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EARLY WARNING SYSTEMS, THE CASE OF TURKEY

ERKEN UYARI SİSTEMLERİ, TURKİYE UYGULAMASI

Sinan AKTAN
Doğuş University

ABSTRACT: We are focusing on two alternative techniques that can be used empirically to select predictors for failure prediction purposes. The selected techniques have all different assumptions about the relationships between the independent variables. Linear discriminant analysis is based on linear combination of independent variables; logit analysis uses logistic cumulative probability distribution function. Our aim is to study if these essential differences between methods affect the empirical selection of independent variables to the models and lead significant differences in failure prediction accuracy; moreover, develop a prediction model that would be benefited by management itself, shareholders, government, vendors, creditors, investors and other stakeholders in their projections and strategies.

Keywords: *Discriminant Analysis, Logit Analysis; Business Failures*

ÖZET: *İşletme başarısızlıklarını tahmin üzerine yapacağımız ampirik çalışmamızda iki alternatif teknik üzerinde duracağız. Seçmiş olduğumuz teknikler bağımsız değişkenler arasındaki ilişki üzerinde farklı varsayımlara sahiptir. Doğrusal ayırma analizi, bağımsız değişkenlerin doğrusal kombinasyonlarına bağlı bir modelken; logit analizi ise bağımsız değişkenlerin lojistik kümülatif olasılık dağılımlarına bağlı bir modeldir. Amacımız, metotlar arasındaki farklılıkların, bağımsız değişkenlerin ampirik seçimleri üzerindeki etkilerini ve başarısızlık tahmini üzerindeki doğruluk paylarını incelemektir. Bunun yanında; işletme yönetiminin, hissedarların, devletin, tedarikçilerin, yatırımcıların ve diğer hak sahiplerinin kolaylıkla faydalana-bilecekleri bir ayırma fonksiyonu geliştirmektir.*

Anahtar Kelimeler: *Ayırma Analizi, Logit Analiz, İşletme Başarısızlıkları*

1. Introduction

The recent bankruptcies of many companies have underlined the importance of failure prediction both in academia and industry. It now seems more necessary 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.

Our purpose in this study is to develop a prediction model that would be benefited by management itself, shareholders, government, vendors, creditors, investors and other stakeholders in their projections and strategies.

Decision makers are intensely interested in the prediction of direction of variables over time; therefore, the initial action ought to construct a model that expose the relationship between variables. As Ackoff 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.

We can summarize targets of the prediction models as letting analyst to act due to the results of the model and pre-intervention to the variables in order to affect the prediction results (Kutman, 1999: 2). In this sense, our models let analyst to take course of action according to the results, because inability to change macroeconomic trends; moreover, pre-intervention to the balance sheet and income statement variables to state organizational strategies.

To achieve the purpose of this study, we have conducted empirical studies on companies which are belonging to real sector revealed from ISE. Our selection criterion is Bankruptcy Law article 179, pursuant to Turkish Trade Law article code 324 and 434. Shortly these codes claims that 2/3 loss in total asset value could be defined as bankrupt. Whereas, our sample mostly dominated by distressed firms except for three bankrupt firms and these firms are compared with their sector means. The subject ratios of selected firms and sector means are between years 1991 and 2001 June balance sheets.

At the beginning of researches on failure prediction, there were no advanced statistical methods or computers available for the researchers. The values of financial ratios in failed and non-failed firms were compared with each other. In 1966 the pioneering study of Beaver presented the univariate approach of discriminant analysis and in 1968 Altman expanded this study to multivariate analysis. Until 1980's discriminant analysis was the dominant method in failure and default prediction. However, it suffered from assumptions that were violated very often. The assumption of normality of financial ratio distributions was problematic. During the 1980's the discriminant analysis was replaced by logistic analysis which until recent years has been the most used statistical method for failure prediction.

Discriminant analysis and logit analysis have different assumptions concerning the relationships between the independent variables. Linear discriminant analysis is based on linear combination of independent variables, logit analysis uses the logistic cumulative probability function. Discriminant analysis assumes variables are normal and suggests no multicollinearity. It is obvious that sustaining normality and non-multicollinearity nearly impossible in financial ratios. Logit analysis satisfies normality assumption whereas there is still an obstacle which is multicollinearity. In order to resolve this problem we have applied factor analysis which is used for two goal; summarization and data reduction. These goals release the multicollinearity by tightening the variables.

