Early Warning System for Bankruptcy: Bankruptcy Prediction

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Chapter 1
Introduction

1.1 Objective

When a company enters a period of financial distress, two impending conflicts may arise. These are shortage of liquidity and pending obligations. Both of them lead to the same result – a lack of sufficient cash flow to meet pending short term obligations. In this situation the company tries to renegotiate on debt covenants or otherwise files for bankruptcy.

The recent bankruptcies of large joint stock companies in U.S. and Europe, such as Enron, WorldCom, Lehman Brothers, WaMu (Washington Mutual), Swissair, ABB, Parmalat shook investors across the world and underlined the importance of failure prediction both in academia and industry. It now seems more necessary than ever to develop early warning systems that can help to prevent or avert corporate default. These systems facilitate the selection of firms to collaborate with or invest in.

Decision makers are intensely interested in the prediction of direction of variables over time; therefore, the initial action ought to construct a model that expose the relationship between variables. As Ackoff (1999) initiated, a symptom indicates the presence of a threat or an opportunity; variables used as symptoms that are properties of the behavior of the organization or its environment. Such variables can also be used dynamically as pre-symptoms or omens, as indicators of future opportunities or problems.

Targets of the prediction models can be summarized as letting analysts act due to the results of the model and pre-intervene to the variables in order to affect the prediction results (Kutman, 1999). In this sense, our models let analysts take course of action according to the results; since inability to change macroeconomic trends; pre-intervention to the balance sheet and income statement variables facilitates stating organizational strategies.

The objective of this study is to develop cost sensitive prediction models employing different classification methods that would be benefited by management itself, shareholders, government, vendors, creditors, investors and other stakeholders in their projections and strategies.

1.2 Approach

At the beginning of researches on failure prediction, there were no advanced statistical methods or computers available for the researchers. The values of financial ratios of failed and non-failed firms were compared with each other. In 1966 the pioneering study of Beaver presented the univariate approach of discriminant analysis and in 1968 Altman expanded this study to multivariate analysis. Until the 1980's, discriminant analysis was the dominant method in failure prediction. However, it suffered from assumptions that were violated very often. Absence of theoretically well-structured models satisfied by introduction of seminal studies of Black-Scholes and Merton's option pricing methodology in default prediction. Later in order to avoid restrictive assumptions of the classical statistical models and due to advent of new regulations like Basel II, financial failure prediction methods moved toward more comprehensive non-parametric machine learning techniques.

In this context, to achieve the objective of the thesis, efficiency of 11 different methods within 3 different approaches are investigated. These approaches and methods are: DA, Logit analysis from classical statistical techniques, option pricing method representing structural market based methods, and 8 machine learning algorithms, such as Naïve Bayes, Bayesian Network, k-NN, ANN, SVM, C4.5, CHAID and CRT. For cost sensitive prediction, variables are selected through two variable elimination phases: ANOVA and cost sensitive attribute evaluator algorithm. For performance evaluation, classification accuracy and AUROC (area under receiver operating characteristic) are taken into consideration.

The initial sample is composed of 180 industrial public companies listed on ISE (Istanbul Stock Exchange). The financially distressed companies are determined according to criteria, such as companies with net loss in each of the preceding three years, companies applied for bankruptcy, negative equity figures, Bankruptcy Law article 179 pursuant to Turkish Trade Law article code 324 and 434. Shortly these codes claim that 2/3 loss in total asset value could be defined as bankrupt.

1.3 Outline

Based on broad investigation of existing theoretical and empirical literature this thesis presents many characteristics of bankruptcy and prediction methods. The study is divided into two parts. Part I is reserved for theoretical background of bankruptcy and its implications. Part II presents the empirical study involving approaches and findings in financial failure prediction, based on the applications of Aktan (2011), Aktan (2009b) and Aktan (2009a).

