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PREDICTING FINANCIAL DISTRESS: EVIDENCE FROM TURKISH MANUFACTURING FIRMS IN ISTANBUL STOCK EXCHANGE

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To My Family

APPROVAL PAGE

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AUTHOR DECLARATIONS

1. The material included in this thesis has not been submitted wholly or in part for any academic award or qualification other than that for which it is now submitted.

2. The program of advanced study of which this thesis is part has consisted of:

i) Research Methods course during the undergraduate study

ii) Examination of several thesis guides of particular universities both in Turkey and abroad as well as a professional book on this subject.

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ABSTRACT

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Today, as a result of the current global crisis and the intensive competition, many companies encounter with financial distress. Taking measures by anticipating the problems to be encountered and circumventing crisis and financial distresses with the fewest losses is an important strategy for companies. Therefore, predicting financial distress becomes more of a subject. and for many years, various statistical techniques have been used for predicting financial distress.

The aim of study is to identify the optimal prediction models, among basic discriminant analysis, discriminant analysis implemented after factor analysis, and logistic regression analysis. These models are developed by using of the statistical techniques over financial ratios of the companies that had been listed in the Istanbul Stock Exchange (ISE) in manufacturing firms, between 1996 and 2003. Then the models are tested with control group by using 2004-2008 data for the same companies. The most appropriate for predicting financial distress before one year is logistic regression model, which is identified by comparing correct classification criteria of the obtained models.

The findings obtained and models established as a result of the thesis study have the qualities that might be considered by many managers, investors and debtors.

Key words:

Financial Distress, Financial Failure, Bankruptcy, Manufacturing Firms, Discriminant Analysis, Factor Analysis, Logistic Regression Analysis

KISA ÖZET

Ersin OKUMUŞ **June 2009**

Günümüzde yaşanan küresel kriz ve krizin bir etkisi olarak yoğun rekabet, sonucunda birçok işletme finansal sıkıntıyla karşı karşıya kalmaktadır. Karşılaşılacak sorunları önceden görerek önlem almak; finansal sıkıntılardan en az zararla çıkmak işletmeler açısından önemli bir stratejidir. Finansal sıkıntının tahmin edilmesi oldukça önem kazandığından dolayı uzun yıllar boyunca, finansal sıkıntıyı önceden tahmin edebilmek için çeşitli istatistikî tekniklerden yararlanılmıştır.

Çalışma; basit diskriminant analizi, bağımsız değişkenlere faktör analizi uygulandıktan sonra elde edilen diskriminant analizi ve lojistik regresyon metodları arasından başarısızlıktan bir yıl önce başarısızlığı tahmin eden en uygun modeli bulmayı amaçlamaktadır. Bu modeller imalat sektöründe işlem gören işletmelerin 1996-2003 yılları arasındaki finansal oranları üzerinde istatistikî teknikler kullanılarak geliştirilmiştir. Daha sonra 2004-2008 yılları arasındaki verileri kullanarak modeller test edilmiştir. Elde edilen modellerin doğru sınıflandırma ölçütleri karşılaştırılarak finansal sıkıntıyı öngörmek için en uygun model olarak lojistik regresyon modeli tespit edilmiştir.

Tez çalışması sonucunda elde edilen bulgular ve kurulan modeller, birçok yönetici, yatırımcı ve firmaya borç verenler için dikkate alınabilecek niteliktedir.

Anahtar Kelimeler:

Finansal Sıkıntı, Finansal Başarısızlık, İflas, İmalat Firmaları, Diskriminant Analizi, Faktör Analizi, Lojistik Regresyon Analizi,

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ISE	Istanbul Stock Exchange
SPSS	Statistical Package for the Social Sciences

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INTRODUCTION

Today, the competition within the business world is much more intensive than it was in the past. This competition is expected to become even more intensive in the future. With the impact of this ever-growing competition, the companies, which are thought to have an unlimited lifespan, encounter with financial distress from time to time. The concept of financial distress expressed as a case where that company is unable to meet its obligations when they are due.

Financial distress is an important issue that shall be considered in terms of national economy. The increase in the number of financial distressed companies is an indicator of the misuse of national resources. Being able to predict financial distress has a significant importance in terms of both corporate and national economy. Therefore, the need for a close examination of financial distress has thus come into prominence.

Financial analysis of a company aims at understanding whether the company structure is financially adequate or not, assessing activity results and making prospective estimations regarding the company. Conditions of companies has been tried to be demonstrated more clearly by means of these analyses. Statistical analyses enabled to develop; models that give information on financial structures of companies and that allow simultaneous assessment of several financial ratios. Today, thanks to these models, causes of company failure can be detected and indicators that reflect financial distress can be obtained beforehand.

Firstly, univariate prediction models are used to predict financial distress. In the course of time, a change from univariate prediction studies to multivariate prediction studies is observed. Discriminant analysis, multivariate analysis of variance, multiple regression analysis and factor analysis are the multivariate statistical models that are widely used in the studies aiming at predicting financial distress. Additionally, the artificial neural networks method, which has recently been attracting the attention of increasing numbers of researchers, is also used as a model to predict financial distress.

Regarding the benefits that financial distress prediction studies will bring to the company, it is seen that financial distress prediction studies can help management policies, investors' decisions and creditors' policies, all at the same time.

Aim of this study is to form a model that is able to predict financial distress of companies before one year to failure, and find out the causes of financial distress for the manufacturing companies. Multivariate discriminant methods, discriminant analysis, factor analysis and logistic regression analysis methods are applied and correct classification criteria of these methods have been compared. As a result of this comparison, it is targeted to develop a model that will most correctly predict financial distress.

The study consists of 3 chapters. In the first chapter, firstly financial distress is defined. Then, causes and phases of financial distress are explained and how to protect financial distress is mentioned. Moreover the cost of financial distress and which factors affect financial distress are also subject of this chapter. In the second chapter; previous studies aimed at predicting financial distress are mentioned. Studies using univariate statistical models and multivariate statistical models are examined in chronological order. Additionally, important studies conducted in Turkey for predicting financial distress are discussed.

In the third and final chapter; financial distress prediction models are developed, by taking all the discussions and previous studies into consideration. In this section, 29 financial ratios calculated from balance sheets and income statements of 45 financially failed and 105 financially non-failed Istanbul Stock Exchange (ISE) companies in manufacturing sector between 1996 and 2003 were used as independent variables. Discriminant Analysis, Discriminant Analysis implemented after Factor Analysis and Logistic Regression Analysis methods are used and they are compared by the correct classification results. As a result of this comparison, among the three methods, the most appropriate model for predicting financial failure from one year prior was determined. In the second section of the this chapter, financial ratios of financially failed and non-failed companies' (between 2004 and 2008) are used to compare financial distress prediction models for different periods and the most appropriate financial distress model in the long term is determined as logistic model.

CHAPTER ONE

CONCEPTS OF FINANCIAL DISTRESS

1.1 Definition of Financial Distress

Theoretically, lifespan of companies are assumed to be unlimited. However some of the companies fail due to various reasons. Failures occurring in companies facing financial difficulties may have different characteristics.

Although the company failure is a concept, that can have different meanings depending on circumstances and users. In several studies on this subject company failure is discussed under two titles, which are economic failure and financial failure. (Brigham & Gapenski, 1997)

1. Economic Failure: When company incomes do not satisfy the total cost, companies experience difficulties in continuing their activities. (Weston & Brigham, 1975) Companies in economic failure can be able to continue their activities through investors' provision of additional resources and by company owners' acceptance of lower-than-market-level rates of return. The companies that do not take precautionary steps encounter with the dangers of closure or turning into a lower-level company, where a normal return can not be obtained.

2. Financial Failure: It can be defined as the case where cash flow is insufficient for meeting current obligations. These obligations can include outstanding debts to suppliers and employees, principal and interests of the bank loans. (Wruck, 1990)

Financial and economic distress is also used in place of financial and economic failure. (Gaughan, 2002)

Altman, who has studies on the "financial distress", defines the "Financial Distress" as "a term in Corporate Finance used to indicate a condition when promises to creditors of a company are broken or honored with difficulty." (Altman, 2006)

In another study analyzing companies, the concept of financial distress is used for situations including negative net value, being unable to pay the debts (insolvency), going into default in paying bond principle and yields, giving overdraft checks (kite flying), failing to pay the dividends to shares, creditors' taking control of management, etc. (Karels & Prakash, 1987). Lin and Mc Clean (2000) also presented definitions of company failure and financial distress, which are widely applied in empiric studies. These definitions can be found in Table-1.1.

Table 1.1 Characteristics of Problematic Companies

1) Going under Control of Creditors	7) Negative Cash Flow
2) Entering a Phase of Reorganization	8) Negative Operational Capital
3) Failing to Meet Interest Payments	9) Being in Loss for Three Consecutive Years
4) Negative Audit Report	10) Being in Loss for Two Consecutive Years
5) Entering a Period of Liquidation	11) Current Year Loss
6) Negative Net Value	12) Loss in Real Operations

Source: Feng Yu Lin, Sally McClean, "The prediction of Financial Distress Using a Cost Sensitive Approach and Prior Probabilities", 17th International Conference on Machine Learning Workshop on Cost Sensitive Learning, Stanford University, USA, 2000, p.2

Financial distress can be described with loss of technical liquidities (technical insolvency) and bankruptcy. When the company loses its technical liquidity, value of company assets are still over its total debts, however, the company is now on the limit of a financial crisis. In this period, if the company's lack of cash can be overcome, financial failure can be prevented. (Gitman, 1992) In case the financial distresses can not be overcome, company may face with bankruptcy. Bankruptcy is defined as the case where total obligations of a company exceed its total assets. (Brigham & Ehrhardt, 2005)

The definitions of financial distress and bankruptcy differ according to legal rules, which show differences from country to country. For instance; the financial distress or insolvency is described in USA; either as the situation that firm's debt exceeds of its assets or as the fact of general non-payment of debts as they become due. Bankruptcy is defined as a procedure that starts with the initiation of formal bankruptcy through the filling of a petition in the bankruptcy court.

In Turkey, Article 324 of the Turkish Commercial Code and Article 179 of Bankruptcy and Enforcement Law define bankruptcy as a case where a company is unable to pay its debts. Concept of bankruptcy, which becomes evident when the assets of the company do not meet its debts, constitutes the last phase of financial failure. (Aktaş, 1997)

The reasons of using the concept of financial distress in the thesis, instead of other concepts related to financial failure are as follows:

i) The most principal reason to use the concept of financial distress is the fact that, only a few companies terminate the financial distress with a bankruptcy. In many cases, companies facing financial distress overcome the last phase of the financial distress with methods such as negotiated moratoriums, giving company shares to debtors, disposal of a part of fixed assets, halting the production, or as a last way, the company is handed over. Furthermore, companies facing such difficulties are sometimes saved directly by the government. Since the numbers of company that had declared bankruptcy do not reflect the actual fact, therefore the concept of "financial distress" was selected to be used in the study.

ii) Secondly, it can be said that, for decision makers, such as investors and creditors, the models for predicting financial distress is more important than predicting merely the bankrupted companies.

Table 1.2 includes concepts and definitions used in studies pioneering in prediction of financial distress.

Table 1.2: Definitions of Financial Failures in Major Studies

Author	Term Used	Definition
Altman	Bankruptcy	"Those firms that are legally bankrupt and either placed in receivership or have been granted the right to reorganize under the provisions of the National Bankruptcy Act."
Beaver	Failure	"The inability of a firm to pay its financial obligations as they mature. Operationally, a firm is said to have failed when any of the following events have occurred: bankruptcy, bond defaults, an overdrawn bank account, or nonpayment of a preferred stock dividend."
Blum	Failure	"Events signifying an inability to pay debts as they come due, entrance into a bankruptcy proceeding, or an explicit agreement with creditors to reduce debts."
Booth	Failure	"No explicit definition provided. Companies those were delisted from trading on any Australian stock exchange."
Deakin	Failure	"The firms which experience bankruptcy, insolvency, or were otherwise liquidated for the benefit of creditors."
El Henawy & Morris	Failure	"Failure was defined as a business which was liquidated, wound up by court order to which a receiver was appointed."
Libby	Failure	See Deakin's definition.
Taffler	Failure	"Failure was defined as receivership, voluntary liquidation (creditors) winding up by court order or equivalent."
Taffler & Tisshaw	Failure	"Failure was represented for our purposes by entry into receivership, creditors' voluntary liquidation, compulsory winding up by order of the court, or government action undertaken as an alternative."

Source: Altman, Edward I.(2006), *Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt*, 3rd edition, New Jersey: Wiley and Sons Inc. p.37

1.2 Reasons of Financial Distress

Identifying the factors that cause financial distress is important for bringing solutions to the problem. In recent years, an increase in the number of financially failed domestic and foreign firms is observed. According to Altman (1993), this increment is due to economic recession, tight monetary and credit policy applied for avoiding inflation, high interest rates and increasing financial risk structures of American companies.

Generally, the factors that lead to financial distress of companies can be gathered under two main titles, which are internal and external reasons.

1.2.1. External reasons

External reasons are those that are not caused by management but rather by factors that can not be controlled by the management, or in other words by the basic structure of the national economy. (David Denis and Diane Denis, 1995)

These are:

- Rapid increases in interest rates, reduction in the companies' possibility of finding long term debts as a result of high inflation
- Rapid increase in prices due to inflation and a decrease in demand thereof. (Aktaş, 1997)
- Immediate fluctuations in exchange rates.
- Immediate changes in policies of exports and imports.
- Wars and natural disasters

According to Stijn Claessens et al (2003), an important increase was observed in the number of companies that went into financial distress and bankruptcy after the beginning of the Asian crisis. In the study where 1472 companies listed to stock exchanges of 5 Southeastern Asia countries were analyzed, it was detected that 644 of these companies went into financial distress within the crisis period. These results are important as indicators of financial crises’ and thus the external factors' impact on the failure of companies.

1.2.2. Internal Reasons:

These are the reasons that generally arise from management and that may be controlled by the management. For a company, reasons of financial distress can be financial as well as non-financial. According to failure data of 1980 published by Dun&Bradstreet Corp., in the USA, financial failure derived from internal causes is calculated as 95.3 %. 50% of this failure was explained with management inexperience and 44% was explained with insufficiency of company facilities. Negligence, with 0.8% and fear, with 0.5% were also shown as reasons of financial failure. (Altman, 2006)

1.2.2.1. Non-financial Internal Reasons of Failure

Problems that mostly arise from management are ineffective methods of production, unsuccessful marketing, inaccurate procurement and personnel policies. As a result of researches, it is found that most of the failures are caused by inexperience and lack of knowledge of management.

1.2.2.1.1. Administrative Failure

Companies may fall into financial distress due to administrative failure such as failure to increase company sales, control the company expenses and being unable to take the steps required for timely fulfillment of company responsibilities.

In the statistics prepared by Dun&Bredstreet for analyzing the relationship between inexperience of management and failure, young and inexperienced companies with insufficient capital are much more likely to fail compared to the similar companies which have been active in the sector for long years. In this statistics it is seen that more than 50% of all the failed companies fail within the first 5 years they have entered into the sector. (Altman, 1993)

Table 1.3 Impact of Age in the Failure of Companies

Age (years)	**Proportion in total failures**	
	1980	**1990**
Rates of failure in first 3 years	25.8	31.4
Rates of failure in first 5 years	53.6	49.8
Rates of failure in first 10 years	81.7	74.1
Over 10 years	18.3	25.9
TOTAL	100.0	100.0
Total number of Failed Companies	11742	60432

Source: Edward I. Altman, Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting from Bankruptcy, 2. Ed., John Wiley@Sons Inc., 1993, p.18

In the United States of America, upon many banking crisis in 1980s numerous studies had been made on this topic and they were focused on executive insufficiencies. In a study on this subject, it was observed that the difference between bankrupted banks and survived banks was the qualities of management. (Berger et al, 1998)

1.2.2.2. Financial Internal Reasons of Failure

Financial reasons of internal failure are insufficient operating capital and over borrowing. (Akgüç, 1994)

An optimal capital structure cannot be achieved due to the insufficiency of resources. Insufficient operating capital thereof puts the companies in technical insolvency. The technically insufficient companies may over borrow in order to meet their obligations. Over borrowing firm becomes unable to compete and goes into financial failure. (Yıldız, 1999)

The internal and external reasons that cause company to fail do not emerge immediately but they slowly come into existence. First of all company's growth stops, executives become unable to find funds for investments, the investments reduce, sales fall and company loses its competition power in the market. Its profits fall and it begins to lose. It becomes unable to meet its obligations and it becomes insolvent, then it cannot fulfill its long term obligations and finally it halts its activities and goes bankrupt. Bankruptcy is the last phase of financial distress.