In this study, we will present our prediction models; result of empirical studies under discriminant analysis, logit analysis, and factor analysis, in chapter 3. In this chapter we will construct a discriminant function that will be easily applied by the readers and other researchers. According to discriminant function's Z score researchers or analysts can easily figure out where their firm stand whether in distressed area or not.

Moreover, this study will enlighten the research of other researchers and the researchers can take this study further in sample size or statistical tools used.

We encountered some limitations while we have been conducting our study, and some main limitations summarized below.

We begin our study under the light of Altman's study which had two sets, failed firms and non-failed firms, his study depends on the discrimination of variables belong to these two set; moreover, he selected non-failed firms according to similarity in capital structure and operation areas of failed firms. On the contrary, we couldn't select nondistressed firms especially according to capital structure similarity of distressed firms, because capital structure of our coted firms varies especially in within sectors. This problem that we face depends on our young stock market, because approximately 190 companies are subject to our study except finance and banking sectors. Although, most crowded sector is textile, no similar capital structure among firms exists.

2. Application of Models

2.1. Discriminant Analysis

Discriminant analysis tries to derive the linear combination of two or more independent variables that will discriminate best between a priori defined groups (Günel, 2003) , which in our case are failing and non-failing companies. The discriminant analysis derives the linear combinations from an equation that takes the following form:

$$Z = w_1x_1+ w_2x_2+...+w_nx_n$$

where

Z = discriminant score
w_i (i=1, 2, ... ,n) = discriminant weights
x_i (i=1, 2, ... ,n) = independent variables, the financial ratios

Thus, each firm receives a single composite discriminant score which is then compared to a cut-off value, which determines to which group the company belongs to.

Discriminant analysis does very well provided that the variables in every group follow a multivariate normal distribution and the covariance matrices for every group are equal. However, empirical experiments have shown that especially failing firms violate the normality condition. In addition, the equal group variances condition is also violated. Moreover, multicollinearity among independent variables is often a serious problem, especially when stepwise procedures are employed. However, empirical studies have proved that the problems connected with normality assumptions were not weakening its classification capability, but its prediction ability (Altman, 2000).

The two most frequently used methods in deriving the discriminant models have been the *simultaneous (direct) method* and the *stepwise method.* The former is based on model construction by e.g. theoretical grounds, so that the model is ex ante defined and then used in discriminant analysis. When the stepwise method is applied, the procedure selects a subset of variables to produce a good discrimination model using forward selection, backward elimination, or stepwise selection (Back, et al., 1996).

The stepwise method is the one most frequently used. It works like the forward method, except, with stepwise, an already entered variable can be removed from the equation. Both methods begin by entering into the model the variable that has the strongest positive or negative correlation with the dependent variable; and at each subsequent step, both add the variable with the strongest partial correlation. With stepwise, at each step, variables are tested for removal (User's Guide, 1998).

2.2. Logit Analysis

Logistic regression analysis has also been used to investigate the relationship between binary or ordinal response probability and explanatory variables. The method fits linear logistic regression model for binary or ordinal response data by the method of maximum likelihood. Among the first users of logit analysis in the context of financial distress was Ohlson (1980). Like discriminant analysis, this technique weights the independent variables and assigns a Z score in a form of failure probability to each company in a sample. The advantage of this method is that it does not assume multivariate normality and equal covariance matrices as discriminant analysis does. Logit analysis incorporates non-linear effects, and uses the logistical cumulative function in predicting a bankruptcy, i.e.,

$$\text{Probability of failure} \quad \frac{1}{1+e^{-z}} = \frac{1}{1+e^{-(w_0+w_1x_1+\dots+w_xx_n)}}$$

Logistic analysis applies the same variable selection methods as discriminant analysis presented above. For model construction we selected, as in the case of discriminant analysis, the stepwise method that is a built in function in the SPSS-program. The procedure starts by estimating parameters for variables forced into the model, i.e. intercept and the first possible explanatory variables. Next, the procedure computes the adjusted chi-squared statistic for all the variables not in the model and examines the largest of these statistics. If it is significant at the specified level, in our study 0.05, the variable is entered into the model. Each selection step is followed by one or more elimination step, i.e. the variables already selected into the model do not necessarily stay. The stepwise selection process terminates if no further variable can be added to the model, or if the variable just entered into the model is the only variable removed in the subsequent elimination (User's Guide, 1998).