Part I consists of three chapters. Chapter 2 covers the basic concepts of corporate financial failure. Different definitions and dimensions of financial failure, as well as causes and implications of bankruptcy are discussed here. Chapter 3 exhibits alternative approaches in resolution of financial distress. Furthermore, the main differences in reorganization process and juridical structure of bankruptcy in U.S., major European countries and Turkey are examined.

The importance of financial failure prediction and accuracy for various parties, such as management, shareholders, vendor, company, state, investors, creditor, labor and labor organizations is discussed in chapter 4.

The empirical part of the thesis is presented in Part II, which consists of three chapters. Chapter 5 presents default risk assessment models, such as two classical statistical models, one market based model and eight machine learning models. Extensive literature research regarding the applied models is summarized alongside the presented models.

Chapter 6 exhibits the empirical design of the thesis. This chapter contains a detailed explanation of data and variable selection as well as selected statistics from Turkey. Next the entire subject methods are applied to the selected 180 public companies and following this results of each applied model are interpreted.

The general interpretation and the performance comparison of the applied methods, as well as inferences are discussed in chapter 7.

Detailed outputs of the applied models with regard to one annual period prior to failure are attached to the appendix.

Part I

Theoretical background

Chapter 2
Corporate Financial Distress

In market economies the entrance and the exit of the companies constitutes fundaments of competition process. Competition process ensures sufficient numbers of companies remaining in the industry and satisfaction of market demand with competitive prices and efficient production process. However, entrance or exit of a company does not always mean physical inclusion in or exclusion from an industry. Entrance or exit can be observed as increase or decrease in operations, resource raise or shortage, or change in field of activity. In this context, competition process could be perceived as remaining or inclusion of efficient resources in the industry and exclusion of inefficient ones from the industry. For example, decreasing demand in some products can cause reserved production resources shift into other production processes or shutdown of a production facility. For large scaled companies, exit process could be defined as restructuring of allocations of production resources. In this context, market economies and competition can be described as a flow or a movement from inefficient processes to efficient processes. Theoretically, in highly competitive markets; insolvency, default, bankruptcy, mill shutdown so called financial distress is rarely observable (Hashi, 1997).

Modern companies could be described as a web of formal and implicit contracts which regulate the claims of different interest groups on the company's assets. These interest groups or claimants are government, banks, secured and unsecured creditors, employees, bondholders, customers, suppliers, and managers and shareholders. This web of contracts, in developed market economies, is a part of property rights. The operation of the subject contracts is facilitated through financial markets and financial system. Financial institution and the market provide information about performances of economic units, reflect the reaction of the market participants, and facilitate the operations of economic units (Hashi, 1997).

In an economic environment with developed financial markets, financial distress manifests itself by decreasing market prices and awakes probable mechanisms. On the other side, density of mergers and acquisitions increases according to financial distress and decreasing market prices. This event is especially caused by market participants' perception of company's financial distress as a temporary situation, which is resulted from inefficient production and managerial systems or production of old fashioned, not demanded products. Acquisition mechanism theoretically provides financially distressed companies to produce the right product range in a more efficient manner under the control of new owners. In this context, acquisition process provides elimination of idle or inefficient resources from the system (Hashi, 1997).

Moreover, a financially distressed company in order to restructure its debts and improve its financial situation can make formal or informal negotiations with creditors. These restructuring programs often involve reorganization of the company through layoffs and closure of loss generating operations. Here, exit of resources from the industry can be the case. At last, when there is no other option left, the liquidation of the financially distressed company is the case; in other term, physical exit of the company from the business is the last option available for the financially distressed company to utilize (Hashi, 1997).

In developed markets, the number of financially distressed companies and among them the number of bankrupt companies was formerly few; whereas, in emerging markets many companies from each scale were faced with financial distress. Liquidation or exclusion of a financially distressed company from the industry could be accepted as a natural selection of the competitive market. However, letting or forcing these companies to liquidate, could cause a potential disaster. This event can dramatically decrease or harm the industrial production and the capacity. Moreover, unemployment insurance and social security payments would be a great strain on government with adverse implications on macroeconomic policies. Therefore, in emerging markets negative outcomes of these processes cannot be accepted from the viewpoint of social welfare and cannot be tolerated by the stakeholders (Hashi, 1997).