1.3 Process of Financial Distress

The stages to be encountered by the companies on the road to bankruptcy, which is the last phase of financial distress, can be listed as follows: (Whitaker, 1999)

1.3.1. Facing Problems

While the companies normally continue their activities, they can encounter difficulties in reaching their targets as a result of company decisions. The problems may be about; (Dağlı, 2004)

- Sales and marketing,
- Production and orders
- Distribution
- Legal issues
- Strategic issues

1.3.2. Financial Distress

If problems encountered by the companies while running their business cannot be eliminated, financial distress will become evident. Companies' failure in achieving their objectives finally turns into a financial distress. (Purnanandam, 2008)

1.3.3. Inability to Cover Daily Expenditures

Companies may not cover their daily expenditures due to difficulties they have in terms of cash. If a company at this phase can not solve the shortage of cash, the creditors can not collect their assets and may take legal actions in this case. (Sayılgan, 2003)

1.3.4. Technical Insolvency

A firm can become technically insolvency, if it cannot meet its current obligations as they fall due. Technical insolvency may be devoted to temporary lacks of liquidity. The firm may be able to pay off its obligations to survive. On the other hand, if technical insolvency is an early symptom of economic failure, it may be the first stop on the road to financial disaster. (Shrader &Hickman, 1993)

1.3.5. Bankruptcy

It is the case where a company becomes unable to meet the debts. (Altman, 1993b)

The bankruptcy proceedings that emerge as a result of bankruptcy have two purposes. These are: preventing the company from possible illegal activities and protecting the rights of creditor, and ensuring the bankrupted company to restart a business after paying all its debts.

1.4 Precautions Preventing Financial Distress

A company whose financial structure is damaged and solvency is weakened must take some measures for boosting its financial status. Some precautions may prevent the company from going bankrupt and enable it to survive.

A company in financial distress has three choices. (Van Horne, 1980)

- Reorganization and Reorganization Process
- Recapitalization
- Liquidation.

1.4.1. Reorganization and Reorganization Process

In a study conducted in the USA, ways to eliminate financial failure in 197 bankrupting public corporations were researched and best result was decided reorganization. (Hotchkiss, 1995)

Implementation of reorganization can be analyzed in 5 steps. (Aktaş, 1997) These steps are applications to a court for starting reorganization process, negotiations between creditor and debtor, acceptance of reorganization plan and finally coverage of the costs that arise throughout the process.

The plan prepared must have two important properties. (Aktaş, 1997)

- The plan must be accurate and fair
- The company's feasible future activities must be very likely to become profitable and successful.

There are two types of reorganization processes: reorganization outside the scope of bankruptcy laws and reorganization within the scope of bankruptcy laws.

1.4.1.1. Reorganization Outside the Scope of Bankruptcy Laws

Usually, an insolvent company will try to make an agreement without using legal procedures, within the scope of the payment plan regarding its debts. This case is called as private work-out. (Brealey et al, 1999). In a private work out reorganization, the debtor has either already failed to fulfill the terms of current agreement, or it is about to violation this agreement. In this period, the debtor will try to convince the creditors that it will have better financial conditions with the new terms within the reorganization agreement, compared to a legal process of bankruptcy. (Gaughan, 2002)

The advantages of reaching a solution with the special payment plan are much lower costs and taking less time compared to an official bankruptcy process. However the more complex the capital structure and the bigger the company, the lower the chance of making such an agreement is. (Brealey et al, 1999) In such reorganization, parties will not stick into the rules and regulations of an official bankruptcy process and they will shape up their own rules as far as they agree upon. Special solution agreements therefore have a more flexible structure.

Reorganization process that takes place outside Bankruptcy Laws typically involves “extension” and “composition”. Those that can be done by a company within the process of reorganization are as follows: (Brigham & Ehrhardt, 2005)

- Extensions
- Compositions

1.4.1.1.1. Extensions

Even it has a strong financial structure; a company may be in a temporary insolvency due to various reasons. In such case, requesting liquidation of the company is meaningless for the creditors, because of unnecessary time loss due to legal obligations, and the loss of money. Allowing the company to continue its existence and completely fulfill its obligations within a longer period is also in favor of the creditors.

1.4.1.1.2. Compositions

For the creditors, abandoning their complete receivables in return for a partial payment may be advantageous. Because if the creditor wants to go into an official bankruptcy and liquidation phase, he will possibly have to agree the bankruptcy costs and a less amount of receivable compared to an agreed amount will be received.

However, in special reorganization cases prepared outside the scope of bankruptcy, the holdout problem emerges. If the risk of emergence of this problem cannot be avoided, reorganization within the scope of legal bankruptcy process becomes a better alternative. (Gaughen, 2002)

1.4.1.2. Reorganization within the Scope of Bankruptcy Laws

"Reorganization is the restructuring of a corporation with an intention to continue the operations in an effective way by changing the constitution of the organization, ownership pattern, management structure etc" (Altman, 2006). If a company's active economic value is higher than its value of liquidation, the company must enter into a reorganization process. In order to protect their companies, most of the company executives tend to enter a reorganization process before liquidation. (Van Horne, 1980)

Reorganization, which emerges as an alternative to liquidation, helps company to keep on going as an entity that continues its activities. Losses of creditors are generally met with the new stocks and shares in the reorganized company. Such reorganizations are in favor of shareholders, who already do not have much to lose if the things go bad. (Brealey et al, 1999)

Reorganization processes within the scope of Bankruptcy Laws also include composition (concordat). Composition is an application that is arranged within the framework of law in order to save for financially distressed companies or their creditors and improve their conditions.

In Turkey, in order a composition to be accepted; (Akgüç, 1994)

- The company with debt must propose paying a percentage in proportion with its current assets, provided that it is not less than 50%
- At least 2/3 of the creditors, both in numbers and in amount of the debt, must accept the proposal for composition
- And approval of the Commercial Court is required.

The purpose of bankruptcy is to protect creditors' rights by dissolving the debtor's assets. In the composition; the purpose is to save the debtor from the bad conditions he/she is in.

In the USA, especially in the recent years, companies with very huge asset values had to apply for reorganization within the process of bankruptcy. These include bigger companies with over US $ 50 billion assets, such as WorldCom Inc., Enron Corp., Conseco Inc., Kmart and Federal Morgul. (Weston et al, 1998) Also in Turkey, after December 2001 crisis, several amendments on bankruptcy laws were made and within this framework, concepts of bankruptcy deferment and reorganization of companies through settlement took their places in the bankruptcy law. (Balcı, 2006; cited by Coşkun, 2006) Some companies had applied for deferment of bankruptcy within this period. For example Raks Electronics and Raks Home Appliances had applied for deferment of bankruptcy.

1.4.2. Recapitalization

Recapitalization "is a change in company's capital structure, in order to make it more stable, to defend against hostile takeovers, and diversify debt to equity ratio in order to improve liquidity or even to minimize taxes." (http://www.coolinvesting.com/dictionary/Recapitalization.htm, 2009)

"Recapitalization is a changing of the capital structure within the framework of the existing corporation. This is usually accomplished through an exchange of securities, including an exchange of stock, either preferred or common, for a new issue of stocks, stocks for bonds, or bonds for stocks." (Broderick, 1982; cited by Muzır, 2004)

Recapitalization may take place in the following cases: (Yıldız, 1999)

- The company gets rid of a potential fixed obligation that may emerge in the future, by replacing shares with common stocks.
- The company may propose the bond holders to replace their bonds with stocks. Thus the company may aim at reducing its long term debts and increase its capital.
- The company may take in new partners by creating the belief that the financial distresses encountered will be overcome.
- It may reappraise its assets and use the increase in value to reduce the losses.
- Gaining incomes by selling fixed physical assets or hiring them out for long term

- Converting the debts into securities through creditor banks
- Enabling the company to merge with other companies (merger)
- Providing resources by selling associates of the company, if available.

1.4.3. Liquidation

Liquidation is the last solution a distresses company may apply. In general, it is applied when no voluntary reorganization or post-bankruptcy reorganization is implemented. In the process of dissolution, the income obtained by selling company assets is distributed to the creditors and the residuals, if any, are distributed to the shareholders, in accordance with the absolute priority rule (Gaughen, 2002). If the active value of the company is lower that its liquidation value, the creditors will try to liquidate the company. Operations of a failed company will cause more loss of firm value. (Weston et al, 1998) The essential method for converting the goods to be dissolved into cash is auction.

1.5 Costs of Financial Distress

Jensen and Meckling (1976) denote that company incomes and activity costs are not independent from the probability of bankruptcy and thus from the capital structure. As the probability of bankruptcy increases, both costs and company incomes will be affected.

Actually; financial distress, which does not only consist of bankruptcy is a process that includes bankruptcy. Therefore financial distress costs may be separated as follows: (Brealey et al, 1999)

- Financial Distress Costs in case Bankruptcy does not Happen ;
- Bankruptcy Costs.

1.5.1. Financial Distress Costs in case Bankruptcy does not Happen;

Brealy et al (1999) defines that costs of financial distress in case bankruptcy does not happen are costs that arise due to; conflicts of interest between bond and stake holders and negative decisions taken by the company owner as a result of these conflicts;

Executive's decisions in his/her own favor by reducing the company's total value, upon conflict between capital owners.

1.5.2. Bankruptcy Costs

Another reason for capital market's being not as perfect as in theory is the costs encountered in case of bankruptcy. When the companies become insolvent, several problems are experienced in company management. The managers neglect managing activities, which are their principal duties, and canalize all their efforts on paying the debts and thus inefficiencies arise at the level of management. This situation increases the probability of bankruptcy, reduces the company value and increases capital cost. (Hatiboğlu, 1995) Bankruptcy is not a reason for the decrease in company value; it is a result of it.

Bankruptcy costs are separated into two, as direct and indirect costs.

1.5.2.1 Direct Bankruptcy Costs

These are the costs that are directly paid out of the pocket during bankruptcy. Fees that companies pay to managers and consultants and fees that must be paid within the framework of laws take place within the direct cost. Direct bankruptcy costs are the most easy-to-detect financial distress costs.

Costs that emerge during bankruptcy include; fees that are paid to bankruptcy office agents, attorney fees, accountant fees, payments to liquidator in case of dissolution and the costs that may emerge if an auction is going to be held.

Until now, many researchers have studied of financial distress. In studies by Warner (1977), Altman (1984) and Weis (1990), attempts were made for determining the costs of direct bankruptcy as a percentage of the value of the company one year before the bankruptcy. As result of their studies, all three had observed that direct costs are quite low and they comprise only some 3- 4.5 % of the financially distressed companies' market values. In another research on companies dissolved as a result of bankruptcy process it was observed that the direct bankruptcy costs comprise approximately 7.5 % of the company dissolution values. (Chua & Mc Connel, 1982)

Table 1.4 Studies That Identify Costs of Direct Bankruptcy

AUTHOR	SAMPLE AUDIENCE	AVERAGE COST	PERIOD	SIZE OF SAMPLE
Warner (1977)	Railway Bankruptcies	%4	1933-1955	11
Ang, Chua and Mc Connel (1982)	Oklohama Bankruptcies	%7.5	1963-1978	55
Altman (1984)	11 small-sized, 7 industrial companies	%4.3	1970-1978	18
Weiss (1996)	Various Bankruptcy Cases	%3.1	1980-1986	31

1.5.2.2 Indirect Bankruptcy Costs

These are the costs that arise while the company is on the verge of entering bankruptcy phase, due to insufficiency of company management, as a result of deferment of debts, deceleration of production and other economic negativities. We can also add the costs of opportunities that are missed due to a company's financially distressed conditions.

According to Moyer et al. (2001), "financial distress costs include the costs incurred to avoid bankruptcy as well as the direct and indirect costs incurred if the firm files for bankruptcy protection." (cited by Kidane, 2004)

Complete finding of indirect costs is quite difficult. Altman (1984) revealed that direct and indirect bankruptcy costs of 11 small-sized companies had made up 8.7% of company value. In industrial corporations this percentage goes up to 15 %. This result means that costs of industrial companies, which do not perform effective business, will become more.

White (1983) also researched bankruptcy cases as Altman (1968) in southern part of New York, in order to identify bankruptcy costs. In his study that contains numerous companies going bankrupt, he finally found out that bankruptcy costs of dissolving companies, comprise 22% of the total amount paid to creditors, and this proportion was 6% in the companies within reorganization process.

As a result of another study, indirect bankruptcy costs were defined as follows. (Arnold, 2002)

- A company's ambiguity in financial distress reduces the costumers' demand to the company. Therefore the sales fall, profits decrease and company reputation decreases.
- Upon company's ambiguity in financial distress, the supplier start to worry about how the financially distressed company can pay its debts and guarantee themselves by adding an amount as much as risk premium to the debt agreement. In this way, the suppliers who had lost their trust in the company reduce the goods they supply or increase their prices.
- The company has to spend a lot of time to get rid of the distress. The time spent for this purpose may also be accepted as indirect cost.
- Executives and employees demoralization also reduces efficiency.
- Assets are tried to be disposed rapidly, prices will fall substantially. In this case, the company will obtain a lower income that it had expected.

- Deferments, legal impositions and problems encountered in reorganization process may hinder the efforts for making the company more efficient.
- The management may also make efforts for increasing short-term liquidity, such as halting R&D studies and reducing commercial loans and stakes but this situation cause more problems in the long run.

1.6 Factors that Affect Costs of Financial Distress

1.6.1. Company Size

Altman, in his study dated 1984, tried to detect direct and indirect bankruptcy costs of companies in financial distress and revealed the following results: In small-sized companies, total of direct and indirect bankruptcy costs just before bankruptcy is up to an average 8.7% of company's total value, while this percentage in bigger industrial companies is an average of 15 %. A company's being in financial distress will cause it to lose its bargaining power in agreements it will make with raw material and semi-finished product manufacturers, transporters and customers, with whom it is in relation with. In bigger companies, as a result of company's more involvement in such relationships, costs of financial distress normally increase because activities of financial distressed companies are more easily affected and immediately lose their effectively.

1.6.2. Management Effectiveness

A company's possession of an effective executive staff usually prevents that company from going into a financial distress. However, negativities in the sector where the company does business and fluctuations in the country's economic conjuncture make failure of the company inevitably. Even a successful company management cannot prevent negative impacts of such a situation.

As long as no extraordinary event is encountered, specialists of economy and finance relate company failures with bad management. According to experts, good conduct of company activities is an indicator of good management. Executives, who know that disruptions may emerge in a financially distressed company's activities, must ensure a precaution that company activities will stay unaffected. Despite all the efforts and precautions, the company may go worse and worse gradually. In this case, good manager takes quick decisions and makes the company recover as soon as possible. Without a doubt, the best example for this explanation is famous executive Jack Welch's success in recovering financial distressed American company General Electric, by radical decisions. In fact, these namely "radical" decisions are called as "conventional methods" today. (Bennet &Langford, 1980)

A good manager is not obliged to make difficult decisions for financially distressed companies. Elimination of asymmetrical information between investor and company may be sufficient. But it is not that easy.

1.6.3. Conflicts between Owners and Managers (Agency Problem)

In financially distressed companies, conflicts between capital owner (principal) and executive (agent) can turn the company upside down.

In case the company executive only works in favor of stake holders and he applies the decisions that we call "the game", the company becomes exposed to agency costs. Therefore, success of the agreement between these two sides closely concerns a company's costs of financial distress.

1.7 Importance of Predicting Financial Distress

The case of financial distress generates various costs not only for the direct periphery of companies, but also for the economy in general. Financial distress costs of a wide ranged company may create negative effects on entire economy with "spillover effects". Thus, a company's financial distress may cause negative results regarding employment and economic welfare. (Andreev, 2006)

Purpose of a scientific study may not only be determined in line with only scientific considerations but it may also be determined with the purpose of finding solutions to the problems of daily life. Prediction of financial distress, which is a scientific study, will reveal the reasons that lie beneath the companies falling into distress, and it will as well create important benefits by allowing investors, creditors, the government, auditors, regulatory organizations and naturally the executives to take necessary steps.

1.7.1. Importance for Administrative Decisions

Each company that wants a successful growth must objectively review its situation periodically. Results of this review will help the executives to decide whether a change is needed in management policies of the company.

As mentioned before, many of the financial distress prediction studies had concluded that the most important reason of failure is company management. A model that accurately predicts failure earlier will definitely become a very useful tool for executives. Additionally, anticipation of distress will not only provide the executive with neutral information on his own company's status, but it will also help him/her to take accurate decisions about the companies he/she is in relationship with.

1.7.2. Importance for Investment Decisions

Today, companies cover their needs for capital from several financial institutions or from many small investors through several stocks. This has generated a wide group of investors that consists of numerous members.

A close relationship between the risk of bankruptcy and the progress of risk prices had been determined through several researches. (Ahorany et al, 1980) Therefore investment decisions are directly related with companies' financial distress.

Investments' orientation to efficient and appropriate areas through financial distress prediction models will provide optimal use on investible funds and will bring important benefits to the national economy.

1.7.3. Importance for Credit Decisions

Banks have been carefully selecting the companies that they will give credits and they have been making efforts for supplying refundable, safe and high-performance credits. Creditor organizations apply logical, rational and scientific analysis for the credits.

