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Financial Failure Prediction Using Financial Ratios: An Empirical Application on Istanbul Stock Exchange

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Abstract

Risk of financial failure is defined as the inability of a firm to pay its current liabilities. Financial failure may lead firms to bankrupt or go into liquidation. This paper aims to develop reliable model to identify the financial failure risk of the firms listed on Istanbul Stock Exchange National-All Share Index. In line with this goal, we calculate 20 financial ratios to predict the financial failure of firms and develop the most reliable model by analysing these ratios statistically. As a result of the analysis using these 20 financial ratios, it is identified that there are 5, 3 and 4 important financial ratios in the discrimination of the successful and unsuccesful firms in 2009, 2010 and 2011, respectively. Thus the discriminant function is formed by using these variables. Capital adequacy and net working capital/ total assets ratios are seemed to be significant in all three periods. According to formed models, classification success are determined as 88,7% 90,4% and 92,2% in 2009, 2010 and 2011 years respectively. These high accuracy ratios indicate that the developed models for three years are efficient to determine the financial failure of the firms traded in Istanbul Stock Exchange.

Jel Classification : M41, C39, G33
Keywords: Financial Failure, Financial Ratio, Discriminant Analysis, ISE All

1 Introduction

Financial failure is defined as the inability of a firm to pay its obligations due to inadequate working capital. In other words, financial failure is the case in which a firm

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goes bankrupt as a consequence of not be able to fulfill its current liabilities [18]. Firm that experiences financial failure can not meet its obligations or has diffuculty in fulfilling its obligations in time ([5], [11],[7])

The case in which cash flows could not meet the financial obligations, the risk of financial failure increases as well [7]. This risk may arise from the unfavourable conditions in national economy as well as the firm spesific factors. Reducing or removing the risk of financial failure, which arise from various factors and leave firms in a difficult situation, is an important subject.

In the literature, there are many papers on the identification of firms at risk of financial failure. In these papers, risk of financial failure is first examined by Beaver [5]. The model of Beaver [5] is criticized in terms of using single variable and calculating limited ratio. Afterwards, Altman [3] have measured risk of financial failure by applying Altman Z Score test. In addition to these papers, Meyer and Pifer [17] have used linear regression model to predict the risk of financial failure. Martin [16] is the first who has used logistic regression to predict financial failure. Deakin [8] has compared the models developed by Beaver [5] and Altman [3] by using financial statements data. The paper of Libby [15] which resembles that of Deakin [8] has tested the financial failure by using discriminant analysis.

In recent periods, it is likely to reach some papers that use expert systems to identify the risk of financial failure. ([21], [1], [4], [14], [6], [19], [22]) have modelled the risk of financial failure by using artificial neural network model and have concluded that artificial neural network model is more successful than multivariate statistical models.

In the literature, there are many papers which predict the financial failure of Turkish firms. Altas and Giray [2], Yuzbasioglu *et.al* [23] have tested the financial failure of textile firms traded in Istanbul Stock Exchange by applying factor analysis and logistic regression analysis. Icerli and Akkaya [11], Terzi [20] have measured the financial failure of manufacturing and food firms respectively by employing Altman Z Score. Eksi [9] has used CART and classification models to predict financial failure of ISE[3] firms.

This paper aims to find discriminant function that separates financially successful from unsuccessful firms by using ratio analysis in ISE firms. In accordance with this purpose, the paper consists of five sections: 1. Introduction, 2. Data and Variables, 3. Methodology, 4. The findings, 5. Conclusion.

2 Data and Variables

The dataset is obtained from the financial statements of 115 firms traded in ISE-All Sector[4] over the period 2009-2011[5]. We have used SPSS 20.0 for statistical analyses. In this paper, we have employed discriminant analysis by using financial ratios of 115 firms. In addition, we have used Altman Z Score to determine the financial success of firms. Z score can be calculated as follows ([3], [20]) :

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[3] Istanbul Stock Exchange

[4] We exclude banks, private finance houses, insurance firms, financial leasing and factoring firms, real estate investment companies and investment trusts from the analysis because they have different asset structure.