2.3. The Sample

The initial sample of financially distressed firms and bankrupt firms composed of 48 firms and 4 of them were bankrupt firms. As three out of 44 companies met our 2/3 criterion twice in different years, total number of cases included in the analysis increased to 51. 44 firms out of bankrupt firms were selected as financially distressed according to Bankruptcy Law article 179, pursuant to Turkish Trade Law articles 324 and 434. According to these articles 2/3 loss in total asset value could be defined as bankruptcy. These firms were selected from ISE (Istanbul Stock

Exchange) in order to establish audited financial statements based study. Firms' financial statements coted to ISE are periodically audited by independent auditors. The distressed companies included in the analysis are listed in Table 1.

We have calculated 2/3 loss in asset value as: **Previous Losses** divided by [**Previous Loses**, plus **Total Asset**].

Initial sample consist of two groups. First group consists of financial distressed firms and the second group consists of nondistressed firms; in order to compare and reveal a model of distressed and nondistressed firms.

We have selected distressed firms according to their last 3 months financial situation revealed from financial statements, stating 2/3 loss in asset value. The computation is mentioned above. The problem aroused when choosing the companies for the second group. Because most of the early prediction studies done under the specification of paired sized companies; here, the set of the cases were same. For example, Altman selected 33 distresses and 33 nondistressed companies; and other researchers did so. The paired cases had same time horizon, same sector (industry) and similar asset size. On the contrary, our source ISE has nearly 190 companies in real sector and the other companies are finance and banking companies. These companies have different asset size; therefore, we have decided to select the second group members as industrial means. It is obvious that, some of the distressed companies were in the same sector; therefore, their against industry means were same as well.

Moreover, according to rescue distressed firms, most of the banks and major finance companies have constituted a moratorium which is coordinated by Banking Regulation and Supervision Agency. This moratorium aims to reconsolidate the depts of the distressed firms via guarantee of government authorization, which is also pronounced as Istanbul Approach. This approach is supported by World Bank and IMF in order to resolve economic crises.

Some of the firms which are included in group 1, applied to reconsolidate their financial positions; these companies are Işıklar Packing, Kerevitaş Food, Makine Takım, Raks Electric, Raks Electronic, ÇBS Dye and Chemicals, ÇBS Print and Ink, Tümteks Textile, Boyasan Textile, Polylen Synthetic, Sifaş Synthetic, and Nergis Holding. This action proves that our sample selection process is valid and logical, cause the reason that force these companies to resolve financial distress through financial reconsolidation by the moratorium (İstanbul Yaklaşımı, 2002).

Table 1. Financially Distressed Firms and Their Sector

Firm Name	Sector/Industry	Nr. Of Firms in Sector
Nergis Holding:	Holding & Investment	7
Turkish Airline:	Transportation	2
Gorbon Işıl:	Ceramics	4
TUPRAS:	Petroleum Products	4
CARSI:	Retailing and Marketing	5
GIMA:	Retailing and Marketing	5
SABAH Marketing:	Retailing and Marketing	5
Sezginler Food	Retailing and Marketing	5
TANSAS:	Retailing and Marketing	5