It is likely that companies with poor financial structure and structural problems enter financial distress and moreover, some of them go bankrupt in economic crises. On the other hand, economic crisis does not necessarily be a prerequisite of the financial distress. Even in good yielded stable economies, lack of contemporary management is a sufficient reason to fall into financial distress. Surprisingly, sometimes even scientific methods are not sufficient to prevent the company from bankruptcy. As Perold (1999) underlined that Long Term Capital

Management, a hedge fund company, had come to the point of bankruptcy even though this company was managed by Nobel Prize awarded scientists. In fact, in order to prevent possible collapse in financial system Fed (Federal Reserve) had to transfer large amount of money to this company.

2.1 Corporate Failure and Dimensions of Financial Distress

Theoretically, the business enterprises are assumed to operate eternally and their basic goal is to gain profit. While those business enterprises continue their successful operations, some of them cannot reach their goals and fall into financial failure mostly in the first two years of their lives. But others' growth and expansion does not mean that they will never come across failure or distress (Gitman, 1992).

Corporate failure can exist in various types and dimensions, and has different effects on stakeholders according to magnitude of the failure and its type. The rise of corporate failure in different types brought about the use of different definitions and different concepts connoting failure. The existence of various situations affecting corporate value and the expectations of stakeholders caused financial distress literature to evolve in confusion and turmoil (Wruck, 1990). Therefore, clear definition of related concepts prevents probable misunderstandings.

Unsuccessful companies have been defined in various ways to portray the formal processes challenging them and to classify the unfavorable economic and financial conditions involved. Four generic terms are found in the literature to characterize unsuccessful companies, these are: Failure, insolvency, default and bankruptcy (Altman and Hotckiss, 2005). These terms are occasionally used interchangeably, but they express different content of financial distress.

Usually corporate failures stem from series of events that can be subject to financial distress and operational distress, which have distinct theoretical infrastructures. Financial distress, in finance theory, involves corporate valuation and determination of optimum capital structure; therefore, it is heavily concentrated on the subjects of debt-capital structure like cash flow generation and debt payment power. In analysis of operational distress managerial and generally qualitative factors are considered rather than financial indicators (Çakır, 2005).

A financial distress process is a dynamic and generally a long process which influences corporate capital structure, investment policies and performance (Kahl, 2002). When a company enters financial distress that means the company is entering a dangerous zone. With the recognition of financial distress, the company should take measures on its operations to stop adversary wearing effects of financial distress. Recognition of financial distress at the preliminary stage and immediate remedial actions facilitate the company to exit from danger zone as soon as possible and to overcome the process with minor losses (Whitaker, 1999; Güvenir, 2003). On the contrary, late recognition of financial distress can deepen the damage and it might be too late to rescue the company and as a result, bankruptcy will be unavoidable.

Financial distress has a wide range of definitions in literature. A long and dynamic financial distress process can start with a short-lived massive single event or consecutive chain events or a long-term repetitive unfavorable events causing company's financial state to decrease below some lower threshold. The dynamic nature of financial distress involves separate stages through which the distressed company passes. Each of the stages has its own characteristics that contribute differently to corporate failure. However, the starting point or intervals of a financial distress process and its characteristics are not easily determinable. Accuracy of bankruptcy prediction models significantly decreases if the prediction period exceeds three years before bankruptcy. The existence of preliminary indicators of declining performance is questionable. Even if the indicators exist, they are very weak and therefore almost impossible to notice. Unfavourable developments generally become visible about a couple of years before default, when the company becomes severely distressed (Hambrick and D'Aveni, 1988). In addition, temporary or permanent characteristics of financial distress determine the continuity of the company. The stages of process interpenetrate and a clear discrimination between them is not possible in intersections. The latter stages are results of previous stages and previous stages are part of latter stages. Therefore financial distress stages cannot be separated from each other with absolute lines.