It is observed that creditor institutions take over two types of risks in the phase of making credits available. First type of risk is making credits available for companies with high risk of experiencing financial distress in the future. In this case, creditor institution will not be able to safeguard the credit it supplied and the credit supplied will not be reimbursed. The creditor will both be lack of the principal and the credit interest incomes. The second type of risk can be summarized as avoiding supply of credit to financially healthy companies which may overcome the credit load. In this case, the creditor will come up against the risk of making a safe credit unavailable. (Libby, 1975)

CHAPTER TWO

FINANCIAL DISTRESS PREDICTION STUDIES

Financial analysis involves examining and assessing the financial statements that emerge as a result of the company's activities. The most commonly used financial analysis is the financial ratio analysis. (Keasey & Watson, 1991) Financial distress predictions made by using financial ratios aim at avoiding financial failure. Predetermining the probability of encountering with financial difficulties will allow both an executive and an investor to take precautions to avoid undesired situations. Therefore, prediction of financial distresses is quite important.

Methods used in the studies conducted on predicting financial distress vary. Major studies and methods used for financial distress prediction are as follows:

2.1 Studies Using Statistical Models

The mathematical-statistical models used in financial distress prediction studies that aim at predicting financial distress can be classified in two groups:

- Univariate models,
- Multivariate models.

In univariate models, financial distress is tried to be predicted according to a single variable. In multivariate models, the dependent variable that determines financial failure is identified according to the values obtained by multiple independent variables.

2.1.1. Financial Distress Prediction Using Univariate Models

In univariate models, predictions about companies and comparisons between companies are made according to the values obtained by a single variable. For analysis of this variable, techniques such as 0-1 Simple Regression Model, Single Discriminant analysis, Markov Chain are used. (Aktaş, 1997)

In statistical analysis made with univariate models, classification is made depending on a single variable. In univariate analysis model, the process applied for classification is repeated for each variable and assessed according to a limit value. The result is obtained by comparing the financial ratio with the limit value. The purpose is to minimize the misclassification. The biggest advantage of this method is its simplicity. However the assumption that the correlation between financial ratio and company's success is linear is its greatest deficiency. Besides the decision about success-failure, which is obtained by comparing financial ratio on the same company with its own limit values may not always be consistent. While the company is found successful with one variable, another variable may not be supporting it. (Marcoulides & Hershberger, 1997)

The major studies for predicting financial distress with univariate statistical models are given below in a chronologic order.

2.1.1.1. Fitzpatrick (1931)

The first empirical study using Univariate statistical models was conducted by P.J.Fitzpatrick in 1931. (cited by Hanson, 2002) In his study, Fitzpatrick compares 19 healthy firms active between 1920 and 1929, with 20 failed firms which had gone bankrupt within the same period. Although he had used many financial ratios, he concluded that the most important ratios in prediction of companies' probability of bankruptcy were net worth/total debt rate and net worth/fixed asset value.

2.1.1.2. Merwin (1943)

A study about financial distress prediction by using Univariate statistical model was conducted by Charles Merwin, in 1943. In Merwin's Study (1943), he had analyzed 900 firms between 1926 and 1936, by separating them into two groups as continuing and non-continuing firms. He had taken non-continuing firms into the first group and continuing firms into the second group. He had detected that the 3 ratios indicated that a company would fail.

- Net working capital/ Total Asset,
- Net worth / Total debt,
- Current ratio

2.1.1.3. Tamari (1966)

M.Tamari was the first researcher to develop a model out of USA by analyzing pre-bankruptcy conditions of companies in Israel, in 1966. In Tamari's study (1966), he used 16 industrial firms that had declared bankrupcy and 11 newly bankrupt firms. Tamari had evaluated risk status of companies according to an index comprised of multiple ratios, instead of a single variable. Tamari had taken the ratios he had used in his study by multiplying them with the following coefficients he had determined.

- (Original Capital + Retained Earnings)/ Total Debts .25
- Profit Trend .25
- Current Ratio .20
- Production Value / Stocks .10
- Sales / Short Term Receivables .10
- Production Value / Operating Capital .10

Even though TAMARI's rating system seems like a totally random system, it had been very useful since it allowed investors, creditors and anyone related with the firm to make correct assessments about a firm, by using several ratios simultaneously.

2.1.1.4. Beaver (1967)

Beaver's financial distress prediction model is the most widely known research of univariate analysis. Beaver defined failure as the inability of a firm to pay its financial obligations as they mature (Altman, 1968).

Beaver's (1967) study comprised of 79 failed and non-failed firms during 1954 to 1964. Asset size of selecting firms changes between 0.6 and 45 million dollars. Beaver computed 30 financial ratios for each of five years prior to failure. The ratios were selected in connection with;

- Popularity in the literature,
- Performance in previous studies,
- Definition of the ratio in terms of each "cash flow" concept.

Based on the lowest percentage error for each group in the five year period, Beaver selected the following six variables as "best"

- Cash flow to total debt,

= (Net Income + Depreciation and Amortization) / Total Debts

- Net income to total assets,

= Net income / Total Assets

- Current plus long term liabilities to total assets,

= Total liabilities / Total Assets

- Working capital to total assets,

= Working Capital / Total Assets

- Current ratio,

= Current assets / current liabilities

- No credit interval.

= Quick assets / (Operating Expenses – Non Cash Expenses)

Beaver's empirical experiment was conducted in three major steps. First step is comparison of mean value of financial ratios which is related to failure and non-failure firms. In second step, Beaver implemented the classification test using dichotomous prediction. Beaver established the cut-off points for each financial ratio and predict financial failure for the firms by using this cut-off point. The last step is analysis of likelihood ratios.

To make predictions about failed or non failed firms, Beaver tried to establish as a suitable cut-off point for each ratio. To this end, he ranked each of 30 ratios in an ascending order for both failed and non failed firms and appoint a certain cut-off point for each ratio that minimize the percentage of incorrect prediction. In this classification, firms' value over cut-off point is called "non failed firms" and otherwise called "failed firms". Beaver found out the "cash flow / total debt ratio" was the most appropriate predictor with the lowest misclassification rate for the first three years prior to failure.

Beaver's failure estimation test bases on "Net Income / Total Assets" ratio for the cut-off point of 2 percent and yields the misclassification percentages, 13%, 20%, 23%, 29%, and 28% respectively for five years before failure.

Table 2.1 Beaver's (1967) Dichotomous Test

	Years Before Financial Failure				
Ratios	**1**	**2**	**3**	**4**	**5**
Cash flow / Total debt	0.13	0.20	0.23	0.24	0.22
Net Income / Total assets	0.13	0.20	0.23	0.29	0.28
Total Debts / Total Assets	0.19	0.25	0.34	0.27	0.28
Working Capital / Total Assets	0.24	0.34	0.33	0.45	0.41
Current Ratio	0.23	0.38	0.43	0.38	0.37
No credit interval	0.23	0.38	0.43	0.38	0.37

Source: Beaver, H. William (1966), "Financial Ratios as Predictors of Failure; Empirical Research in Accounting: Selected Studies", *Journal of Accounting*, p.105

Beaver calculated two types error. Type I Error is error in predicting bankrupt firm and Type II Error is error in predicting non-bankrupt firms.

Misclassification rate in Beaver's analysis is in the following table:

Table 2.2: Percentage of Misclassification Errors in Beaver's (1967)Study

Year Before Financial Distress	Type I Error (%)	Type II Error (%)	Total Percent Misclassifications
1	22	05	13
2	34	08	21
3	37	08	23
4	47	03	24
5	43	05	22

Source: Beaver, H. William (1966), "Financial Ratios as Predictors of Failure; Empirical Research in Accounting: Selected Studies", Journal of Accounting, p.107

The most important criticism against Beaver's study was about the dichomotus sampling technique he had used. Controlling two important variables such as year and total assets, which may affect financial failure, may have adverse effects on prediction of financial failure. Additionally, the study is also criticized in terms of its definition of failure

2.1.1.5. Weibel (1972)

Weibel's study (1972, cited by Hanson, 2002) is related to small firms which were customers of Swiss bank. In this research, he paired of 36 firms that did not to pay their debts with 36 firms that were successful with their financial statuses. The criteria of selecting failed or non failed firms were sector of the firms, size of the firms, age of the firms, place of incorporation and economic situation.

Weibel used 42 financial ratios with the assistance of Wilcoxon Test. Before analyzing, these 42 ratios were downed to 20 ratios. And in this study, following six ratios were found to predict financial failure from one year before.

- Cash Flow / Short Term Liabilities ,
- Current Assets / Short Term Liabilities ,
- (Current Assets - Liabilities) / (Corporate Expenditure- (Depreciation and Amortization)) ,
- Inventories / Expenditures ,
- Credits / Sales ,
- Outsourcing / Capital.

Weibel used Wilcoxon test which is univariate statistical analysis method. This test ruled out sample's independency and relationship between variables. When assessed subjectively, selected order of ratios may reach different conclusions compared to the personal preferences of another analyst under different predicted conditions. Moreover, explanation of these results is not connected to an absolute result.

2.1.1.6. Sinkey (1975)

Sinkey's (1975) study is a univariate statistical analysis of the balance-sheet and income statement characteristics of problem banks. The problem bank as determined by the FDIC has greater risk to the FDIC insurance fund than a nonproblem bank. 90 insured commercial banks were identified as problem bank. In addition, twenty banks were recognized as problem banks during the first months of 1973. 110 banks are the problem banks analyzed in his research.

Financial ratios which were used in this analysis consisted seven main groups.

These are;

- Liquidity,
- Loan Volume,
- Loan Quality,
- Capital Adequacy,
- Efficiency,
- Sources of Revenue,
- Uses of Revenue.

Finally, Sinkey (1975) introduced the differences between problem and non-problem banks from their structure using univariate variance analysis. And he realized that an effective early warning system is major potential advantages of firms.

Consequently, in order to predict financial distress, univariate statistical models are superior to multivariate statistical models, in terms of applicability. However, noting that univariate models may produce contradictory results, Altman had criticized the statistical studies conducted with univariate models. Furthermore, the fact that multivariate models offer the ability of measuring both a company's all characteristics and the correlation between these characteristics, while there is no such possibility for univariate models, pushed the researchers to prefer multivariate statistical models for their financial distress prediction studies.

2.1.2. Financial Distress Prediction Using Multivariate Models

With the aim of eliminating univariate models' aforementioned disadvantages, financial distress was tried to be predicted by using multivariate models. The conception of making predictions with multivariate models is based on obtaining information about future by making different predictions for the same company with various ratios. In other words, it is a prediction model made by using multiple financial ratios in the same equation.

There are 3 conditions that must take place in a multivariate model. (Dikmen, 2007)

- Determining the structure of the model
- Identifying the variables that will take place in the model
- Identifying the coefficients of variables

In the Table 2.3, the multivariate statistical models to predict financial distress are classified according to their function and when they are used.

Table 2.3 Multivariate Statistical Models to Predict Financial Distress

Multivariate Analysis	**When it is used?**	**Function**
Factor Analysis	It is used when the aim is to find and explore a few conceptually significant new variables by gathering many correlated variables.	It analyzes the relations between many variables and explains the common dimensions underlying beneath these variables.
Cluster Analysis	Is is used when the aim is to classify non-grouped data according to their counterparts and to obtain summative information.	The sample is classified as common special sub-groups between less number of assets.
MANOVA	In order to test the hypothesis by considering the variance of group response, it is used to analyze the impact of two or more independent variables on multiple dependent variables.	It simultaneously analyzes the relationship between independent variables in different categories and two or more dependent metric variables.
Discriminant Analysis	With Discriminant Functions, the separator which has the most impact on the separation between the groups is used in determination of variables, and to which group a unit coming from an unknown group shall be included.	It is used for understanding group differences and it predicts an asset's probability of belonging to a certain class.
Multiple Regression Analysis	It is used for analyzing a single dependant variable's relationship with one or more independent variables.	In response to the changes in independent variables, it predicts the changes in dependent variables.

Source: Dikmen, Burcu (2007), Finansal Başarısızlık Tahminlerinde Matematiksel Model Uygulamaları, Ankara: Sermaye Piyasası Kurulu Press., p.7

The major studies conducted for predicting financial failures with multivariate models are given below in chronological order:

2.1.2.1. Altman (1968, 1977)

2.1.2.1.1. Z Score (1968)

Only one year after Beaver's (1967) study, Altman applied multiple discrimant analysis to predict corporate failure using financial ratios. There are two classification groups in Altman's study which were failed and non failed firms between the years 1946 and 1965. Altman studied on 22 financial ratios and his sample consisted of 33 failed and 33 non-failed firms. The ratios were selected by Altman (1968) based on

- Their popularity in the literature,
- Potential relevancy to the study, and a few "new" ratios"

Altman had defined failure as petition in a bankruptcy in respect of federal bankruptcy law (Altman, 1968). Failed banks's asset sizes are between $0.7 and $25.9 million whereas non-failed firms's asset sizes were between $1 and $25 million. The result was a model consisting of five ratios which best discriminated between failed and non-failed firms and developed a function of Z-Score.

$$Z=0,012(X1)+ 0,014(X2)+ 0,033(X3)+ 0,006(X4)+ 0,999(X5)$$

where

X1 = Working capital / Total Assets

X2 = Retained earnings / Total Assets

X3 = Earnings before interest and tax (EBIT) / Total Assets

X4 = Market value of equity / Book value of total debt

X5 = Sales / Total Assets

All firms with Z scores < 1,81 were failed and

All firms with Z scores > 2,99 were non failed

1.81 < Z scores < 3,00 were a " zone of ignorance" or "grey area"

According to Altman's Z-score, accuracy rate of one year prior to failure is 95%. The type I and type II missclassification rate of the models were respectively 6% and 3%. In the following table shows accuracy rate, Type I and type II missclassification rate for one year prior to failure.

Table 2.4 Altman's (1968) Misclassification Rate for One Year Prior to Failure

	Number Correct	Percent Correct	Number Error	Percent Error	n
Group I	31	94	2	6	33
Group II	32	97	1	3	33
Total	63	95	3	5	66

Source: Altman, I. Edward (1968), "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy", *The Journal of Finance*, Volume 23 (4) : p.599

Altman reported that his model's accuracy rates for each five years prior to failure were respectively 95%, 72%, 48%, 29%, and 36%.

According Altman's Z model, if Z-score of firm is less than 1.81 than it is defined as failed firm and if Z score of firm is more than 2.99 it is defined as "non failed" firm. If a firm' Z score is between 1.81 and 2.99, it is in the "grey area". Altman's Z score model's power of prediction is weaker from year to year because of type I error which is defined Alfa error were respectively 6%, 28%, 52%, 71% and 64%.

2.1.2.1.2. ZETA Model (1977)

ZETA score was developed by Altman, Haldeman and Narayan (1977) who believed that there were five reasons to revise a new failure model different from Altman's (1968) model. These were;

In 1968, Altman, Haldeman and Narayana had found the 5 variables Zeta Model as insufficient due to the following reasons and they developed Zeta model by adapting the model to a bigger company and updating the years of research.

- Change of profiles and rules in company bankruptcies
- Need to update available data
- Need to aggrandize the model by including certain industries and commercial companies
- Inclusion of financial reporting and used accounting applications to the new model
- Availability of new techniques developed in application of discriminant analysis

The study used a match sample of 53 failed firms and 58 non-failed firms between the years 1969 and 1975. The matched sample included both manufacturing and retail firms. The most important feature that distinguishes this model from Z Model is its ability to predict companies' bankruptcies even five years prior.

The following seven financial ratios were selected in the model as independent variables.

X1 = Return on assets

EBIT / Total Assets

X2 = Stability of Earnings

Standard Deviation of the EBIT / Total Assets ratio for five years

X3 = Debt service

Log (EBIT / Interest)

X4 = Cumulative profitability

Retained earning / Total Assets

X5 = Liquidity

Current Assets / Current Liabilities

X6 = Capitalization

Common Equity (Market Value) / Total capital

X7 = Size

Log (Total Assets)

Altman and his colleagues applied Quadratic Discriminant Analyses and Multiple Discriminant Analyses to revise ZETA model in the study. Both methods composed similar results. The model used firm's financial statements of 2-5 years prior to failure date. The model's accuracy, based on one year prior data to failure, is 96.2% for the bankrupt group (Type I error: 3.8%) and 89.7% for the nonbankrupt (Type II error: 10.3).

Although Altman's 1968 Z score is the most important one among multivariate models, Zeta Model developed gave better results.

2.1.2.2. Deakin (1972)

Edward B. Deakin, developed a financial distress model in 1972 which based on studies of Beaver (1967) and Altman (1968). Deakin (1972) planned to mix Beaver's empirical results for his prediction with Altman's multivariate model. He aimed to define the linear combination of 14 ratios that were used by Beaver (1967) with greatest accuracy. He analyzed 32 firms that failed between years 1964 and 1970. Deakin (1972) defined failed firms as bankrupted, forced into liquidation and wounded up firms. Each failed firms matched with a non-failed firm on the bases of industry, asset size and year of financial data. Deakin's research was used as Beaver's 14 financial ratios with the best predictive power.