[5] www.kap.gov.tr

Z Score = 1,2 (Working Capital / Total Assets) + 1,4 (Retained Earnings / Total Assets) + 3,3 (Earnings Before Interest and Tax / Total Assets) + 0,6 (Equity Capital / Total Debts) + 1,0 (Sales Income / Total Assets)

If the Z score is less than 1.81 ($Z < 1.81$), firms are exposed to increase risk of financial failure [23] At this point, the value considered for financial failure is 1.81.

We have used financial success as a dependent variable in analysis. We have created a dummy variable, with a value of “1” if the firm is succesfull and “2” if the firm is unsuccessful. In addition we have used 20 independent variables in the study and examined the multicollinarity between the pair of these independent variables. Thus, we have excluded from these variables one of each pair with correlation > 0.70. We have summarised the dependent and independent variables in Table.1.

Table 1: Dependent-Independent Variables

Variables	**Explanation**
Group	Financial Success Situation
X1	Current Assets/Short Term Debts
X2	(Current Assets-Inventories)/ Short Term Debts
X3	Sales/Inventories
X4	Receivables/(Sales /365)
X5	Sales/Fixed Assets
X6	Sales /Total Assets
X7	Total debts/ Total Assets
X8	Equity Capital/ Total Assets
X9	Total debts / Equity Capital
X10	Net Profit-Loss/ Sales
X11	Net Profit-Loss / Total Assets
X12	Operating Profit-Loss/ Total Assets
X13	Net Profit-Loss / Equity Capital
X14	Cash and Cash Equivalents/ Short Term Debts
X15	(Current Assets - Short Term Debts)/ Total Assets
X16	Short Term Account Receivable/ Current Assets
X17	Sales / Equity Capital
X18	Short Term Debts / Total Assets
X19	Long Term Debts/ Total Assets
X20	Profit-Loss Before Tax/ Equity Capital

3 Methodology

In this paper, we have used discriminant analysis which is one of the multivariate statistical classification and prediction methods. Discriminant analysis is one of the most frequently used methods in examination of financial failure. Discriminant analysis is a technique that provides to separate groups from each other accurately by using mathematical techniques [13].

Discriminant analysis also provides to identify in which variables the discrepancy is intensified and to determine the factors affecting the differantiation between groups.

Comparison of the classification obtained as a result of analysis with the original group membership provides to test the sufficiency of known function [10].
In discriminant analysis, we have tested the validity and significance of models which is taken from stepwise method. Discriminant function can be described as follows:

$$Z = \alpha + b_1 X_1 + b_2 X_2 + \dots\dots\dots + b_n X_n \quad (1)$$

In equation (1),

"Z" discriminant score,
"α" constant,
"$b_1, b_2, \dots b_n$" discriminant coefficients of independent variables ,
"$X_1, X_2, \dots X_2$" independent variables,
n= the number of independent variables.

4 Empirical Findings

In discriminant analysis, it is crucial to meet optimality conditions and main assumptions to prevent the misclassification problem. The key assumptions of discriminant analysis are equality of covariance within group and low multicollinearity of the variables. To test the equality of covariance, Box's M test can be used. In Box's M test, the null hypothesis is formed as "covariance matrix of the groups are equal".

Table 2 : Box's M Test

Box's M (2009)		191,24	**Box's M (2010)**		98,963	**Box's M (2011)**		382,835
F	Approx.	12,055	F	Approx.	16,007	F	Approx.	36,481
	df1	15		df1	6		df1	10
	df2	26060,83		df2	77449,04		df2	22579,24
	Sig.	.053		Sig.	.061		Sig.	.057

In Table.2, we can not reject the null hypothesis at (,05) significance level. Therefore the assumption of equal covariance matrices between groups is valid over the three years.
The another important assumption of discriminant analysis is low multicollinearity of the variables. Therefore, we have excluded from these variables one of each pair with correlation > 0.70[6]. To identify how important the discriminant functions are, we have examined canonical correlation, Eigenvalue and Wilks' Lambda statistics.