Firm Name	Sector/Industry	Nr. Of Firms in Sector
Arat Textile:	Cotton & Wool	22
Bisaş Textile:	Cotton & Wool	22
Lüks Kadife Textile:	Cotton & Wool	22
Park Textile:	Cotton & Wool	22
SOKSA:	Cotton & Wool	22
Boyasan Textile:	Cotton & Wool	22
Polylen Synthetic:	Cotton & Wool	22
Sifaş Synthetic:	Cotton & Wool	22
Parsan Machinery Parts:	Automotive Parts	8
Makina Takım:	Metal Processing	8
Tezzan:	Metal Processing	8
Bayraklı Dye:	Chemicals and Plastics	5
ÇBS Dye and Chemical:	Chemicals and Plastics	5
ÇBS Print and Inks:	Chemicals and Plastics	5
Meges Dye:	Chemicals and Plastics	5
Duran Offset and Press:	Paper and Packing	8
Işıklar Packing:	Paper and Packing	8
Viking Paper:	Paper and Packing	8
DOGUSAN Pipe:	Construction Supplies	8
Koniteks Textile:	Apparell	16
APEKS:	Food	21
BIRLIK TUTUN:	Food	21
Kerevitas Food:	Food	21
Dardanel Onentas Food:	Food	21
Mudurnu Chicken:	Food	21
Gümüssuyu Carpet:	Home Textile	3
Tümteks Textile:	Home Textile	3
Aktas Electricity:	Energy	6
Cukurova Electricity:	Energy	6
Abana Elekromechanic:	Electronic	8
Emek Electric:	Electronic	8
Raks Electronic:	Electronic	8
Sun Electronic:	Electronic	8
TURKCELL:	Electronic	8
Kardemir Karabük:	Iron&Steel	2
Metas Izmir Metallurgy:	Iron&Steel	2
Emsan Beş Yıldız:	Durable Goods	6
Emsan Paslanmaz:	Durable Goods	6
Raks Electricity Home S.:	Durable Goods	6

2.4. Variable Selection

After we defined initial groups and selected firms subject to analysis, we have calculated financial ratios that we would use for our study from collected balance sheets and income statements. We have compiled 26 ratios used by Altman (1968), Deakin (1972), Mervin (1942), Beaver (1966), Altman-Haldeman-and Narayanan (1977), El Hennavy and Morris (1983), Fitzpatrick (1932), Ramser-Foster (1931), Winakor-Smith (1935), and Blum (1974) in their studies best indicators; which we consider potentially helpful for our study. These ratios are listed in Table 2 below:

Table 2. Variables in the Study

V1	*Liqudity Ratio*	cash/current liabilities
V2	*Liqudity Ratio*	cash/net sales
V3	*Liqudity Ratio*	cash/total assets
V4	*Liqudity Ratio*	current assets/ current liabilities
V5	*Activity Ratio*	current assets / net sales
V6	*Liqudity Ratio*	current assets/total assets
V7	*Leverage Ratio*	current liabilities/equity
V8	*Solvency Ratio*	equity/fixed assets
V9	*Profitability Ratio*	equity/net sales
V10	*Activity Ratio*	inventory/net sales
V11	*Leverage Ratio*	long term debt/equity
V12	*Leverage Ratio*	total debt/equity
V13	*Activity Ratio*	net income/total assets
V14	*Liqudity Ratio*	net quick assets/inventory
V15	*Activity Ratio*	net sales/total assets
V16	*Liqudity Ratio*	quick assets/current liabilities
V17	*Activity Ratio*	quick assets/net sales
V18	*Liqudity Ratio*	quick assets/total assets
V19	*Activity Ratio*	working capital/net sales
V20	*Liqudity Ratio*	working capital/equity
V21	*Liqudity Ratio*	working capital/total assets
V22	*Profitability Ratio*	ebit/total assets
V23	*Leverage Ratio*	ebit/total interest payments
V24	*Leverage Ratio*	total debt/total assets
V25	*Leverage Ratio*	retained earnings/total assets
V26	*Profitability Ratio*	return on equity

We can classify these ratios in five category; Liquidity, Profitability, Leverage, Solvency, and Activity. These ratios were chosen on the basis of their popularity in the literature and their potential relevancy to the study.

We analyze two year period prior to financial distress and our criteria is 2/3 loss in asset value. For each case we had 8 periods on 3 months bases; cause we have studied on 3 months based financial statements.

3. Application and Results

In this research we applied discriminant analysis, logit analysis and factor analysis.

3.1 Discriminant Analysis

We have used SPSS 11 statistical program to run discriminant analysis. We have mentioned discriminant analysis in above in this chapter. In our analysis the set of variables would subject to be used in discriminant function was chosen by using stepwise selection. Variables were chosen on, enter or leave the model using the significance level of F-test from an analysis of variance, where the selected variables act as covariates due to under consideration of dependent variable (1 - 0: 1 stands for nondistressed firms and 0 stands for distressed firms). In our analysis we have selected the significance level 0,05 for adding or retaining variables in the model.