Deakin concluded that "Total Debt / Total Assets" ratio had greatest prediction power of failure similar to Beaver's study. Using discrimant analysis, he developed functions for five years before failure. F statistical test gave good results for the model to predict failure. In his study, Deakin stated that reducing the number of variables, which is 14, was ruining the prediction capacity of the model and that the discriminant analysis, in its current status, was able to predict failures 3 years prior, with a high accuracy rate.

2.1.2.3. Blum (1974)

Blum (1974) developed a failing company model to aid antitrust division of the Justice Department. Blum's (1974) study consisted of 115 failed and 115 non-failed firms with a minimum of $1 million in liabilities from 1954 to 1968. Failure was defined as "inability to pay debts as they come due, entrance into a bankruptcy proceeding, or an explicit agreement with creditors to reduce debts" (Blum, 1974:3). In his study, Blum (1974) used 12 ratios to measure liquidity, profitability and variability. He used Multiple Discriminant Analysis (MDA) methods based on the five years prior to failure.

The accuracy rates of the results produced in the study increase as the year of failure is more estimated. In his study, a predictive accuracy is 93 percent for one year prior to bankruptcy, 80 percent for two years, and 70 percent for the third, fourth, and fifth year prior to bankruptcy.

2.1.2.4. Libby (1975)

Libby (1975) studied the prediction financial firms by interviewing with bank loan officers about Deakin's 14 ratios. Libby's sample consisted of 30 failed firms. The failed firms paired with 30 non-failed firms which were selected in Deakin's sample. Libby used Multiple Discriminant Analysis methods and identified 5 ratios within selected 14 ratios which are:

Table 2.5 Selected Financial Ratios on Libby's (1975) Study

FACTORS	**FINANCIAL RATIOS**
Profitability	Net Income / Total Assets
Liquidity	Current Asset / Sales
Asset Balance	Current Assets / Current Liabilies
Cash Position	Current Assets / Total Assets
Activity	Cash / Total Assets

Source : Libby, R. (1975). Accounting ratios and the prediction of failure: some behavioral evidence. *Journal of Accounting Research*, 13(1): p:157

Libby concluded that prediction models provide a sufficient means for assisting bank loan officers in predicting corporate failure (Libby, 1975). The model introduced by Libby distinguished between failing and nonfailing firms with a 85 % accuracy rate when failure occurred within one year from the prediction. Libby had reached 4 important results in his study about the prediction of bank loan officers. These are:

- There is significant difference between predictions by representatives of small and big banks.
- No relationship was detected between the participants ages and experiences, and accuracy rate of their predictions.
- No difference was encountered between study groups, in terms of short term test reliability.
- Bankers' interpretations over accounting data show parallelism with each other.

This study has shown that factor analysis may be used as the first important step of discriminant analysis. However, the most important criticism for this study is the fact that it informs the participant bankers beforehand about the fail of the analyzed bank.

2.1.3. Financial Distress Prediction Using Logit Analysis

Logit Analys, is a regression technique in which the financial ratios of a sample of failed and non-failed firms are placed in a regression formula. When a logit model is applied to a company's financial statements, the resulting dependent variable, stated between 0 and 1, represents the probability of the company's fail. (Marcoulides & Hershberger, 1997)

Logistic Regression Analysis is a more secure technique that is not affected by the data that does not match with the normal distribution. The first study with logistic regression was conducted by Paul A. Meyer and Howard W.Pifer, in 1970. In this study, they matched and analyzed 39 banks closed between 1948 and 1965 in USA, with 39 successful banks that have similar characteristics. While matching, being located in the same city, being at similar size and similar age and availabilities of data pertaining to the same dates, were taken as criteria. In this research 32 financial ratios were used as independent variables. As dependent variable, they generated linear regression function which takes (0,1) dummy value.

As result of this study, it is found that 80% of the banks were separated into correct groups one or two years prior to the date of bankruptcy. However, in further dates the model's prediction ability had vanished. Additionally, the fact that only one of nine variables was financial ratio, while the other eight were related to economic trend- and change-dependent ratios, was criticized in other studies.

2.1.3.1. Edmister (1972)

Edmister (1972), tried to predict failure of small firms using financial ratios. He defined a small business as business with a loan from the Small Business Administration (SBA) between years 1954 and 1969. Average asset size of firms is determined as $164,940 by Edmister (1972). In this study; Edmister (1972) analyzed 42 non-failed firms and 42 failed firms. He analyzed 19 financial ratios, which were important in previous failure prediction studies. His methodology included four different hypothesesis tests.

- A ratio's level as a predictor of small business failure,
- The three-year trend of a ratio as a predictor of small business failure,
- The three-year average of a ratio as predictor of small business failure
- The combination of the industry relative trend and the industry level for each ratio as a predictor of small business failure.

In this study, Edmister (1972) used zero-one linear regression with seven variables for each failed and non failed firms. And he developed equation as follows:

$$Z = 0.951 - 0.523\ X1 - 0.293\ X2 - 0.482\ X3 + 0.277\ X4 - 0.452\ X5 - 0.352\ X6 - 0.924\ X7$$

Following ratios were used the equation:

X1 = Annual funds / Current liabilities

X2 = Equity / Sales

X3 = Net working capital / Sales, divided by RMA* average ratio

X4 = Current liabilities / Equity, divided by RMA average ratio

X5 = Inventory / Sales, divided by RMA average ratio

X6 = Quick ratio divided by the trend in RMA quick ratio

X7 = Quick ratio divided by RMA quick ratio

As a result of this study, Edmister (1972) stated that the most important elements that make a prediction powerful were analytical method and ratio selection. Additionally, Edmister (1972) stated that grouping the ratios into three months periods were useful. Edmister's model is criticized for 0-1 technique's information reducing aspect. The method of completing into 0 or 1 by taking certain sections in variable coefficients was adopted in 0-1 technique.

2.1.4. Gambler’s Ruin Mathematical/Statistical Model

The main idea of this theory is establishing relationship with a gambler's game, who gambles with random money. A gambler gambles with a certain probability of benefit and loss. The game continues until the gambler loses all his money.

Regarding financial distress prediction, companies are personified with the gambler. They can continue their activities until net value of the company is zero. The theory assumes that a company has cash inputs and outputs according to its activities. The company may have a negative or positive cash flow in any period. In case a company experiences consecutive periods of negative cash flow, it will go bankrupt. (Kidane, 2002)

In the most important study using Gambler’s ruin mathematical model; Wilcox (1971) aimed at developing a model that explains the results in Beaver's study dated 1971 and that predicts failure better. With this purpose, in a 7 variable model he used 52 companies that had failed in 1955-1971 period. These companies were grouped with same number of successful companies by considering industry, size and data adequacy.

In accordance with the result obtained from the study; Wilcox (1971) stated that, in order to weaken probability of failure in companies, net liquid value may be increased by mergers or obtaining emission income from stake sales. And he stated that the company may increase its periodic profits with a net cash flow that will be provided with a balanced budgeting. Also he stated that the risky corrected cash flow can be reduced each year by ensuring investment stability with appropriate dividend policies and incomes.

2.2 Financial Distress Prediction Studies in Turkey by Using Statistical Models

Since predicting financial distress is quite important for a company and its environment, financial distress studies within literature were also conducted in Turkey. However, probably the most important problem encountered in such a prediction study is limited numbers of regular and reliable data. When various sources are skimmed, only the data of the companies that are obliged to publicize their financial statements regularly can be reached. On the contrary, data obtained from other sources may cause reliability problems. Therefore, the obligation of working with the companies that publicize their financial statements brings together the problem of having only a few samples.

The first study in Turkey regarding financial failure was conducted by Göktan (1981). In this study, multivariate discriminant analysis was used and unmatched sampling method was utilized. In order to establish a model for Turkey, 19 financial ratios from three years' financial statements of 14 bankrupt companies and 35 successful companies between 1976 and 1980, were used. Study’s examination was extended back to 4 years prior to bankruptcy, a separate differentiation function was calculated for each year and predictions were made separately for each year based on these functions. The study predicts financial distress at the rate of 92.9% down to 1 year prior to bankruptcy, as the date goes further back from the date of bankruptcy, probability of a correct classification decreases.

In Turkey, the first financial distress prediction study made with logistic regression analysis technique, was conducted in 1997 by Aktas, who may be called as the pioneer of these studies in Turkey. Aktas (1997) discussed that sectors' financial characteristics are different from each other and developed financial distress prediction models for 6 sectors separately. For the analyses he used a sample of over 711 successful and 174 failed, a total of 885 companies in food, services, commerce, chemicals, machinery and textile sectors. He developed a separate prediction model for each sector. Using 26 financial ratios as independent variables, he tried to predict financial distress 1, 2 or 3 years before. He also developed a discriminant analysis method on the same sample for comparing it with logistic regression model and stated that logistic regression was able to assign companies to groups more successfully compared to discriminant analysis.

Atan and Gunes (2004), examines multidimensional financial failure prediction models in Turkish banking sector with multivariate statistical analysis methods. Commercial banks that take place within Turkish banking system were included into the sample. Regarding these banks, ratios obtained from financial statements published by Turkish Banks Association for three months' periods between September 2002 and September 2003 periods were used. In the model where discriminant analysis and regression analysis were used for financial distress prediction model, commercial banks transferred to Saving Deposit Insurance Fund and continuing commercial banks were examined. In the study, 68 financial ratios are examined under 8 main groups. Ratios effective in prediction of financial distress for each three months period between September 2002 and September 2003 for banks active in Turkish banking system, were determined. Atan and Gunes (2004), concluded that it may be possible to take measures for eliminating financial distress by detecting it beforehand via examination of banks' financial performances.

In a study conducted by Benli (2005), whether sectoral differences created any differences in ratios of industrial companies that were active in ISE in 2002 was examined. Benli (2005), used MANOVA statistical method to detected which rates originated these sectoral differences. She calculated 36 financial ratios by utilizing balances and income tables of 140 industrial companies, whose data were available to him. With the factor analysis where he applied 36 financial ratios, he had taken 10 factors as independent variables. In his study, Benli(2005) made a Multivariate Variance Analysis and observed that sectoral differences caused significant differences on ratios.

CHAPTER THREE

AN EMPIRICAL STUDY TO PREDICT FINANCIAL DISTRESS

It is a truism that companies' financial failures have high costs. Therefore, several models using different methods have been developed to predict financial distress. These models estimate whether the company would be in financial distress even before it starts business and enables taking certain measures in order to act in accordance with the situation.

The economic crisis that had been experienced in Turkey in the last 20 years, have high importance to take required precaution by predicting companies' bankruptcies. Senior managers are trying to estimate in which direction and how the financial ratios of the sector and of their companies will move. Therefore many models to predict financial distress of the companies have been developed. The conventional statistical models used for predicting the failures of the companies are: discriminant analysis, factor analysis and logistic regression analysis.

The aim of this study is to develop financial distress prediction model by using the financial statements of companies listed on Istanbul Stock Exchange (ISE) in Turkey, by utilizing these three methods, on the basis of their performances.

3.1 Application Method

As the methods of the study; discriminant analysis, factor analysis, and the logistic regression analysis method are used. In order to use these analysis methods, SPSS 17.0 for Windows package software is utilized. Stepwise method had been applied while practicing discriminant analysis and logistic regression analysis.

3.2 Sample Selection

In this study, manufacturing companies listed on Istanbul Stock Exchange comprised the samples. The main reason for this selection is the difficulty of accessing data pertaining to the companies which are not listed on ISE. The companies whose shares are traded in the stock exchange are obliged to present their independently audited financial statements regularly to the exchange. ISE listed companies' 3, 6, 9 and 12 months' financial statements and footnotes are provided in the ISE website.

Studies conducted on ISE listed companies have both advantages and disadvantages. These companies' financial statements' being independently audited uniform tables prepared in accordance with the standards determined by The Capital Market Board has prevented us from encountering any problem regarding the reliability of the data. The most important disadvantage of studying with these companies is the narrow of the companies in the study. Despite the fact that the number of firms within manufacturing sector in Turkey is over a thousand, it is observed that their number, within ISE is not more than 190. When the subsectors of ISE listed manufacturing companies are examined by years, approximately 35 companies are available within "textile, garment and leather" sectors. Even though this number changes by years, it has the highest number among the subsectors. However, in an environment where data is so few, making sector distress prediction is quite difficult. Thus, within the manufacturing sector, companies from various subsectors which may show different characteristics have been included in the sample.

Among the companies listed on ISE, financial institutions, holdings, trade and services companies, finance and insurance companies have not been included in the analysis, since they have different characteristics in terms of financial statements, and only the firms within manufacturing companies have been included in the analysis. Sample is dividend into two groups:

- Experimental group ,
- Control Group.

The experimental group constitutes the first phase of the study. 12 month balance sheets and income statements of 150 firms listed on ISE between 1996 and 2003, has been standardized in Microsoft Excel software. Financial statements available in the ISE website have been standardized and the firms have been identified within the definition of financial failure.

It is required to identify failure and non-failure, specify companies as failed and non-failed and develop the model by determining which financial ratios will be used in the analysis.

Within this context, financial failure companies are determined according to the following criteria: (Altman 1968)

- Companies that bankrupted,
- Companies that had loss for three or more consecutive years.

When financial statements between 1996 and 2003 of the experimental group companies are considered, the year of bankruptcy, or the first year loss for consecutive years has been accepted as the starting year of failure (t). The companies identified within this context have been called financially failed. In order to create a model that predicts financial failure one year prior, financial ratios of the firms that are selected according to the foregoing criteria are calculated based on their data one year prior to such failure (t-1). As for the financially non-failed group; the firms that are not coherent with any of these criteria are included. Thus, the companies that had negative income for two year but then achieved to have positive income also take place within the non-failed group. Existence of such companies in the sample requires the models to be quite sensitive. Because a company with loss figures may either be located in the financially failed group or the financially non-failed group. Lowest profit amount of non-failed firms between these years has been determined and financial ratios of these years are used for non-failed companies.

When the previously mentioned criteria are taken into consideration, among the manufacturing sector firms traded in ISE between 1996 and 2003, 105 non-failed companies against 45 failed companies have been identified. List of the experimental group companies included in the first phase of the study and their sectors are shown in the ANNEX I. In the list, the companies shown with "0" in their status column belong to financially failed companies group, while those with "1" belong to the financially non-failed company group.

In the years that belong to within the first phase of the study, "Historical Cost Series X. No:1" type financial statements determined by The Capital Market Board have been used. Based on the ground of uniformity in application, years between 1996 and 2003 are included in the first part of the study. Since Consolidated system was adopted after year 2004, these years will be included in the control group at the second part of the study.

Since financial ratios had been used as independent variable in the study, macroeconomic indicator data such as Gross National Product, interest rates and inflation rates have not been included in the scope of this analysis.

The experimental group data referred in the first phase of the study has been analyzed using discriminant analysis, factor analysis and logistic regression analysis, which are defined as multivariate statistical analysis models. Reliability of the function obtained on the dependent variables between 1996 and 2003, in terms of classification of the failed and the non-failed companies up to one year before failure has been tested individually for each of three analysis methods.

In the second part of the study; 2004-2008 financial statements of 35 failed and 115 non-failed manufacturing companies are considered. Blum's (1967) study was considered as control group data made up. In this context, the models obtained for each analysis method in the first part of the study have been applied to the companies between 2004 and 2008 separately. The per-sector list of companies included in the test group, named control group, is shown in the ANNEX II.

3.3 Selection of Independent Variables

Independent variables to predict financial distress are financial ratios which are applied in almost all the studies. Twenty-nine financial ratios have been determined after a comprehensive literature review regarding determination of financial ratios, 29 most effective financial ratios have been identified.