[6] We excluded following variables from the analysis: X2, X7, X9, X10, X12, X13, X17, X18 and X19 in 2009, X2, X4, X6, X9, X11, X12, X13, X19 and X20 in 2010, X1, X2, X6, X11, X14, X16 and X18 in 2011.

Table 3: Eigenvalue Statistics

Eigenvalues (2009)				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1,201a	100	100	,739

Eigenvalues (2010)				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1,305a	100	100	,752

Eigenvalues (2011)				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1,057a	100	100	,717

Canonical Correlation measures the relationship between discriminant scores and groups and states the total variance explained. In Table.3, canonical correlation values are calculated as ,739 ,752 and ,717 in 2009, 2010 and 2011 years respectively. This finding indicates that formed models explain % 55, %57 and %51 variance of dependent variables in 2009, 2010 and 2011 years, respectively.

In discriminant analysis, the larger the eigenvalue is, the more amount of variance of dependent variable is explained by that function. Although not a certain value, eigenvalues greater than 0.40 are considered as good [12]. The eigenvalue values are 1,201, 1,305 and 1,057 in 2009, 2010 and 2011 respectively. This finding denotes that functions have differentiated the groups well. Since the dependent variable is binary, there will be only a single discriminant function.

Table 4 : Wilks' Lambda Statistics

Wilks' Lambda (2009)				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,454	87,154	5	0
Wilks' Lambda (2010)				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,434	93,097	3	0
Wilks' Lambda (2011)				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,486	80,064	4	0

In Table.4, Wilks' Lambda statistic shows the unexplained part of the total variance of discriminant scores by the differences between the groups. Nearly 45%, 43% and 49% of total variance of discriminant scores can not be explained by differences in groups in 2009, 2010 and 2011, respectively. In addition, Wilks' Lambda statistic tests the significance of eigenvalue statistic for each discriminant function. There is one for each function in all three year and all of these are significant.

Table 5 : Standardized Canonical Discriminant Function Coefficient

		Function			**Function**			**Function**
2009		1	**2010**		1	**2011**		1
	X1	-,413		X8	,712		X8	,898
	X4	,280		X15	,437		X9	-,443
	X6	,776		X18	-,286		X15	1,033
	X8	1,128					X17	,683
	X15	,536						

To evaluate the importance of independent variables, it is necessary to examine the coefficients of discriminant function and the weight of each independent variable in the structure matrix. In Table.5, in differentiating the successful and unsuccessful firms, X1, X4, X6, X8 and X15; X8, X15 and X18; X8, X9, X15 and X17 are important discriminant independent variables in 2009, 2010, 2011, respectively. The coefficient of variables shows the relative importance of independent variables in the prediction of dependent variable.

Table 6 : Structure Matrix

	Function			**Function**			**Function**
2009	1		**2010**	1		**2011**	1
X8	,621		X8	,797		X15	,614
X15	,560		X18	-,689		X9	-,331
X1	,346		X1a	,621		X8	,305
X6	,156		X17a	-,540		X7a	-,263
X5a	,153		X15	,538		X13a	,205
X20a	,149		X14a	,342		X10a	,174
X11a	,126		X10a	,188		X20a	,148
X16a	,115		X16a	-,146		X12a	-,131
X14a	,100		X5a	-,088		X3a	-,130
X4	,076		X7a	-,049		X17	-,080
X3a	-,053		X3a	-,047		X5a	,061
						X19a	-,033
						X4a	,018

a. This variable not used in the analysis.

Structure matrix is used to evaluate the importance of independent variables and shows the correlation between each variable and discrimination function. In Table.6 the highest correlated independent variables are X8, X15; X8, X18 and X15; X15 in 2009, 2010, 2011, respectively.