Financially distressed companies have different properties in early and latter stages of financial distress process. In early stage of financial distress, drop in sales, negative stock returns (Opler and Titman, 1994), decreasing operating income (Whitaker, 1999), customer complaints, losing crucial customers (breakdown of customer portfolio), late financial and managerial information (Scherrer, 1988), discrete cash deficits, and matters in receivable collection are the observed challenging problems that a financially distressed company is exposed to.

In the mid-stage of financial distress, deteriorated profitability, cash shortage consequence of continuous operating losses (Makridakis, 1991), cut or suspension of dividend payments (Turetsky and McEwen, 2001) petition for additional time or adjournment of debt payments, violation of debt covenants, interruptions in payment of debt to core suppliers, and shortening of the maturities by the suppliers (Altman and Hotchkiss, 2005) are the common threats that financially distressed company has to endure.

In the latter stage, firms have permanent operating losses, cash deficits grow incrementally and debt covenant violations become a chronic problem, which can be a reason for bankruptcy petition (Altman and Hotchkiss, 2005). Bad debt recovery becomes almost impossible and resignation of qualified employees increases (Hambrick and D'Aveni, 1988).

Determinations of financial distress in literature:

- Decrease of assets value below a certain threshold level (Purnanandam, 2007),
- Deferring or reduction in dividend payments (Jaggi and Lee, 2002),
- Insolvency (Purnanandam, 2007),
- Insufficient liquid assets covering debts,
- Insufficient level of current assets to satisfy debt payments and investment expenditures (Reese and Mc Mahon, 2003),
- Insufficient cash flow to satisfy short term debts (Wruck, 1990),
- Inefficiency losses caused by low level of cash flows (Reese and Mc Mahon, 2003),
- Company’s deprivation of dept payment means (Ross et al., 2002)

According to above sample definitions, financial distress can be identified with cash flow generation and solvency. Moreover, failure, insolvency, default and bankruptcy (liquidation and reorganization) can be listed as stages of financial distress, each of which is briefly described below.

In the most common way, financially distressed companies have two ways to solve the debt payment problem. Debt payment problem solution without bankruptcy petition constitutes the first way. In this situation, reorganization of company’s assets or debts or both of them is the case. The second way, the hardest one, is the bankruptcy itself. When a company files petition for bankruptcy, power weights and responsibility of stakeholders over the distressed company are reshaped. In this case, the bankrupt company would be liquidated or reorganized. Bankruptcy reorganization is different from reorganization before bankruptcy, at the end of this process the capital structure of the company will be changed in favor of creditors and ownership of company switches to creditors. The other options laid in front of distressed company can be listed as merger, debt restructuring and voluntary liquidation (Gilbert et al., 1990).

As mentioned above, origins of financial distress lie in the period of 6 or more years before bankruptcy. At this period, the indicators of beginning of financial distress are very weak to be recognized. In fact, some minor deterioration started in company's financial state but even modern estimation methods, such as Ohlson's model (1980), Shumway's hazard model (1999), Altman's Z-Score (2002), Hillegeist et al.'s market based model (2004) couldn't foresee the coming danger earlier than 5 years in advance. What is known that, in this stage the companies make long-term strategic failures or take wrong strategic decisions (Gless, 1996), yet the outcomes of long-term strategic decisions are not visible, it is not possible to take countermeasures. Miller (1977) underlined that possible strategic failures cause corporate downturn. If a company does not recognize the change in the upward trend of overall economic expansion or overestimate the current stable economic trend, the company can lose comparative advantages and technological benefits, follow a wrong strategic expansion policy in declining industries or overheated markets. These can happen if the management has overambitious, incautious expansion strategies or is highly convinced of past growth strategies. In another term, if the company cannot anticipate the changing environmental conditions, it cannot pursue the right strategy to sustain success.