The 29 financial ratios, classified in 6 basic ratio groups are presented below. The ratios that are used in the study are as follows:

X1: Current Ratio

Current Asset / Current Liabilities

X2: Quick Ratio

(Current Liabilities-Inventories) / Current Liabilities

X3: Cash Ratio

(Cash+Cash Equivalents+Invested Funds) / Current Liabilities

X4:Net Working Capital to Total Asset Ratio

Net Working Capital / Total Asset

X5: Liquid Asset Ratio

Liquid Asset / Total Assets

X6: Debt Ratio

Total Debt / Total Asset

X7: Debt to Capital Ratio

Total Debt / (Shareholder’s Equity + Total Debt)

X8: Equity Multiplier

Total Asset / Shareholder’s Equity

X9: Short Term Debt to Total Asset Ratio

Short Term Debt / Total Asset

X10: Short Term Debt to Total Debt Ratio

Short Term Debt / Total Debt

X11: Long Term Debt to Total Debt Ratio

Long Term Debt / Total Debt

X12: Long Term Debts to Total Assets Ratio

Long Term Debt / Total Assets

X13: Capital to Equity Ratio

(Shareholder’s Equity + Total Debt) / Shareholder’s Equity

X14: Fixed Asset to Equity Ratio

Fixed Asset / Shareholder’s Equity

X15: Fixed Asset to Long Term Ratio

Fixed Asset / Long Term Debt

X16: Receivables Turnover Ratio

Annual Sales / Accounts Receivable

X17: Days Sales Outstanding Ratio

(365*Accounts Receivable) / Annual Sales

X18: Inventory Turnover Ratio

Annual Sales / Inventory

X19: Net Working Capital Turnover Ratio

Net Sales / Average Net Operating Working Capital

X20: Current Asset Turnover Ratio

Net Sales / Current Asset

X21: Tangible Fixed Asset Turnover Ratio

Net Sales / Tangible Fixed Asset

X22: Total Asset Turnover Ratio

Net Sales / Total Asset

X23: Equity Turnover Ratio

Net Sales / Shareholder's Equity

X24: Gross Profit Margin Ratio

Gross Margin / Net Sales

X25: Profit Margin Ratio

Net Income / Net Sales

X26: Operating Profit Margin Ratio

Operating Income / Net Sales

X27: EBIT Margin Ratio

EBIT / Net Sales

X28: Return on Equity

Net Income / Shareholder's Equity

X29: Return on Asset

Net Income / Total Asset

3.4 Models for Financial Distress

This part of the study compares models predicting the financial failure of company one year prior, then the most powerful model in terms of classification have been determined. For this purpose, SPSS 17.0 for Windows software has been utilized. Multiple Discriminant Analysis and

Logistic Regression Analysis conducted on factors obtained after Multiple Discriminant Analysis and Factor Analysis have been used as models for financial distress prediction.

3.4.1. Multiple Discriminant Analysis Model

Multiple Discriminant Analysis is a statistical method widely used in financial failure prediction studies. Multiple Discriminant Analysis reveals whether a significant discrepancy exists between two or more groups. The following is a Multiple Discriminant Analysis Model.

$$Z_i = B_0+B_1X_1+B_2X_2+..........+B_mX_m$$

Here

Z_i= Discriminant Score

B_0=Constant Value

B_m= Discriminant Coefficients

X_m= Independent Variables.

In this part of the study; a Discriminant Analysis is applied for the data obtained one year prior to the failure of the company matching the failed criterion and Discriminant function is developed. Twenty-nine financial ratios have been entered in the software. Six variables discriminant model was obtained through stepwise method. The Discriminant Analysis Model obtained is as follows:

Table 3.1 : Discriminant Analysis Function

Dependent Variables	Ratios	Coefficient
X4	Net Working Capital to Total Asset Ratio	0.700
X9	Short Term Debt to Total Asset Ratio	2.073
X10	Short Term Debt to Total Debt Ratio	3.169
X22	Total Asset Turnover Ratio	0.02
X24	Gross Profit Margin Ratio	0.196
X25	Profit Margin Ratio	3.922
Constant		-0.175

$$Z = + 0.700*X4 + 2.073*X9 + 3.169*X10 + 0.02*X22 + 0.196*X24 + 3.922*X25$$

Table 3.2 Discriminant Analysis Results

Function	Eigenvalues	Canonical Correlation	Wilks' Lambda	Sig.
1	4.540	0.905	0.181	0,000

The Eigen values under Canonical Discriminant Functions which are listed among the Discriminant Analysis Results in Annex 4 are used in assessing the success of Discriminant Analysis. The Eigenvalue we obtained is found as 4.540. Eigenvalues have no upper limit, however for the Discriminant Analysis values above 0.40 are accepted as successful. Again "canonical correlation" coefficient under "Canonical Discriminant Functions" shows the degree of the relationship between separation scores and groups. Canonical correlation takes a value between 0 and 1. There is no relationship between groups with "0" Discriminant Analysis score, and there is an absolute relationship with "1". Wilks' Lambda value is an indicator of whether there is difference between group means. Big Wilks' Lambda value reveals that the group means are not different, while small lambda shows that the group means are different. The smaller this value is, higher the distinctive force of the function. Wilks' Lambda value of 0.181 obtained through the Discriminant Analysis does not make a clear statement regarding group means, however what it says is that the 18.1% of the total variance can not be explained with the function developed as a result of the model.

Table 3.3 The Group Average of Failed and Non-Failed Company

Group	Function
Failed	2.464
Non-Failed	-1.807

The average of group means gives the critical value that will be used in determination of the separation group members. Therefore;

Critical Value = (2.464 + (-1.807)) / 2 = 0.3285

0.3285 means that; if the discriminant score of the firm is higher than 0.3285, the firm should have failed; and if this score is lower than 0.3285, then the firm should not failed. The discriminant scores obtained through application of discriminant functions into data set, comparisons with groups that they are selected and the groups that the companies belong are given as Discriminant Result in ANNEX III.

Finally, the discriminant analysis's results in Table 3.4 classify only 2 of the 45 failed companies as non-failed. This means that ALFA type error rate is 4.4%. Similarly according to the discriminant analysis's results obtained, none of 105 non-failed companies are classified as failed. This shows that BETA type error rate is zero. Average correct classification of this analysis has been observed as 98.7%. This is a substantially good rate in terms of classification.

Table 3.4 Classification Rate of Disciriminant Analysis on the Experimental Data

	Failed	**Non-failed**	**Total**
Failed **%**	44 97.8	1 2.2	45 100
Non-failed **%**	1 1.0	104 99.0	105 100
The Average of Correct Classification=(45* 0.978+ 105 * 0.99) / 150 = 98.7%			

Aim of the second phase of the study is to test the failure prediction of model by using control group companies between 2004 and 2008. In other words, the aim is to apply discriminant function to the control data that belong to 35 failed and 115 non-failed companies between 2004 and 2008.

Six financial ratios of the companies are obtained through the control group data which are gathered from financial statements between 2004 and 2008. Ratios have been put into their places in the previous function and each firm has been classified, as failed or non-failed. If the value revealed is higher than 0.3285, it has been included in the financially failed group, and if it is lower than 0.3285 it has been included in non-failed group. The Discriminant Analysis result obtained within the control group is shown in the following table.

Table 3.5 Classification Rate of Disciriminant Analysis on the Control Data

	Failed	**Non-failed**	**Total**
Failed **%**	27 77.1	8 22.9	35 100
Non-failed **%**	16 14.0	99 86.0	115 100
The Average of Correct Classification= (35* 0.771 + 115 * 0.86) / 150 = 85.3%			

The discriminant function developed according to this result has produced significantly successful results on new data. It has correctly predicted 27 of the 35 failed companies, and 99 of the 115 non-failed companies. ALFA type error rate of the model that classified 8 of 35 failed companies as non-failed company is 22.9%. Similarly, the BETA type error rate of the model that included 16 of the 115 non-failed companies into the group of failed company is 14.0 %. Finally, correct classification mean of the discriminant analysis on test data is found as 85.3%.

As acquired function taking part financial ratios coefficients and failed-nonfailed firms determine that appreciate critical value relation, the signs in front of the coefficients that found this function was seen not enough expressive. So Factor Analysis method and Logistic Regression method were used so that financial analyses give more sensitive results. Lowering the number of independent variables was targeted by making factor analysis. The aim is to make a Discriminant Analysis again using the newly formed independent variables. Consequently, the Discriminant Analysis has not yet been finalized.

3.4.2. Discriminant Analysis Developed Using Factor Analysis

In order to reduce the number of variables, in other words to reduce the size, a factor analysis has been primarily applied to the variables. In this way, many correlated variables have been converted into small number of independent factors. In the following phase, discriminant analysis method has been applied on the factors obtained.

Factor analysis results are given in ANNEX-5. In order to understand whether it is appropriate to apply factor analysis to our data set consisting of 29 ratios pertaining to 150 companies selected in accordance with the failed and non-failed criteria, we need to use KMO test. As seen in the following table, KMO test score is 0.514. This value's being over 0.40 means that our data set is appropriate for factor analysis.

Table 3.6 KMO and Bartlett Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Mesaure of Sampling Adequacy		0.514
Bartlet's Test of Sphericity	Appro Chi Square	6068.902
	Df	406
	Sig.	0.000

As a result of factor analysis, 29 financial ratios explain 81.392% of total variance under 9 factors.

"Rotated Component Matrix" is used to make decision concerning how should the groups factor the 29 variables in factor analysis. In this matrix, variables are placed in horizontal columns and factors are in vertical columns. The Factor Analysis SPSS outputs are in ANNEX IV, where there is a table regarding which factor groups are included the factor ratios.

Discriminant Analysis is applied over of 9 new independent variables obtained as a result of Factor Analysis explaining the 81.392% of 29 independent variables.

Table 3.7 Rotated Factor Analysis Table

Rotated Component									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
x27	.978								
x26	.978								
x28	.978								
x17	-.930								
x4	-.832								
x8	-.830								
x29	.824								
x21		.971							
x23		.894							
x20		.861							
x16		.850							
x2			.909						
x1			.904						
x9			-.731						
x24				.815					
x5				.795					
x10				-.685					
x25				.526					
x22					.868				
x3					.812				
x18					-.613				
x12						-.823			
x11						.813			
x13							.866		
x14							.815		
x15								.960	
x19									.586
x6									.583
x7									-.527

Table 3.8 Results of Discriminant Analysis Implemented after Factor Analysis

Function	Eigen values	Canonical Correlation	Wilks' Lambda	Sig.
1	2.019	0.818	0.331	0.000

As a result of factor analysis, 29 independent variables are collected under 9 factors and factor scores related to the mentioned factors are obtained. The factor scores obtained through factor analysis will be used in Discriminant Analysis. Wilks' Lambda value, which shows whether the group means are different, is obtained as 0.331. It says that 33.1% of the total variance can not be explained with the function developed as a result of the model. 0.331 shows high the distinctive force of the function.

Discriminant Analysis Method will be applied by using the factors of grouped companies. That is, Discriminant Analysis is applied on the 9 new independent variables containing financial ratios obtained by factor analysis. The Eigenvalues, which shows the success of the Discriminant Analysis model, is calculated as 2.019. Eigenvalues have no upper limit and its being over 0.4 shows that the method applied is successful.

When we look at the values related to separation analysis in Table 3.8, Canonical Correlation coefficient showing the relation between separation scores and groups is calculated as 0.818. Which means that function developed as a result of the model can explain the relation between Discriminant Analysis scores and groups, at a rate of 81.8%.

Table 3.9: Discriminant Analysis Function Implemented after Factor Analysis

Factors	Function
FACT 1	-0.256
FACT 3	-0.736
FACT 4	1.062
Constant	0.000

The Discriminant Function predicts companies' failures one year before. It is developed by applying Discriminant Analysis to the 9 factors. 3 factors enter into the equation.

Z= -0. 256 * FACTOR 1 + - 0,736 * FACTOR 3 + 1.062 * FACTOR 4

Table view of the function obtained is available in Table 3.10.

Table 3.10: Financial Ratios in the Functions of Discriminant Analysis Implemented after Factor Analysis

FACTORS	RATIOS
FACTOR 1	Operating Profit Margin Ratio EBIT Margin Ratio Return On Equity Return on Asset Days Sales Outstanding Ratio Equity Multiplier Net Working Capital to Total Asset Ratio
FACTOR 3	Current Ratio Quick Ratio Short Term Debt to Total Asset Ratio
FACTOR 4	Liquid Asset Ratio Short Term Debt to Total Debt Ratio Gross Profit Margin Ratio Profit Margin Ratio

The experimental data consisting of 45 failed and 105 non-failed, a total of 150 companies are used in this part of the study. Failure from one year before prediction power of the function is shown in Table 3.11:

Table 3.11: Classification Rate of Disciriminant Analysis Implemented after Factor Analysis on the Experimental Data

	Failed	Non-failed	Total
Failed	38	7	45
%	84.4	15.6	100
Non-failed	0	105	105
%	0	100	100
The Average of Correct Classification= (45* 0.844 + 105 * 0) / 150 = 95.3%			

As seen on Table 3.10, significantly successful results are reached on the function. ALFA type error rate of the model that classified 38 of 45 failed companies as failed and 7 of them as non-failed is 15.6%. BETA type error rate of the function that classified none of 105 non-failed companies as failed is 0%. According to this result, it is seen that the developed model is effective for predicting non-failed companies. Finally, the average of correct classification success on the data where discriminant analysis is developed is found as 95.3%.

In the second part, the aim was to test the Discriminant Analysis result of the model developed after the Factor Analysis. The model was applied on the firms between 2004 and 2008. The group centers obtained for the previous discriminant function is 1.643 for failed companies and -1.205 for non-failed companies. The separating value to be used for classifying companies into groups in accordance with the discriminant values is;

$$(1.643 + (-1.205)) / 2 = 0.219.$$

0.219 is the mean of these two group centers. Consequently, the companies with a discriminant score lower than 0.219 will be classified as non-failed and those over 0.219 as failed. According to the Discriminant Analysis score, the function's success in classifying new data is shown in Table 3.12:

Table 3.12 Classification Rate of Disciriminant Analysis Implemented after Factor Analysis on the Control Data

	Failed	**Non-failed**	**Total**
Failed **%**	31 88.6	4 11.4	35 100
Non-failed **%**	13 11.3	102 88.7	115 100
The Average of Correct Classification=(35* 0.886 + 105 * .887) / 150 =88.7%			

31 of 35 failed companies were classified as failed and 4 of them as non-failed in the control group. Similarly, 102 of 115 non-failed companies were classified as non-failed and 13 of them as failed. According to this result, ALFA type error which shows failed company as non-failed company was found as 11.4%, while BETA type error, which shows non-failed company as failed, was found as 11.3%. Finally, correct classification mean of the discriminant analysis on new data is found as 88.7%. This result revealed that the prediction capacity of the Discriminant Analysis model conducted in different periods with 9 independent variables determined after applying factor analysis is significantly high.

3.4.3. Logistic Regression Analysis

In Logistic Regression Analysis, dependent variables are simply the logarithm of the probability of a special event. In other words, in Logistic Regression Analysis, odds ratio (the ratio of belonging a group) logarithm is tried to be modeled, instead of modeling the group membership itself. We model the logarithm of probabilities as follows:

$$Logit_i = \ln (P / (1-P)) \qquad (1)$$

In a sample whose financial failure probability is P, probability of not becoming financially failed is 1-P. As a result, P and 1-P are two events that complete each other.

In Logistic Regression Analysis, parameters are calculated using a non-linear method of calculating maximum probability.

Logit variable is calculated on the basis of logarithm,

$$Z_i = B_0+B_1X_{i1}+B_2X_{i2}+..........+B_mX_{im} \quad (2)$$

based on the formula;

$$(P / (1-P) = e^Z \qquad (3)$$

From (3);

$$P=e^z / (1+e^z) \qquad (4)$$

is found. When the denominator is divided by e^{z}';

$P=1 / (1+ e^{-Z})$ is obtained.

Here;

Z; Logistic regression model

P; failure probability for given characteristics vector

B_m; coefficient of characteristic

B_0; constant

X_{im}= value of characteristic m of company i

e= base of natural logarithm

Since this equation is linear according to its parameters, the process of prediction becomes simplified. (Maddala, 1999: 24-25). Probability of success for each individual is predicted. If this probability is more than 0.5, it is in non-failed and if its is less than that it is in failed group. (Wooldridge, 2003)

By considering financial statements between 1996 and 2003, logistic regression model has been established on the experimental group data from one year prior to failure, through SPSS 17.0 for Windows software. Twenty-nine financial ratios have been entered to the software and 3-variable logistic model was obtained through forward stepwise method. Program outputs related to logistic regression model are given in ANNEX-V. The model obtained is as follows:

$Z_i = 2.755 + 42.210 * X10 - 0.18 * X22 - 129.745\ X25$

X10: Short Term Debt to Total Debt Ratio

X22: Total Asset Turnover Ratio

X25: Profit Margin Ratio

In order to be able to predict a company's failure and non-failure status through this model, initially three of the company's financial ratios available within the model are calculated and appropriately placed in the model. Through the following formula, calculated Z value of the company is converted into the the company's probability of success.

$$P=1/ (1+ e^{-Z})$$

If the probability obtained is bigger than 0.50, the company is classified as non-failed, or otherwise, as failed.

Table 3.13 Classification Rate of Logistic Regression Analysis on the Experimental Data

	Failed	**Non-failed**	**Total**
Failed **%**	45 100	0 0	45 100
Non-failed **%**	1 1	104 99	105 100
The Average of Correct Classification=(45* 1.0 + 105 * .99) / 150 =99.3%			

Accordingly, all of the failed companies were identified as failed as a result of the Logistic Regression Analysis and none of the failed companies were included in the group of non-failed companies. In this case, ALFA type error rate, which is also called as first type error that includes failed companies to the group of non-failed companies, is 0%. Similarly, 104 of the 105 non-failed companies were included in the non-failed company group, while 1 of them was included in the failed group. Alike the failed company grouping; misclassification of non-failed companies, in other words BETA type error rate, which is also called as second type error, that classifies non-failed companies as failed, is merely 1%.

