal of Accounting Research, Vol.25,No.1,127- 138, 1987.

[31] P.H.Bahson, J.W.Bartley, The Sensitivity of Failure Prediction Models to Alternative Definitions of Failure, Advances in Accounting, Vol.10,255- 278, 1992.

[32] T.J.Ward, "An Emprical Study of Incremental Predictive Ability of Beaver's Naive Operating Csh Flow MeasurE Using Four-State Ordinal Models of Financial Distress, Journal of Business Finance and Accounting, 547- 561, 1994.

[33] T.J.Ward, B.F.Foster, An Emprical Analysis of Thomas's Financial Accounting Allocation Fallacy Theory in a Financial Distress Context, Accounting and Business Research,137-152, 1996.

[34] J.A.Gentry, P.Newbold and D.T.Whitford, Classifying Bankrupt Firms with Funds Flow Components", Journal of Accounting Research**,** Vol. 23, No:1, 146- 160,Spring 1985.

[35] S.J.Press and S.Wilson, Choosing Between Logistic Regression and Discriminant Analysis, Journal of American Statistical Association, Vol.73, No.364,699- 705, 1978.

[36] R.A.Collins, R.D.Green, Statistical Methods for Bankruptcy Forecasting, Journal of Economics and Business 34,349- 354, 1982.

[37] M.M. Hamer, Failure Prediction: Sensitivity of Classification Accuracy to Alternative Statistical Models and Variable Sets, Journal of Acounting and Public Policy 2, 289-307, 1983.

[38] W.J. Conover, Practical Nonparametric Statistics, John Wiley and Sons, 2nd Edition, New York,1980, http://www.blackwellpublishing.com/specialarticles/jcn_10_715.pdf, 28 Aralık,2008

[39] S.Sharma, Applied Multivariate Tecniques, John Wiley&Sons,Inc.,1996,p.238.

[40] J.F. Hair, R.E. Anderson,R.L.Tatman, W.C.Black, Multivariate Data Analysis, Prentice Hall, 5th Edition,2006.p.306

[41] J.F.Hair at all, p.323.

[42] J.F.Hair at all, p.355.

[43]G.V. Kaplan, G.Urwitz, Statistical Model of Bond Ratings:A Methodological Inquiry, Journal of Businee, 231-261, 1979.