Table 7 : Canonical Discriminant Function Coefficients

	Function			**Function**			**Function**
2009	**1**		**2010**	**1**		**2011**	**1**
X1	-,221		X8	4,117		X8	3,405
X4	,001		X15	2,204		X9	-,105
X6	1,09		X18	-1,785		X15	4,021
X8	6,209		(Constant)	-2,225		X17	,255
X15	2,71					(Constant)	-3,086
(Constant)	-4,632						

The discriminant function described as $Z = \alpha + b_1 X_1 + b_2 X_2 + \ldots\ldots\ldots + b_n X_n$ is a linear combination of independent variables. This equation is assumed to resemble the multiple regression and b values maximize the distance between the means of independent variables. Table.7 shows nonstandard discriminant coefficients over the 2009-2011 period. In this case, discriminant functions which is used in classification of new observations and formation the actual prediction model can be described as follows:

2009 year:

Z = -4,632 + (-,221) (X1) + (,001) (X4) + (1,09) (X6) + (6,209) (X8) + (2,71) (X15)

2010 year:

Z = -2,225 + (4,117) (X8) + (2,204) (X15) + (-1,785) (X18)

2011 year:

Z = -3,086 + (3,405) (X8) + (-,105) (X9) + (4,021) (X15) + (,255) (X17)

In discriminant analysis, the success of the analysis depends on the percentage of correct classification The higher the percentage of correct classification, the more successful the analysis is. Table.8 shows the classification results for each year:

Table 8 : Classification Results

Classification Results[a] 2009					
		Group	**Predicted Group Membership**		**Total**
			1	2	
Original	Count	1	71	4	75
		2	9	31	40
	%	1	94,7	5,3	100
		2	22,5	77,5	100
a. 88,7% of original grouped cases correctly classified.					
Classification Results[a] 2010					
		Group	**Predicted Group Membership**		**Total**
			1	2	
Original	Count	1	43	7	50
		2	4	61	65
	%	1	86	14	100
		2	6,2	93,8	100
a. 90,4% of original grouped cases correctly classified.					
Classification Results[a] 2011					
		Group	**Predicted Group Membership**		**Total**
			1	2	
Original	Count	1	77	2	79
		2	7	29	36
	%	1	97,5	2,5	100
		2	19,4	80,6	100
a. 92,2% of original grouped cases correctly classified.					

Although 71 of 75 successful firms are predicted correctly, 4 of 75 successful firms are classified incorrectly in 2009. Besides, 31of 40 unsuccessful firms are predicted correctly, 9 of 40 unsuccessful firms are classified incorrectly in 2009. First and second group affiliation have been classified correctly with the percentage of 94,7% 77,5%, respectively. 88,7% of the firms included analysis are classified correctly.

In 2010 year, although 43 of 50 successful firms are predicted correctly, 7 of 50 successful firms are classified incorrectly. Additionally, while 61 of 65 unsuccessful firms are predicted correctly, 4 of 65 unsuccessful firms are classified incorrectly. First and second group affiliation have been classified correctly with the percentage of 86% 93,8% respectively. 90,4% of the firms included analysis are classified correctly.

In 2011 year, 77 of 79 successful firms are predicted correctly, 2 of 79 successful firms are classified incorrectly. Furthermore, while 29 of 36 unsuccessful firms are predicted correctly, 7 of 36 unsuccessful firms are classified incorrectly. First and second group affiliation have been classified correctly with the percentage of 97,5% 80,6% respectively. 92,2% of the firms included analysis are classified correctly.

5 Conclusion

In this paper, we have developed a reliable model which differantiates financially successful and unsuccessful firms in ISE All Sector over the period 2009-2011 by employing discriminant analysis. We have used Altman Z score to differantiate successful and unsuccessful firms. To examine the financial success of the firms, we have identified 20 key financial ratios classified under following topics: liquidity, operation, debt management and profitability. As a result of the analysis using these 20 financial ratios, it is identified that there are 5, 3 and 4 important financial ratios in the discrimination of the successful and unsuccesful firms in 2009, 2010 and 2011, respectively. Thus the discriminant function is formed by using these variables. Capital adequacy and net working capital/ total assets ratios are seemed to be significant in all three periods. According to formed models, classification success are determined as 88,7% 90,4% and 92,2% in 2009, 2010 and 2011 years respectively. These high accuracy ratios indicate that the developed models for three years are efficient to determine the financial failure of the firms traded in ISE. This finding consistent with those of ([15], [8], [11], [20]).

The variables used in the study provide useful information related to the financial situation of the firms in ISE. The models developed by using these variables are important for financial analysts, investors and other company officials.

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