While correct classification status of the function obtained through Discriminant Analysis and expressible with 6 independent variables is 97.3%; correct classification status of the function obtained through Logistic Regression Analysis and expressible with 3 independent variables is 99.3 %, which is a significantly strong result of model success. Such a high percentage in correct classification of the model that predicts failure back to one year prior to the failure is due to the fact that the Logistic Regression Analysis is more advantageous than Discriminant Analysis in non-linear situation.

The second phase of the Logistic Regression Analysis tests the correct classification of the Logistic Regression Function, which is obtained according to 3 financial ratios in Logistic Regression Analysis on 35 failed and 115 non-failed control group companies determined using financial statements between 2004 and 2008. As in the other two methods, it aims to determine the success of correct classification of companies one year prior to failure, yet for different years and different companies. Using the Logistic Regression Analysis obtained, a value P has been found, by calculating the 35 failed and 115 non-failed companies' financial ratios available in the function, between

2004 and 2008. If the value P is bigger than 0.50, the company is classified as non-failed, or otherwise, as failed.

In Table 3.14, correct classification rate of predicting failure one year prior on the control data of the function obtained as a result of Regression Analysis is given.

Table 3.14: Classification Rate of Logistic Regression on the Control Group

	Failed	**Non-failed**	**Total**
Failed **%**	33 94.3	2 5.7	35 100
Non-failed **%**	110 95.7	5 4.3	115 100
The Average of Correct Classification=(35* 0.943 + 105 * .957) / 150 =95.3%			

According to Table 3.14, Logistic Regression Function classified has included 33 of 35 failed companies into the group of failed companies and 2 of them into the group of non-failed companies, on the control data. In other words, ALFA type error rate, which is also called as first type error which includes failed companies to the group of non-failed companies, is calculated as 5.7%. Similarly, it classified 110 of 115 non-failed companies into the group of non-failed companies, and included 5 of them into the group of failed companies. BETA type error rate, is calculated as 4.3%. Finally, correct classification mean of the logistic regression analysis on control data is found as 95.3%. Such a high test performance compared to the two other models is due to the reasons described above.

Table 3.15 shows the 1996-2003 experimental data's and 2004-2008 control data’s value of correct classification of failure one year prior, according to each of the three models. In this case, the rate of correct classification in each three model actualized is over 80%. This rate shows that all these 3 models developed are significantly effective in predicting failures, one year prior to such failure.

Table 3.15 Comparison of the Models Classification Rate

Analysis Method	Experimental Data (1996-2003)	Control Data (2004-2008)
Discriminant Analysis	98.7	85.3
Discriminant Analysis with Factor Analysis	95.3	88.7
Logistic Regression Analysis	99.3	95.3

CONCLUSION

The issue of predicting financial failure covers an important place in the scope of financial analysis, since all the interested groups related to the company will be affected by financial failure. Financial failure is an undesired situation, and prediction of financial failure is crucial for managers, investors, creditors, government, market regulating organizations and independent auditors. A model to be used for predicting financial failure is significantly important, since it will help managers in providing objective information on the future of their companies; creditors in swiftly and correctly eliminating credit applications; investors in determining companies at various risk levels as well as the timing for the investment; and government in making appropriate macroeconomic decisions.

Lack of a perfect prediction method that may be used in any environment under any condition leads to continuation of the search for an appropriate model by using different methods on different data. Hence in this study, by using the conventional statistical techniques, identification of the most appropriate method is aimed by comparing the performance in predicting companies' failures. In this study, performance of the techniques will be compared by using the Turkish Manufacturing companies to predict financial failure one year before.

First part of the study uses the experimental group data, which consists 150 manufacturing sector companies, active between 1996 and 2003. They are also subject to Capital Markets Regulations and listed on Istanbul Stock Exchange. 45 of these companies are financially failed companies and other 105 are non-failed companies. Twenty-nine financial ratios pertaining to these companies have been included in the models as independent variables. In the second part, which uses the control group, 35 failed and 115 non-failed companies active between 2004 and 2008 were selected. Over the test group sampling data consisting of a total of 150 companies, validity analysis test was applied on the models. The correct classification capacity of the models tested in different periods with different companies was found out to be significantly high.

Independent variables of Discriminant Analysis function which are obtained through Discriminant Analysis method are the following ones:

X4: Net Working Capital to Total Asset Ratio

X9: Short Term Debt to Total Asset Ratio

X10: Short Term Debt to Total Debt Ratio

X22: Total Asset Turnover Ratio

X24: Gross Profit Margin Ratio

X25: Profit Margin Ratio

These ratios are the financial ratios that explain the function obtained with the Discriminant Analysis method best. The variables found significant as a result of model built by Discriminant. As a result of Discriminant Analysis, correct classification on experimental group data 98.7%, while it was observed as approximately 85.3% on the control group. Discriminant Analysis method practiced after the Factor Analysis method is also applied

Mean capacity of these 3 new factors in predicting failure one year before is observed as 99.3% on experimental data. According to this model, the capacity of correctly classifying non-failed company is significantly more successful than its capacity of classifying failed companies. On the test data processed for different companies according to 2004-2008 financial statements, it is seen that the correct classification rate of companies one year prior to failure was observed as 88.7%. When we examine the result of first two models on the control group, the Discriminant Analysis give better classification rate than Factor Analysis results.

Thirdly, correct classification of companies one year prior to failure in the Logistic Regression Analysis has been observed as 99.3%, according to the results obtained with the forward stepwise method applied to the experimental group formed by using the financial statements between 1996 and 2003. Finally, the independent variables used in Logistic Regression Analysis were controlled on the experimental groups determined by using the financial statements between 2004 and 2008. The correct classification of companies one year prior to failure has been observed as 95.3%. Regarding the highness of the value compared to the other two, it can be said that this result is due to the fact that the logistic regression model has non-linear characteristics. The 3 independent variables in the function obtained from the Logistic Regression Model are respectively:

X10: Short Term Debt to Total Debt Ratio

X22: Total Asset Turnover Ratio

X25: Profit Margin Ratio

Among these financial ratios; in each of these three models Short Term to Total Debt and Profit Margin Ratio have important value.

The findings obtained in the study reveals that the logistic regression model makes predictions with higher correct classification ratios, compared to the discriminant analysis and the discriminant analysis that is applied to the factors that take shape after the factor analysis.

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APPENDIX I

EXPERIMENTAL DATA

NO	COMPANY CODE	COMPANY NAME	FAILED / NON-FAILED *
1	ADANA	Adana Çimento	1
2	ADEL	Adel Kalemcilik	1
3	AEFES	Anadolu Efes	1
4	AFYON	Afyon Çimento	1
5	AKALT	Akal Tekstil	1
6	AKCNS	Akçansa Çimento	1
7	AKIPD	Aksu İplik Dokuma ve Boya Apre Fabr.	1
8	AKSA	Aksa Akrilik Kimya	1
9	ALCAR	Alarko Carrier	1
10	ALKA	Alka Kağıt	1
11	ALKIM	Alkım Alkali Kimya	1
12	ALTIN	Altınyıldız	1
13	ALYAG	Altındağ Yağ	1
14	ANACM	Anadolu Cam	1
15	ARCLK	Arçelik	1
16	ARSAN	Arsan Tekstil	1
17	ASUZU	Anadolu Isuzu	1
18	ATEKS	Akın Tekstil	1
19	AYGAZ	Aygaz	1
20	BAGFS	Bagfaş	1
21	BAKAB	Bak Ambalaj	1
22	BANVT	Banvit	1
23	BEKO	Beko Elektronik	1
24	BERDN	Berdan Tekstil	0
25	BFREN	Bosch Fren	1
26	BISAS	Bisaş Tekstil	0
27	BOLUC	Bolu Çimento	1

28	BOSSA	Bossa	1
29	BRISA	Brisa	1
30	BRMEN	Birlik Mensucat	0
31	BRSAN	Borusan Boru	1
32	BSHEV	Bosh Ev Aletleri	1
33	BSOKE	Batı Söke Çimento	1
34	BTCIM	Batıçim	1
35	BUCIM	Bursa Çimento	1
36	BURCE	Burçelik	0
37	BYSAN	Boyasan Tekstil	0
38	CBSBO	ÇBS Boya Kimya	1
39	CELHA	Çelik Halat	1
40	CEMTS	Çemtaş	1
41	CEYLN	Ceylan Giyim	1
42	CIMSA	Çimsa	1
43	CMBTN	Çimbeton	1
44	CMENT	Çimentaş	0
45	DARDL	Dardanel	1
46	DENCM	Denizli Cam	0
47	DENTA	Dentaş Ambalaj	0
48	DERIM	Derimod	1
49	DEVA	Deva Holding	1
50	DGZTE	Doğan Gazete	1
51	DITAS	Ditas Doğan	0
52	DMSAS	Demisaş Dokum	1
53	DOBUR	Dogan Burada Rizzoli Dergi	0
54	DOKTS	Doktas	0
55	DURDO	Duran Ofset	1
56	DYOBY	Yasaş	1
57	ECILC	Eczacıbaşı İlaç	1
58	ECYAP	Eczacıbaşı Yapı	1
59	EGEEN	Ege Endüstri	1
60	EGGUB	Ege Gübre	0

61	EGSER	Ege Seramik	0
62	EMKEL	Emek Elektrik	0
63	EMNIS	Eminiş Ambalaj	0
64	EMPAS	Empas Ambalaj	0
65	EMSAN	Emsan	1
66	ERBOS	Erbosan	0
67	EREGL	Ereğli Demir Çelik	1
68	ERSU	Ersu	1
69	ESEMS	Esemspor	1
70	FENIS	Feniş Alüminyum	0
71	FMIZP	Federal Mogul İzmit Piston	1
72	FRIGO	Frigo Pak	1
73	FROTO	Ford Otosan	0
74	GEDIZ	Gediz İplik	1
75	GOODY	Gentaş	0
76	GUBRF	Gübre Fabrikaları A.Ş	1
77	GUMUS	Gümüşsuyu	1
78	HEKTS	Hektaş	1
79	HURGZ	Hürriyet Gazetecilik	1
80	HZNDR	Hazneder Ateş Tuğla	1
81	IDAS	İdaş	0
82	IHEVA	İhlâs Ev Aletleri	0
83	ISAMB	Işıklar Ambalaj / Çumra Kağıt	1
84	IZMDC	İzmir Demir Çelik	1
85	IZOCM	İzocam	0
86	KAPLM	Kaplamin Ambalaj	1
87	KARSN	Karsan	0
88	KARTN	Kartonsan	0
89	KENT	Kent Gıda	0
90	KERVT	Kerevitaş Gıda	1
91	KLBMO	Kelebek Mobilya	0
92	KLMSN	Klimasan	1
93	KNFRT	Konfrut Gıda	1

94	KONYA	Konya Çimento	1
95	KORDS	Kordsa Sabancı Dupont	0
96	KOZAD	Koza Davetiye	1
97	KRDMA	Kardemir Demir Çelik	1
98	KRSTL	Kristal Kola	1
99	KRTEK	Karsu Tekstil	0
100	KUTPO	Kütahya Porselen	1
101	LUKSK	Lüks Kadife	0
102	MARDN	Mardin Çimento	0
103	MDRNU	Mudurnu Tavukçuluk	0
104	MEMSA	Mensa Mensucat	0
105	MERKO	Merko Gıda	0
106	METAS	Metaş	1
107	MNDRS	Menderes Tekstil	1
108	MRSHL	Marshall Boya	1
109	MTEKS	Metemteks Tekstil	0
110	MUTLU	Mutlu Akü	1
111	NUHCM	Nuh Çimento	1
112	OKANT	Okan Tekstil	1
113	OLMKS	Omluksa	1
114	OTKAR	Otokar	0
115	PARSN	Parsan	1
116	PEKTM	Pektim	0
117	PENGD	Penguen Gıda	0
118	PETUN	Pınat Et ve Un	1
119	PIMAS	Pimaş	1
120	PINSU	Pınar Su	0
121	PNSUT	Pınar Süt	1
122	PRKAB	Türk Prysmian Kablo Ve Sistemleri	1
123	PRTAS	ÇBS Printai	0
124	PTOFS	Petrol Ofisi	1
125	SARKY	Sarkuysam	0
126	SASA	Sasa	1

127	SERVE	Serve Kırtasiye	0
128	SEZGD	Sezginler Gıda	1
129	SKPLC	Şeker Piliç	0
130	SKTAS	Söktaş	1
131	SODA	Soda Sanayii	1
132	SOKSA	Söksa	1
133	TATKS	Tat Konservecilik	1
134	TBORG	Türk Tuborg	1
135	TIRE	Tire Kutsan	0
136	TOASO	Tofaş Oto Fabrika	1
137	TRKCM	Trakya Cam	0
138	TUDDF	Türk Demir Döküm	1
139	TUKAS	Tukaş Gıda	1
140	TUMTK	Tümteks Tekstil	1
141	TUPRS	Tüpraş	1
142	ULKER	Ülker Gıda	1
143	UNYEC	Ünye Çimento	1
144	USAK	Uşak Tarım	1
145	UZEL	Uzel Makine	1
146	VAKKO	Vakko	1
147	VANET	Van Et	1
148	VESTL	Vestel	1
149	YATAS	Yataş	1
150	YUNSA	Yünsa	1

* FAILED = 0
  NON-FAILED = 1

APPENDIX II

CONTROL DATA

NO	COMPANY CODE	COMPANY NAME	FAILED / NON-FAILED *
1	ADANA	Adana Çimento	1
2	ADBGR	Adana Çimento(B)	1
3	ADEL	Adel Kalemcilik	1
4	ADNAC	Adana Çimento(C)	1
5	AEFES	Anadolu Efes	1
6	AFYON	Afyon Çimento	1
7	AKALT	Akal Tekstil	0
8	AKCNS	Akçansa Çimento	1
9	AKIPD	Aksu İplik Dokuma ve Boya Apre Fabr.	0
10	AKSA	Aksa Akrilik Kimya	1
11	ALCAR	Alarko Carrier	1
12	ALKA	Alka Kağıt	1
13	ALKIM	Alkım Alkali Kimya	1
14	ALTIN	Altınyıldız	1
15	ALYAG	Altındağ Yağ	0
16	ANACM	Anadolu Cam	1
17	ARAT	Arat Tekstil	0
18	ARCLK	Arçelik	1
19	ARSAN	Arsan Tekstil	0
20	ASUZU	Anadolu Isuzu	1
21	ATEKS	Akın Tekstil	0
22	AYGAZ	Aygaz	1
23	BAGFS	Bagfaş	1
24	BAKAB	Bak Ambalaj	1
25	BANVT	Banvit	1
26	BERDN	Berdan Tekstil	0
27	BFREN	Bosch Fren	1

28	BOLUC	Bolu Çimento	1
29	BOSSA	Bisaş Tekstil	1
30	BRISA	Brisa	1
31	BRSAN	Birlik Mensucat	1
32	BSHEV	Bosh Ev Aletleri	1
33	BSOKE	Batı Söke Çimento	1
34	BTCIM	Batıçim	1
35	BUCIM	Bursa Çimento	1
36	BURCE	Burçelik	0
37	BURVA	Burçelik Vana	0
38	CELHA	Çelik Halat	1
39	CEMTS	Çemtaş	1
40	CIMSA	Çimsa	1
41	CMBTN	Çimbeton	1
42	CMENT	Çimentaş	1
43	COMDO	Componenta Dökümcülük	1
44	DARDL	Dardanel	1
45	DENCM	Denizli Cam	1
46	DENTA	Dentaş Ambalaj	1
47	DERIM	Derimod	1
48	DESA	Desa Deri	1
49	DEVA	Deva Holding	1
50	DGZTE	Doğan Gazete	1
51	DITAS	Ditas Doğan	1
52	DMSAS	Demisaş Dokum	1
53	DURDO	Dogan Burada Rizzoli Dergi	0
54	DYOBY	Yasaş	0
55	ECILC	Eczacıbaşı İlaç	1
56	ECYAP	Eczacıbaşı Yapı	1
57	EGEEN	Ege Endüstri	1
58	EGGUB	Ege Gübre	1
59	EGIYM	Egeser Giyim	0
60	EGSER	Ege Seramik	1