All the 26 ratios for every firm and sector averages were put into discriminant analysis in SPPS; through stepwise selection, we defined the variables for **eight periods**. The variables that were selected into the discriminant analysis models as below:

Table 3. Variables Selected for Discriminant Analysis

3 Months Prior To Failure	6 Months Prior To Failure	9 Months Prior To Failure	12 Months Prior To Failure
V2, V16, V18, V23	V16,V21,V22, V24	V1,V3,V6,V14, V16, V22, V23	V1, V2, V4, V15, V22
15 Months Prior To Failure	**18 Months Prior To Failure**	**21 Months Prior To Failure**	**24 Months Prior To Failure**
V2, V3, V4	V3, V16, V18	V4, V6, V8	V1, V4, V8

3.2 Logit Analysis

For the logit analysis we have used the same cases and variables in the discriminant analysis. We used binary logistics from SPPS 11, and we again used stepwise (forward) selection and the same significance level 0,05 for adding or retaining variables as in discriminant analysis we have done. The models were selected for the logistic analysis fro eight period presented below:

Table 4. Variables Selected for Logit Analysis

3 Months Prior To Failure	6 Months Prior To Failure	9 Months Prior To Failure	12 Months Prior To Failure
V2, V4, V16, V21, V22, V23, V24	V18, V22, V24	V16, V22, V24	V1, V3
15 Months Prior To Failure	**18 Months Prior To Failure**	**21 Months Prior To Failure**	**24 Months Prior To Failure**
V2, V9, V11, V13, V24	V2, V3, V11, V13, V24	V4, V16, V24	V3, V6, V8, V11, V22, V23

3.3 Analyzing the Models

In analyzing the variables that were included in two models we pay attention to the number of variables included. For instance, variables 5, 7, 10, 12, 17, 19, 20, 25, and 29 never been included any of two separate eight models. On the other hand variables 9, 11, and 13 weren't used in discriminant models; on the contrary, these variables used in logit models. Whereas, variables 12, 14, and 15 weren't used in logit models; on the contrary, these variables used in discriminant models.

Numbers of variables used in discriminant and logit models are nearly same. Totally 14 variables used in discriminant models, and 15 variables used in logit models.

As it is seen in the Table 4, logit uses few variables for the periods in the first year; 3, 6, 9, and 12 months prior to failure models. Whereas, discriminant uses few variables for the periods in the second year; 15, 18, 21, and 24 months prior to failure models.

We observed that, the variables chosen for the eight models of logit models with 3 variables exception, are the subset of the variables chosen for the discriminant models.

We have employed factor analysis to study further if the models really measure the different characteristics of the cases (firms), using the same variables in discriminant and logit analysis separately. And the other reason for our application of factor analysis is to release the multicollinearity among variables; therefore, factor analysis decreases the variable in number and presents significant factor components in the cases.

We have got these factors for the eight periods:

We have applied discriminant and logit methods through SPPS 11 on factor solutions, and we have found these eight factor based models (results are same for discriminant and logit):

Table 5. Variables (Factors) Selected for Factor Analysis

3 Months Prior To Failure	6 Months Prior To Failure	9 Months Prior To Failure	12 Months Prior To Failure
2, 5, 6	2, 3, 4, 6, 7	2, 4	NO FACTOR SOLUTION
15 Months Prior To Failure	**18 Months Prior To Failure**	**21 Months Prior To Failure**	**24 Months Prior To Failure**
1, 3, 4, 5, 8	2, 3, 5	3, 5, 6	2, 5, 6, 7

Characteristics of variables in 8 models are quite similar in comparison with each other. Mainly liquidity is the main factor in all models. On the contrary, activity factor is the least diagnostic for the models.

Factor analysis that we applied to study further if the models really measuring the right factors characteristics of the cases (firms) we analyze; also, we were interested in more sophisticated classification of the original variables.