61	EMKEL	Emek Elektrik	1
62	EMNIS	Eminiş Ambalaj	0
63	ERBOS	Erbosan	1
64	EREGL	Ereğli Demir Çelik	1
65	ERSU	Ersu	0
66	FENIS	Feniş Alüminyum	1
67	FMIZP	Federal Mogul İzmit Piston	1
68	FRIGO	Frigo Pak	0
69	FROTO	Ford Otosan	1
70	GEDIZ	Gediz İplik	0
71	GENTS	Gentaş	1
72	GEREL	Gersan Elektrik	1
73	GOLDS	Goldaş Kuyumculuk	1
74	GOLTS	Göltaş Çimento	1
75	GOODY	Goodyear Lastik	1
76	GRUND	Grunding Elektronik	0
77	GUBRF	Gübre Fabrikaları A.Ş	1
78	HEKTS	Hektaş	1
79	HURGZ	Hürriyet Gazetecilik	1
80	HZNDR	Hazneder Ateş Tuğla	1
81	IHEVA	İhlâs Ev Aletleri	1
82	ISAMB	Işıklar Ambalaj	1
83	IZMDC	İzmir Demir Çelik	1
84	IZOCM	İzocam	1
85	KAPLM	Kaplamin Ambalaj	1
86	KARSN	Karsan	1
87	KARTN	Kartonsan	1
88	KENT	Kent Gıda	1
89	KERVT	Kerevitaş Gıda	1
90	KLBMO	Kelebek Mobilya	0
91	KLMSN	Klimasan	1
92	KNFRT	Konfrut Gıda	1
93	KONYA	Konya Çimento	1

94	KORDS	Kordsa	1
95	KOTKS	Koniteks Tekstil	0
96	KOZAA	Koza Anadolu	1
97	KRDMA	Kardemir	1
98	KRSTL	Kristal Kola	0
99	KRTEK	Karsu Tekstil	1
100	KUTPO	Kütahya Porselen	1
101	LIOYS	Lio Yağ	0
102	LUKSK	Lüks Kadife	1
103	MEGES	Meges Boya	0
104	MERKO	Merko Gıda	0
105	MNDRS	Menderes Tekstil	1
106	MRDIN	Mardin Çimento	1
107	MRSHL	Marshall Boya	1
108	MTEKS	Metaş	0
109	MUTLU	Mutlu Akü	1
110	NUHCM	Nuh Çimento	1
111	OLMKS	Omluksa	1
112	OTKAR	Otokar	1
113	PARSN	Parsan Makine	1
114	PENGD	Penguen Gıda	0
115	PETKM	Pektim	1
116	PETUN	Pınat Et ve Un	1
117	PIMAS	Pimaş	1
118	PINSU	Pınar Su	1
119	PNSUT	Pınar Süt	1
120	PRKAB	Türk Prysmian Kablo Ve Sistemleri	1
121	PTOFS	Petrol Ofisi	1
122	RAKSE	Raks Elektronik	0
123	RKSEV	Raks Elektrikli Ev Aletleri	0
124	SABAH	Sabah Yayıncılık	0
125	SARKY	Sarkuysan	1
126	SASA	Sasa	0

127	SERVE	Serve Kırtasiye	1
128	SKPLC	Şeker Piliç	0
129	SODA	Soda Sanayii	1
130	TATKS	Tat Konserve	0
131	TBORG	Türk Tuborg	0
132	TIRE	Tire Kutsan	1
133	TOASO	Tofaş Oto Fabrika	1
134	TRCAS	Türcas Petrol	1
135	TRKCM	Trakya Cam	1
136	TTRAK	Türk Traktör	1
137	TUDDF	Türk Demir Döküm	1
138	TUKAS	Tukaş Gıda	1
139	TUPRS	Tüpraş	1
140	UKIM	Uki Konfeksiyon	0
141	ULKER	Ülker Gıda	1
142	UNTAR	Ünal Tarım	0
143	UNYEC	Ünye Çimento	1
144	UZEL	Uzel Makine	1
145	VAKKO	Vakko	1
146	VANET	Van Et	1
147	VESBE	Vestel Beyaz	1
148	VKING	Viking Kağıt	0
149	YATAS	Yataş	1
150	YUNSA	Yünsa	1

* FAILED = 0
NON-FAILED = 1

DISCRIMINANT ANALYSIS RESULTS

Summary of Canonical Discriminant Functions

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	4.540[a]	100.0	100.0	.905
a. First 1 canonical discriminant functions were used in the analysis.				

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.181	169.480	6	.000

Canonical Discriminant Function Coefficients	
	Function
	1
x4	-.700
x9	2.073
x10	-3.169
x22	.002
x24	.196
x25	3.922
(Constant)	-.175
Unstandardized coefficients	

Functions at Group Centroids	
V31	Function
	1
0	2.464
1	-1.807
Unstandardized canonical discriminant functions evaluated at group means	

Casewise Statistics

	Case Number	Actual Group	Predicted Group	Highest Group: P(D>d | G=g) p	Highest Group: P(D>d | G=g) df	Highest Group: P(G=g | D=d)	Highest Group: Squared Mahalanobis Distance to Centroid	Second Highest Group: Group	Second Highest Group: P(G=g | D=d)	Second Highest Group: Squared Mahalanobis Distance to Centroid	Discriminant Scores: Function 1
Original	1	0	0	.675	1	.999	.175	1	.001	14.838	2.045
	2	0	0	.782	1	1.000	.077	1	.000	20.686	2.741
	3	0	0	.648	1	1.000	.208	1	.000	22.348	2.920
	4	0	0	.522	1	1.000	.409	1	.000	24.116	3.104
	5	0	0	.696	1	1.000	.153	1	.000	21.734	2.855
	6	0	0	.209	1	1.000	1.577	1	.000	30.544	3.720
	7	0	0	.795	1	1.000	.068	1	.000	20.529	2.724
	8	0	0	.121	1	.924	2.409	1	.076	7.392	.912
	9	0	0	.254	1	.986	1.299	1	.014	9.804	1.324
	10	0	0	.061	1	.752	3.520	1	.248	5.735	.588
	11	0	0	.050	1	.682	3.827	1	.318	5.357	.508

	12	0	0	.515	1	1.000	.423	1	.000	24.223	3.115
	13	0	0	.820	1	1.000	.052	1	.000	20.240	2.692
	14	0	0	.547	1	1.000	.363	1	.000	23.753	3.067
	15	0	0	.211	1	.978	1.566	1	.022	9.118	1.213
	16	0	0	.382	1	.995	.764	1	.005	11.540	1.590
	17	0	0	.582	1	1.000	.303	1	.000	23.245	3.014
	18	0	0	.913	1	1.000	.012	1	.000	17.324	2.355
	19	0	0	.784	1	1.000	.075	1	.000	15.975	2.190
	20	0	0	.890	1	1.000	.019	1	.000	19.446	2.603
	21	0	0	.028	1	1.000	4.811	1	.000	41.787	4.657
	22	0	0	.019	1	1.000	5.543	1	.000	43.895	4.818
	23	0	0	.129	1	1.000	2.309	1	.000	33.531	3.984
	24	0	0	.795	1	1.000	.068	1	.000	20.530	2.724
	25	0	0	.687	1	.999	.162	1	.001	14.967	2.062
	26	0	0	.042	1	.603	4.152	1	.397	4.987	.426
	27	0	0	.307	1	.991	1.044	1	.009	10.556	1.442
	28	0	1^{**}	.053	1	.699	3.757	0	.301	5.441	.131
	29	0	0	.773	1	1.000	.083	1	.000	20.786	2.752
	30	0	0	.048	1	.659	3.926	1	.341	5.242	.483
	31	0	0	.893	1	1.000	.018	1	.000	17.109	2.329
	32	0	0	.637	1	1.000	.222	1	.000	22.488	2.935

	33	0	0	.709	1	1.000	.140	1	.000	21.572	2.838
	34	0	0	.201	1	.975	1.634	1	.025	8.955	1.186
	35	0	0	.004	1	1.000	8.491	1	.000	51.622	5.378
	36	0	0	.461	1	1.000	.542	1	.000	25.074	3.200
	37	0	0	.002	1	1.000	9.201	1	.000	53.351	5.497
	38	0	0	.127	1	1.000	2.333	1	.000	33.621	3.991
	39	0	0	.252	1	1.000	1.310	1	.000	29.328	3.609
	40	0	0	.697	1	.999	.152	1	.001	15.067	2.075
	41	0	1**	.152	1	.953	2.048	0	.047	8.064	-.376
	42	0	0	.957	1	1.000	.003	1	.000	17.783	2.410
	43	0	0	.593	1	.999	.285	1	.001	13.963	1.930
	44	0	0	.358	1	1.000	.846	1	.000	26.946	3.384
	45	0	0	.849	1	1.000	.036	1	.000	19.899	2.654
	46	1	1	.902	1	1.000	.015	0	.000	19.307	-1.930
	47	1	1	.899	1	1.000	.016	0	.000	17.172	-1.680
	48	1	1	.968	1	1.000	.002	0	.000	17.897	-1.766
	49	1	1	.881	1	1.000	.022	0	.000	19.543	-1.957
	50	1	1	.872	1	1.000	.026	0	.000	16.891	-1.646
	51	1	1	.495	1	.998	.465	0	.002	12.882	-1.125
	52	1	1	.818	1	1.000	.053	0	.000	20.254	-2.036
	53	1	1	.651	1	1.000	.205	0	.000	22.311	-2.259

	54	1	1	.922	1	1.000	.010	0	.000	19.086	-1.905
	55	1	1	.093	1	1.000	2.825	0	.000	35.424	-3.488
	56	1	1	.932	1	1.000	.007	0	.000	18.977	-1.892
	57	1	1	.730	1	1.000	.119	0	.000	21.302	-2.151
	58	1	1	.812	1	1.000	.056	0	.000	16.268	-1.569
	59	1	1	.894	1	1.000	.018	0	.000	17.124	-1.674
	60	1	1	.600	1	.999	.275	0	.001	14.035	-1.282
	61	1	1	.041	1	.596	4.181	0	.404	4.956	.238
	62	1	1	.995	1	1.000	.000	0	.000	18.190	-1.801
	63	1	1	.541	1	.999	.374	0	.001	13.392	-1.196
	64	1	1	.629	1	1.000	.233	0	.000	22.597	-2.290
	65	1	1	.503	1	1.000	.448	0	.000	24.404	-2.476
	66	1	1	.779	1	1.000	.079	0	.000	20.718	-2.088
	67	1	1	.527	1	.998	.401	0	.002	13.234	-1.174
	68	1	1	.668	1	.999	.184	0	.001	14.757	-1.377
	69	1	1	.872	1	1.000	.026	0	.000	19.641	-1.968
	70	1	1	.545	1	1.000	.366	0	.000	23.773	-2.412
	71	1	1	.806	1	1.000	.060	0	.000	16.205	-1.561
	72	1	1	.323	1	1.000	.976	0	.000	27.653	-2.795
	73	1	1	.645	1	1.000	.213	0	.000	22.395	-2.268
	74	1	1	.941	1	1.000	.005	0	.000	18.878	-1.881

	75	1	1	.822	1	1.000	.050	0	.000	20.208	-2.031
	76	1	1	.365	1	1.000	.820	0	.000	26.797	-2.713
	77	1	1	.340	1	1.000	.909	0	.000	27.294	-2.760
	78	1	1	.505	1	1.000	.445	0	.000	24.385	-2.474
	79	1	1	.659	1	1.000	.195	0	.000	22.206	-2.248
	80	1	1	.345	1	.994	.893	0	.006	11.062	-.862
	81	1	1	.954	1	1.000	.003	0	.000	18.736	-1.865
	82	1	1	.286	1	1.000	1.136	0	.000	28.482	-2.873
	83	1	1	.648	1	1.000	.209	0	.000	22.355	-2.264
	84	1	1	.810	1	1.000	.058	0	.000	20.353	-2.047
	85	1	1	.903	1	1.000	.015	0	.000	17.217	-1.685
	86	1	1	.449	1	.997	.573	0	.003	12.348	-1.050
	87	1	1	.399	1	.996	.710	0	.004	11.752	-.964
	88	1	1	.756	1	1.000	.097	0	.000	15.678	-1.496
	89	1	1	.611	1	1.000	.259	0	.000	22.847	-2.316
	90	1	1	.984	1	1.000	.000	0	.000	18.415	-1.827
	91	1	1	.381	1	.995	.767	0	.005	11.528	-.931
	92	1	1	.831	1	1.000	.045	0	.000	20.108	-2.020
	93	1	1	.888	1	1.000	.020	0	.000	19.460	-1.947
	94	1	1	.528	1	.998	.398	0	.002	13.252	-1.176
	95	1	1	.808	1	1.000	.059	0	.000	16.222	-1.564

	96	1	1	.348	1	1.000	.882	0	.000	27.144	-2.746
	97	1	1	.692	1	1.000	.157	0	.000	21.785	-2.203
	98	1	1	.710	1	.999	.138	0	.001	15.207	-1.436
	99	1	1	.395	1	.996	.722	0	.004	11.703	-.957
	100	1	1	.189	1	.971	1.729	0	.029	8.738	-.492
	101	1	1	.813	1	1.000	.056	0	.000	16.278	-1.571
	102	1	1	.204	1	.976	1.616	0	.024	8.998	-.536
	103	1	1	.787	1	1.000	.073	0	.000	20.627	-2.078
	104	1	1	.874	1	1.000	.025	0	.000	19.624	-1.966
	105	1	1	.920	1	1.000	.010	0	.000	19.107	-1.907
	106	1	1	.816	1	1.000	.054	0	.000	20.288	-2.040
	107	1	1	.905	1	1.000	.014	0	.000	19.279	-1.927
	108	1	1	.571	1	.999	.321	0	.001	13.721	-1.240
	109	1	1	.601	1	.999	.274	0	.001	14.043	-1.283
	110	1	1	.929	1	1.000	.008	0	.000	17.484	-1.717
	111	1	1	.692	1	.999	.157	0	.001	15.017	-1.411
	112	1	1	.920	1	1.000	.010	0	.000	17.395	-1.707
	113	1	1	.287	1	.990	1.135	0	.010	10.277	-.742
	114	1	1	.569	1	.999	.324	0	.001	13.705	-1.238
	115	1	1	.695	1	.999	.154	0	.001	15.043	-1.415
	116	1	1	.444	1	1.000	.585	0	.000	25.357	-2.572

	117	1	1	.897	1	1.000	.017	0	.000	19.361	-1.936
	118	1	1	.717	1	1.000	.132	0	.000	21.473	-2.170
	119	1	1	.792	1	1.000	.070	0	.000	16.056	-1.543
	120	1	1	.184	1	1.000	1.765	0	.000	31.353	-3.135
	121	1	1	.931	1	1.000	.008	0	.000	17.508	-1.720
	122	1	1	.717	1	.999	.131	0	.001	15.280	-1.445
	123	1	1	.957	1	1.000	.003	0	.000	17.780	-1.753
	124	1	1	.741	1	1.000	.109	0	.000	21.169	-2.137
	125	1	1	.884	1	1.000	.021	0	.000	17.016	-1.661
	126	1	1	.640	1	1.000	.218	0	.000	22.452	-2.274
	127	1	1	.122	1	1.000	2.395	0	.000	33.856	-3.355
	128	1	1	.505	1	.998	.445	0	.002	12.987	-1.140
	129	1	1	.714	1	1.000	.134	0	.000	21.507	-2.174
	130	1	1	.596	1	.999	.281	0	.001	13.995	-1.277
	131	1	1	.824	1	1.000	.049	0	.000	16.394	-1.585
	132	1	1	.796	1	1.000	.067	0	.000	20.512	-2.065
	133	1	1	.960	1	1.000	.002	0	.000	18.668	-1.857
	134	1	1	.916	1	1.000	.011	0	.000	17.351	-1.702
	135	1	1	.656	1	.999	.198	0	.001	14.636	-1.362
	136	1	1	.610	1	1.000	.261	0	.000	22.861	-2.317
	137	1	1	.632	1	.999	.230	0	.001	14.377	-1.328

	138	1	1	.301	1	1.000	1.071	0	.000	28.150	-2.842
	139	1	1	.543	1	.999	.369	0	.001	13.420	-1.199
	140	1	1	.934	1	1.000	.007	0	.000	18.954	-1.890
	141	1	1	.866	1	1.000	.029	0	.000	16.826	-1.638
	142	1	1	.669	1	.999	.183	0	.001	14.769	-1.379
	143	1	1	.922	1	1.000	.009	0	.000	17.418	-1.709
	144	1	1	.695	1	.999	.153	0	.001	15.048	-1.415
	145	1	1	.721	1	1.000	.128	0	.000	21.419	-2.164
	146	1	1	.925	1	1.000	.009	0	.000	17.447	-1.713
	147	1	1	.735	1	1.000	.115	0	.000	21.247	-2.145
	148	1	1	.619	1	.999	.247	0	.001	14.242	-1.310
	149	1	1	.449	1	1.000	.574	0	.000	25.288	-2.565
	150	1	1	.414	1	1.000	.668	0	.000	25.888	-2.624

**. Misclassified case

Classification Results[a]

		V31	Predicted Group Membership		Total
			0	1	
Original	Count	0	43	2	45
		1	0	105	105
	%	0	95.6	4.4	100.0
		1	.0	100.0	100.0

a. 98.7% of original grouped cases correctly classified.