The criterion based on eigenvalues higher than 1 yielded a six factor solution for 3 months prior to failure, seven factor solution for 6 months prior to failure, seven factor solution for 9 months prior to failure, no factor solution for 12 months prior to failure, eight factor solution for 15 months prior to failure, seven factor solution for 18 months prior to failure, seven factor solution for 21 months prior to failure, seven factor solution for 24 months prior to failure. Factor analysis presented same factors for discriminant and logit; and domain factor was liquidity again, then leverage factor and profitability came next.

3.4. Prediction Results

In previous paragraphs we have presented separate models for each period and each technique. It was noticed that the underlying assumption concerning the relationships between independent variables would not affect the model selection in a prominent way. When three alternative models seem all to use similar information liquidity, the interesting question is if there are differences in their prediction ability. To study further the consequences of different model selection approaches we have applied corresponding statistical method to test the predictive ability of constructed models. In Table 6 the cross-validated prediction accuracy results are presented for every techniques separately.

Table 6. Cross-validated prediction results for Discriminant Analysis (DA), Logit, and Factor analysis (FA) prediction results.

	TYPE 1 ERROR			TYPE 2 ERROR			TOTAL ERROR		
Period	**DA**	**LOGIT**	**F. A.**	**DA**	**LOGIT**	**F. A.**	**DA**	**LOGIT**	**F. A.**
3 months	13,04	**2,17**	4,35	14,81	**3,70**	18,52	13,70	**2,74**	9,59
6 months	13,64	**4,65**	9,30	**5,56**	6,90	10,34	10,00	**5,56**	9,72
9 months	8,89	**2,22**	6,67	**6,67**	**6,67**	16,67	8,00	**4,00**	10,67
12 months	14,29	**6,25**	N/A	**19,44**	23,33	N/A	16,50	**12,82**	N/A
15 months	10,20	**4,17**	6,25	17,14	**3,33**	13,33	13,10	**3,85**	8,97
18 months	7,84	**4,17**	8,00	24,32	**3,33**	21,43	14,80	**3,85**	12,82
21 months	7,84	**6,00**	8,00	8,11	**6,67**	13,33	8,00	**6,25**	10,00
24 months	11,76	**0,00**	6,00	16,22	**3,45**	20,69	13,60	**1,27**	11,39

3 months prior to failure the logit based model performed better than the two other models. It produces only 2,17% type I errors and 3,7% type II errors while discriminant analysis and factor analysis produces 13,04% and 4,35% type I errors respectively, and 14,81% and 18,52% type II errors. The overall errors amount 2,74% for logit but to 13,7% and 9,59% for discriminant analysis and factor analysis.

6 months prior to failure the model with fewest errors was constructed using stepwise selection method for logit with 4,65% type I errors and DA with 5,56% type II errors and with 5,56% logit model lead to highest misclassification rate in overall errors.

9 months prior to failure the best classifier is again the logit model. The type I error is remarkably low 2,22%. Type II errors amount to 6,67% the same amount with

DA, and the overall performance is also best with total errors amounting 4,00% compared to 8,00% for discriminant analysis and 10,67% for factor analysis.

12 months prior to failure the logit is better than two other methods in type I error amounts with 6,25% compared to 14,29% for discriminant analysis, unfortunately we could not derive any results for factor analysis. On the contrary, discriminant analysis has lover type II error amount with 19,44% than 23,33% of logit. The overall errors amount to 12,82% for logit and 16,50% for discriminant analysis.

15 months prior to failure the prominent classifier is logit with 4,17% type I error respect to 10,20% of discriminant analysis and 6,25% of factor analysis. Logit produces 3,33% type II errors and discriminant analysis and factor analysis produce 17,14% and 13,33% respectively. The overall errors amount to 3,85% for logit but to 13,10% and 8,97% for discriminant analysis and factor analysis.

18 months prior to failure the logit is again best classifier with 4,17% type I error, 3,33% type II error, and 3,85% overall error same in 15 months prior to failure. Whereas, discriminant analysis and factor analysis have 7,84% and 8,00% of type I errors; 24,32% and 21,43% type II errors; have 14,80% and 12,82% overall errors respectively.

21 months prior to failure the logit based model performed better than the two other models. It produces only 6,00% type I errors and 6,67% type II errors while discriminant analysis and factor analysis produces 7,84% and 8,00% type I errors respectively, and 8,11% and 13,33% type II errors. The overall errors amount 6,25% for logit but to 8,00% and 10,00% for discriminant analysis and factor analysis.

24 months prior to failure it is amazing that logit produces least amount of errors; it produces zero 0,00% of type I error, 3,45% type II error, and 1,27% overall error. Discriminant analysis and factor analysis produce 11,76% and 6,00% type I errors; 16,22% and 20,69% type II errors; and last, 13,60% and 11,39% overall errors.

3.5. Cut off Scores

As a result we construct a Discriminant Function extracted from Discriminant Analysis; moreover we stated cut off scores upper and lower limits, between these boundaries can be called grey area in which a company's financial situation has question marks whether it would fell into distress or vice versa. Below the lower limit signals that the company is financially distressed; above the upper limit signals that a healthy financial situation the company has.

Our Z function is as follows:

$$Z= 3,7X_1 + 3,32X_2 + 6,02X_3 - 0,02X_4 - 2,77$$

X_1=**cash/net sales**
X_2=**quick assets/current liabilities**
X_3=**quick assets/total assets**
X_4=**ebit/total interest payments**
Constant term= -2,77

When we applied this function to each of eight period variables we got many results for each case, company and sector mean, but we need centroids to define cut off scores and centroids can be calculated by taking averages of all cases or taking the median of all cases, we did both and presented cut off scores extracted from averages and median based cut off score definition in Table 7; nevertheless, normality test and T-test were executed for z-scores of all cases.

Table 7. Cut off Scores

	Cut Score
Average	2,495829
Median	2,055745

Moreover; we have constructed a hold out sample which has never been used in our main analysis. The companies have been chosen among financially healthy ones, because all financially distressed cases have been included in discriminant and other analysis we have done. Our discriminant function has been applied to these cases and their Z-Scores have been calculated; the result is promising because 5 cases out of 42 cases have been defined as financially distressed, and 37 of cases defined as non-distressed. The hold out sample is presented in Table 8. The percentage of classification of hold out sample is presented in Table 9; 88% of hold out sample classified as non-distress and 12% stated as distressed.

Table 8. The Hold Out Sample And Z-Scores

Hold Out Sample	**Z-Scores**
Arçelik A.Ş.	7,397081
Vestel Elektronik Sanayi ve Ticaret A.Ş.	3,519071
Ereğli Demir ve Çelik Fabrikaları T.A.Ş.	3,08066
Alcatel Teletaş Telekomünikasyon End.Tic.A.Ş.	7,807577
Türk Siemens Kablo ve Elektrik Sanayii A.Ş.	3,687499
Kepez Elektrik T.A.Ş.	6,311067
İdaş İstanbul Döşeme Sanayii A.Ş.	7,475757
Yataş Yatak ve Yorgan San. Tic.A.Ş.	3,727378
Frigo-Pak Gıda Maddeleri San.ve Tic.A.Ş.	***1,07834***
Kent Gıda Maddeleri Sanayi ve Ticaret A.Ş.	4,230782
Maret Marmara Besicilik ve Et San.ve Tic.A.Ş.	2,570435
Merko Gıda	***1,43251***
Altınyıldız Mensucat ve Konfeksiyon Fab.A.Ş.	3,518579
Uki Uluslararası Konfeksiyon İmalat ve Tic. A.Ş.	4,116095
Pimaş Plastik İnşaat Malzemeleri A.Ş.	4,312624
T.Demir Döküm Fabrikaları A.Ş.	5,115291
Bak Ambalaj Sanayi ve Ticaret A.Ş.	4,520686
Kaplamin Ambalaj Sanayi ve Ticaret A.Ş.	3,854211
Marshall Boya ve Vernik Sanayii A.Ş.	12,47587
Yasaş Yaşar Boya ve Kimya Sanayi Ve Ticaret A.Ş.	3,527216
Feniş Alüminyum Sanayi ve Ticaret A.Ş.	5,824972
Burçelik Bursa Çelik Döküm Sanayii A.Ş.	2,500395
Transtürk Fren Donanım Endüstrisi Sanayi ve Ticaret A.Ş.	3,859063
Döktaş Dökümcülük Tic. ve Sanayi A.Ş.	4,648726