APPENDIX IV

FACTOR ANALYSIS RESULTS

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,514
Bartlett's Test of Sphericity	Approx. Chi-Square	6068,902
	df	406
	Sig.	,000

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6,589	22,722	22,722	6,589	22,722	22,722	6,039	20,824	20,824
2	4,224	14,565	37,287	4,224	14,565	37,287	3,605	12,433	33,257
3	2,890	9,964	47,251	2,890	9,964	47,251	2,721	9,384	42,641
4	2,521	8,692	55,943	2,521	8,692	55,943	2,447	8,437	51,078
5	2,143	7,388	63,331	2,143	7,388	63,331	2,316	7,988	59,066
6	1,687	5,817	69,149	1,687	5,817	69,149	2,123	7,321	66,387
7	1,448	4,991	74,140	1,448	4,991	74,140	1,941	6,691	73,078
8	1,078	3,716	77,856	1,078	3,716	77,856	1,330	4,586	77,664
9	1,025	3,536	81,392	1,025	3,536	81,392	1,081	3,728	81,392
10	,990	3,412	84,804						
11	,902	3,109	87,913						
12	,705	2,431	90,344						
13	,677	2,333	92,677						
14	,555	1,912	94,590						
15	,421	1,451	96,040						
16	,307	1,059	97,099						
17	,219	,756	97,855						

18	,176	,605	98,461						
19	,151	,521	98,981						
20	,096	,332	99,313						
21	,076	,263	99,576						
22	,069	,237	99,813						
23	,035	,119	99,932						
24	,017	,058	99,991						
25	,002	,006	99,997						
26	,001	,002	99,999						
27	,000	,001	100,000						
28	3,348E-6	1,154E-5	100,000						
29	5,143E-7	1,773E-6	100,000						
Extraction Method: Principal Component Analysis.									

Rotated Component Matrix[a]									
	Component								
	1	2	3	4	5	6	7	8	9
x27	,978	-,012	,050	,030	-,002	,093	,014	,012	-,021
x26	,978	-,013	,050	,029	-,002	,093	,015	,012	-,021
x28	,978	-,013	,050	,030	-,002	,093	,012	,012	-,021
x17	-,930	-,052	-,013	,051	-,025	-,117	-,009	-,019	-,038
x4	-,832	-,017	-,029	,081	-,013	,406	-,176	-,002	-,036
x8	-,830	-,093	-,010	,107	-,058	,350	-,182	,045	,026
x29	,824	,010	,361	,132	-,047	-,226	-,066	-,004	,040
x21	,026	,971	,021	-,037	,203	-,006	,062	-,048	,019
x23	,017	,894	-,020	-,051	-,333	,007	,123	-,109	,026
x20	,028	,861	,035	-,009	,498	-,015	,015	-,002	,011
x16	,029	,850	,034	-,052	,211	-,018	,023	,453	,014
x2	,085	-,021	,909	,065	,085	-,041	-,126	,084	-,105
x1	,136	-,033	,904	,002	,139	-,082	-,141	-,029	-,006
x9	-,126	-,191	-,731	,428	,108	-,169	-,135	-,017	-,024
x24	,068	-,026	,050	,815	,027	-,163	,080	,002	,112

x5	,117	-,066	,056	,795	-,030	-,195	,281	,009	,031
x10	,164	,013	,295	-,685	-,026	-,066	,283	,146	,162
x25	-,356	-,009	-,237	,526	-,048	,477	-,303	-,021	-,127
x22	,019	,402	,061	,033	,868	-,016	-,072	,080	-,007
x3	,029	,316	,342	-,042	,812	-,003	-,093	,049	-,089
x18	,011	,245	,134	-,025	-,613	,027	-,014	,311	-,064
x12	,095	-,037	,157	,238	-,048	-,823	,165	-,074	-,101
x11	,028	-,038	,122	-,087	-,063	,813	,068	-,086	-,035
x13	,046	,084	-,010	,136	-,047	-,022	,866	-,032	,089
x14	,111	,074	-,188	-,043	-,061	-,083	,815	-,005	-,113
x15	,002	,039	,039	-,063	-,086	-,030	-,034	,960	-,002
x19	-,009	-,025	,078	-,196	,079	,124	,036	,043	,586
x6	,052	,043	,029	,181	-,081	-,219	-,265	,133	,583
x7	,020	-,034	,174	-,082	,039	-,017	-,086	,127	-,527
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.									
a. Rotation converged in 9 iterations.									

Standardized Canonical Discriminant Function Coefficients

	Function
	1
REGR factor score 1 for analysis 1	-,256
REGR factor score 3 for analysis 1	-,736
REGR factor score 4 for analysis 1	1,062

Casewise Statistics													
				Highest Group					Second Highest Group			Discriminant Scores
					P(D>d | G=g)							
	Case Number	Number of Predictors with Missing Values	Actual Group	Predicted Group	p	df	P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Group	P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Function 1
Original	1		0	0	,500	1	,895	,454	1	,105	4,729	,970
	2		0	0	,645	1	,940	,212	1	,060	5,702	1,183
	3		0	1**	,366	1	,815	,816	0	,185	3,784	-,302
	4		0	0	,943	1	,979	,005	1	,021	7,713	1,572
	5		0	0	,927	1	,978	,008	1	,022	7,601	1,552
	6		0	0	,604	1	,996	,269	1	,004	11,335	2,162
	7		0	0	,742	1	,958	,108	1	,042	6,346	1,314
	8		0	0	,905	1	,976	,014	1	,024	7,451	1,524
	9		0	1**	,161	1	,515	1,969	0	,485	2,088	,198
	10		0	0	,154	1	,500	2,028	1	,500	2,028	,219
	11		0	0	,852	1	,971	,035	1	,029	7,087	1,457

	12		0	0	,462	1	,998	,541	1	,002	12,843	2,379
	13		0	0	,763	1	,993	,091	1	,007	9,924	1,945
	14		0	0	,947	1	,986	,005	1	,014	8,500	1,710
	15		0	0	,428	1	,858	,628	1	,142	4,226	,851
	16		0	0	,837	1	,990	,042	1	,010	9,330	1,849
	17		0	0	,497	1	,998	,462	1	,002	12,447	2,323
	18		0	0	,879	1	,974	,023	1	,026	7,272	1,492
	19		0	0	,839	1	,970	,041	1	,030	6,998	1,440
	20		0	0	,922	1	,987	,010	1	,013	8,680	1,741
	21		0	0	,052	1	1,000	3,787	1	,000	22,987	3,589
	22		0	0	,005	1	1,000	7,939	1	,000	32,103	4,461
	23		0	0	,114	1	1,000	2,495	1	,000	19,607	3,223
	24		0	0	,914	1	,977	,012	1	,023	7,507	1,535
	25		0	0	,693	1	,950	,155	1	,050	6,023	1,249
	26		0	1^{**}	,256	1	,694	1,290	0	,306	2,932	-,069
	27		0	0	,368	1	,816	,812	1	,184	3,793	,742
	28		0	1^{**}	,389	1	,832	,742	0	,168	3,949	-,344
	29		0	0	,941	1	,986	,006	1	,014	8,542	1,718
	30		0	0	,267	1	,710	1,232	1	,290	3,023	,534
	31		0	0	,808	1	,991	,059	1	,009	9,557	1,886
	32		0	0	,682	1	,995	,168	1	,005	10,614	2,053

	33		0	0	,460	1	,998	,545	1	,002	12,866	2,382
	34		0	0	,178	1	,555	1,812	1	,445	2,257	,297
	35		0	0	,000	1	1,000	32,482	1	,000	73,064	7,343
	36		0	1**	,631	1	,936	,230	0	,064	5,611	-,725
	37		0	0	,050	1	1,000	3,846	1	,000	23,132	3,604
	38		0	0	,603	1	,996	,271	1	,004	11,350	2,164
	39		0	0	,174	1	,545	1,851	1	,455	2,214	,283
	40		0	0	,427	1	,998	,632	1	,002	13,273	2,438
	41		0	1**	,400	1	,840	,708	0	,160	4,027	-,364
	42		0	0	,262	1	,999	1,256	1	,001	15,755	2,764
	43		0	0	,791	1	,992	,070	1	,008	9,691	1,908
	44	3	0	1**	,228	1	,651	1,452	0	,349	2,701	,000
	45		0	0	,680	1	,995	,171	1	,005	10,637	2,056
	46		1	1	,822	1	,991	,051	0	,009	9,445	-1,430
	47		1	1	,435	1	,998	,609	0	,002	13,166	-1,985
	48		1	1	,853	1	,972	,034	0	,028	7,093	-1,020
	49		1	1	,916	1	,977	,011	0	,023	7,527	-1,100
	50		1	1	,946	1	,986	,005	0	,014	8,506	-1,273
	51		1	1	,623	1	,934	,241	0	,066	5,556	-,714
	52		1	1	,759	1	,993	,094	0	,007	9,953	-1,512
	53		1	1	,860	1	,972	,031	0	,028	7,137	-1,028

	54		1	1	,877	1	,974	,024	0	,026	7,259	-1,051
	55		1	1	,514	1	,997	,426	0	,003	12,258	-1,858
	56		1	1	,787	1	,964	,073	0	,036	6,645	-,935
	57		1	1	,545	1	,911	,367	0	,089	5,028	-,599
	58		1	1	,666	1	,944	,186	0	,056	5,844	-,774
	59		1	1	,974	1	,981	,001	0	,019	7,932	-1,173
	60		1	1	,866	1	,973	,028	0	,027	7,180	-1,036
	61		1	1	,464	1	,878	,537	0	,122	4,476	-,472
	62		1	1	,760	1	,960	,093	0	,040	6,466	-,900
	63		1	1	,689	1	,949	,160	0	,051	5,993	-,805
	64		1	1	,975	1	,981	,001	0	,019	7,937	-1,174
	65		1	1	,484	1	,998	,489	0	,002	12,587	-1,904
	66		1	1	,767	1	,961	,088	0	,039	6,514	-,909
	67		1	1	,806	1	,966	,061	0	,034	6,772	-,959
	68		1	1	,554	1	,915	,350	0	,085	5,094	-,614
	69		1	1	,884	1	,974	,021	0	,026	7,306	-1,060
	70		1	1	,546	1	,912	,365	0	,088	5,036	-,601
	71		1	1	,655	1	,942	,200	0	,058	5,765	-,758
	72		1	1	,611	1	,996	,259	0	,004	11,274	-1,714
	73		1	1	,483	1	,998	,491	0	,002	12,598	-1,906
	74		1	1	,585	1	,996	,298	0	,004	11,521	-1,751

	75		1	1	,928	1	,978	,008	0	,022	7,604	-1,114
	76		1	1	,581	1	,923	,305	0	,077	5,271	-,652
	77		1	1	,844	1	,971	,039	0	,029	7,028	-1,008
	78		1	1	,636	1	,938	,224	0	,062	5,642	-,732
	79		1	1	,736	1	,993	,114	0	,007	10,150	-1,543
	80		1	1	,997	1	,983	,000	0	,017	8,090	-1,201
	81		1	1	,944	1	,979	,005	0	,021	7,722	-1,135
	82		1	1	,364	1	,999	,823	0	,001	14,104	-2,112
	83		1	1	,997	1	,983	,000	0	,017	8,091	-1,201
	84		1	1	,315	1	,999	1,010	0	,001	14,849	-2,210
	85		1	1	,780	1	,963	,078	0	,037	6,602	-,926
	86		1	1	,684	1	,995	,165	0	,005	10,594	-1,612
	87		1	1	,294	1	,999	1,102	0	,001	15,195	-2,255
	88		1	1	,590	1	,996	,291	0	,004	11,477	-1,744
	89		1	1	,884	1	,974	,021	0	,026	7,302	-1,059
	90		1	1	,810	1	,991	,058	0	,009	9,541	-1,446
	91		1	1	,232	1	,999	1,431	0	,001	16,360	-2,401
	92		1	1	,845	1	,990	,038	0	,010	9,269	-1,401
	93		1	1	,386	1	,830	,752	0	,170	3,926	-,338
	94		1	1	,841	1	,970	,040	0	,030	7,013	-1,005
	95		1	1	,698	1	,950	,150	0	,050	6,054	-,817

	96		1	1	,964	1	,985	,002	0	,015	8,373	-1,250
	97		1	1	,589	1	,996	,292	0	,004	11,485	-1,746
	98		1	1	,828	1	,969	,047	0	,031	6,920	-,987
	99		1	1	,280	1	,728	1,165	0	,272	3,130	-,126
	100		1	1	,738	1	,957	,112	0	,043	6,321	-,871
	101		1	1	,985	1	,984	,000	0	,016	8,223	-1,224
	102		1	1	,472	1	,882	,517	0	,118	4,535	-,486
	103		1	1	,973	1	,981	,001	0	,019	7,921	-1,171
	104		1	1	,495	1	,998	,465	0	,002	12,466	-1,887
	105		1	1	,670	1	,995	,181	0	,005	10,720	-1,631
	106	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	107	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	108	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	109	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	110	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	111	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	112	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	113	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	114	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	115	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	116	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000

	117	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	118	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	119	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	120	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	121	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	122	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	123	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	124	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	125	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	126	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	127	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	128	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	129	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	130	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	131	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	132	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	133	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	134	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	135	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	136	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	137	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000

	138	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	139	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	140	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	141	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	142	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	143	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	144	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	145	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	146	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	147	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	148	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	149	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000
	150	3	1	1	,228	1	,651	1,452	0	,349	2,701	,000

**. Misclassified case

Classification Results[a]					
		V31	Predicted Group Membership		Total
			0	1	
Original	Count	0	38	7	45
		1	0	105	105
	%	0	84,4	15,6	100,0
		1	,0	100,0	100,0

a. 95,3% of original grouped cases correctly classified.

APPENDIX V
LOGISTIC REGRESSION ANALYSIS

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	x10	9,561	1,704	31,497	1	,000	14201,179
	Constant	-4,411	,880	25,111	1	,000	,012
Step 2[b]	x10	11,046	3,708	8,873	1	,003	62689,923
	x25	-25,129	8,175	9,448	1	,002	,000
	Constant	-1,373	1,546	,789	1	,375	,253
Step 3[c]	x10	38,971	41,103	,899	1	,343	8,414E16
	x22	-,017	,027	,389	1	,533	,983
	x25	-119,156	134,014	,791	1	,374	,000
	Constant	2,378	5,286	,202	1	,653	10,782

a. Variable(s) entered on step 1: x10.

b. Variable(s) entered on step 2: x25.

Variables not in the Equation[a]					
			Score	df	Sig.
Step 1	Variables	x1	1,809	1	,179
		x2	3,702	1	,054
		x3	,133	1	,715
		x4	2,626	1	,105
		x5	5,366	1	,021
		x6	,055	1	,815
		x7	1,006	1	,316
		x8	1,999	1	,157
		x9	10,693	1	,001
		x11	,017	1	,896
		x12	4,396	1	,036
		x13	1,086	1	,297
		x14	,965	1	,326
		x15	,007	1	,932
		x16	1,105	1	,293
		x17	,395	1	,530

		x18	,965	1	,326
		x19	,768	1	,381
		x20	1,455	1	,228
		x21	1,009	1	,315
		x22	1,680	1	,195
		x23	,041	1	,839
		x24	12,389	1	,000
		x25	20,007	1	,000
		x26	,024	1	,876
		x27	,020	1	,886
		x28	,025	1	,874
		x29	,419	1	,518
Step 2	Variables	x1	,033	1	,855
		x2	,357	1	,550
		x3	26,080	1	,000
		x4	1,214	1	,271
		x5	1,194	1	,275
		x6	,020	1	,888
		x7	,146	1	,702
		x8	1,277	1	,258
		x9	5,611	1	,018

		x11	7,444	1	,006
		x12	,072	1	,789
		x13	,116	1	,734
		x14	,074	1	,786
		x15	,000	1	,983
		x16	66,587	1	,000
		x17	,004	1	,947
		x18	1,570	1	,210
		x19	,607	1	,436
		x20	72,043	1	,000
		x21	67,062	1	,000
		x22	73,259	1	,000
		x23	,001	1	,975
		x24	1,319	1	,251
		x26	5,694	1	,017
		x27	1,261	1	,261
		x28	2,627	1	,105
		x29	3,527	1	,060
Step 3	Variables	x1	,205	1	,651
		x2	,200	1	,654

		x3	,030	1	,862
		x4	2,292	1	,130
		x5	3,384	1	,066
		x6	,076	1	,783
		x7	,000	1	,993
		x8	1,674	1	,196
		x9	3,367	1	,067
		x11	2,377	1	,123
		x12	2,504	1	,114
		x13	,268	1	,605
		x14	2,252	1	,133
		x15	,294	1	,588
		x16	3,573	1	,059
		x17	,088	1	,767
		x18	,003	1	,955
		x19	2,335	1	,126
		x20	3,125	1	,077
		x21	,877	1	,349
		x23	3,070	1	,080
		x24	2,033	1	,154
		x26	3,041	1	,081

		x27	2,964	1	,085
		x28	,234	1	,629
		x29	2,769	1	,096
a. Residual Chi-Squares are not computed because of redundancies.					

Classification Table

	0	1	Total
0	45	0	45
%	100	0	100
1	1	104	105
%	1	99	100