Hold Out Sample	Z-Scores
Ege Endüstri ve Ticaret A.Ş.	4,444671
Yünsa Yünlü Sanayi ve Ticaret A.Ş.	3,749423
Bossa Ticaret ve Sanayi İşletmeleri T.A.Ş.	6,628694
Köytaş Tekstil Sanayi ve Ticaret A.Ş.	8,521212
Aksu İplik Dokuma ve Boya Apre Fabrikaları T.A.Ş.	8,801801
Kipa Kitle Pazarlama Ticaret ve Gıda Sanayi A.Ş.	3,543439
Migros Türk T.A.Ş.	3,052084
Petkim Petrokimya Holding A.Ş.	9,073992
Eczacıbaşı Yapı Gereçleri Sanayi ve Ticaret A.Ş.	3,190028
Netaş Northern Electrıc Telekomünikasyon A.Ş.	8,111695
Zorlu Enerji Elektrik Üretimi Otoprodüktör Grubu A.Ş.	11,4171
Banvit A.Ş.	3,027165
Tukaş Turgutlu Konservecilik A.Ş.	***2,30028***
İzocam Ticaret ve Sanayi A.Ş.	8,436592
Borusan Birleşik Boru Fabrikaları A.Ş.	4,488536
Gimsan Gediz İplik ve Mensucat Sanayii A.Ş.	8,628575
Karsu Tekstil Sanayii ve Ticaret A.Ş.	***1,17828***
Uşak Seramik Sanayii A.Ş.	***1,25851***

Table 9. Classification of Hold out Sample

	Financially Distressed	Financially Non-distressed	Total
Hold Out Sample	5	37	42
Accuracy	12%	88%	100%

4. Summary and Conclusion

The failure prediction research has suffered from the lack of any unified theory since the 1930's when first empirical studies on this subject were published. In spite of that, empirical prediction results have been promising. Without theoretical background alternative models have predicted the future of a firm usually correctly in 80% of the cases, in some studies the amount of correct classifications is even higher. The problem is that before the theoretical construction for failing firms is settled, the prediction accuracy is dependent on the best possible selection of variables included in prediction models and also on the statistical method that is used.

Until 1980's the prominent method in failure prediction was discriminant analysis. In 1980's logistic analysis replaced this method and today even logistic analysis has some challengers. Some of these are neural networks, fuzzy logic, which are seem to lead to high prediction accuracy beside to the two other methods discriminant analysis and logit analysis. In this study, we have compared these two central methods and also suggested a new possibility to be used in model selection, i.e., factor analysis. While stepwise ratio selection procedures have already been constructed for DA and logit, also stepwise ratio selection procedures were conducted for factor analysis solutions when DA and logit applied to these solutions.

This study shows that the use of DA, logit analysis or factor analysis all lead to different failure prediction models. The amount of variables included in the models varies. Also, different methods lead to the selection of different financial ratios. Despite of the selection method used, liquidity seems to be very important factor in failure prediction. Two reasons for this were discussed. First, the liquidity failure is more general failure type in Turkey which stresses the importance of this factor in the models. Second, the variables in our original sample were mostly factors describing liquidity.

In this study the group of original variables was formed by selecting those variables which in previous central studies have been found good predictors of failure. These variables were then roughly divided into four categories, namely profitability, solvency, activity and liquidity. To analyze further the constructed models factor analysis was done. It indicated that in addition to the different number of variables in different models also the information content of the models varied. In all three years prior to failure the stepwise model selection for the logit model used the information connected to the fewest number of factors. The number of factors in factor solutions, 7-8 factors each year indicated also that the group of original ratios must be divided into more than four categories.

Furthermore, the prediction accuracy of selected models was tested using corresponding statistical methods for DA logit analysis and factor analysis. The results indicated that logit analysis outperformed two other methods one and eight period prior to failure. The misclassification rate one three months prior to failure was extremely low, only 2.74%. Eight months prior to failure logit analysis led to a lowest misclassification rate with 1,27%.

In summary, three conclusions can be made. First, the differences between alternative model selection methods affect the number of independent variables to be selected. Second, not only the number of variables but also the information content of the models varies due to the variables that are measuring different economic dimensions of a firm. Finally, connected with alternative failure prediction methods, also the prediction accuracy varies.

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