The downturn of corporate performance begins with discernible breaks in profitability; drop in sales and operating income, negative stock returns are the further indicators of decline (Opler and Titman 1994). In this period the company is still solvent. Since countermeasures need observable adverse outcomes, managerial responses do not come at the right time, this lag incurs belated measures for recovery. Then management overreacts to restore the company's previous financial state, this situation continues for a while like a wave's peak and bottom. Unfortunately temporary improvements cannot ease the accumulated deterioration in operating activities that leads corporate failure.

2.2 Corporate Failure (Definitions)

Altman and Hotckiss (2005) define failure *"by economic criteria, means that the realized rate of return on invested capital, with allowances for risk consideration, is significantly and continually lower than prevailing rates on similar investments Somewhat different economic criteria have also been utilized, including insufficient revenues to cover costs and where average return on investment is continually below the firm's cost of capital. These economic situations make no statements about the existence or discontinuance of the entity."* The decision of continuance of operations depends on expected returns and the ability of the firm to cover variable costs (Gaughan, 2011). Nevertheless, when economic failure considered as insufficient corporate revenues to cover operating costs including capital cost, a company in this situation could continue its operations if its investors consent to get low rate of returns (Kuhn and Morton, 1990). It is hard to categorize a company, which confronts above situations, as financially distressed. A company could be categorized as economically failed in a matter of years according to criteria mentioned above; however it could not be failed in fulfilling current obligations due to its small amount of debts or absence of debts (Altman and Hotckiss, 2005).

Failure, by financial criteria, can be defined as insufficient cash flow to satisfy current obligations. These obligations might include outstanding debts to suppliers and employees, incurred losses from ongoing legal processes, default in repayment of principal and interests (Wruck, 1990).

As a general approach financial failure, which is defined as inability of a company to meet its current obligations as they come due, is a less ambiguous concept than economic failure. The company does not have sufficient liquidity to meet current liabilities. This can occur even when the company has a positive net worth, with the exceeding asset values over liabilities (Gaughan, 2011). As it is understood from the definition, besides inability of a company to meet due debts, in other term default, having difficulties in meeting due debts can also be considered as financial failure.

Insufficient cash flow is often used as an indicator of financial failure in many empirical studies. For example Whitaker (1999) used the measure of cash flow and market value of the company in order to identify when a firm enters into financial distress. He defined financial distress as a situation when a company has insufficient cash flows to cover its obligations and incurs a decline in its market value. However, insufficient cash flows are necessary for default but solely they are not an adequate cause for default. While the cash flows exceed the debts come due, the company has the fund to carry on payments to the creditors. In another term, a company can have a temporary cash shortage which can be eliminated by utilizing other alternative sources of coverage in the face of a temporary lack of liquidity. These alternatives can be listed as reduction in inventory level, extension of terms of trade credits, restructuring of debts before default, recapitalization and liquidation of un-pledged assets. When the insufficiency of cash flows continues, the alternatives expire and unfortunately the company defaults (Gaughan, 2011).

Financial failure brings the company about renegotiation with at least one of the creditors. The definition of creditor can be indistinct. In a broader sense, these can be listed as Wruck (1990) underlined, external capital providers, unpaid debts to suppliers and employees, actual or potential damages from litigation and violation of debt covenants. It is necessary to mention that financial failure is not a synonym of liquidation or bankruptcy but theoretically all companies are vulnerable to financial or economic failure.

Moreover, Andrade and Kaplan (1998) underline the necessity of distinguishing financial failure from economic failure. They define a company violating debt payment as financially failed and a company with standing operating losses as economically failed.

Insolvency is another term depicting negative firm performance and is generally used in a more technical fashion (Altman and Hotchkiss, 2005). An insolvent company can be defined as inability to meet its obligations including debts to employees, suppliers, creditors, public and actual or potential damages from litigation (Shrader and Hickman, 1993). This definition suits Whitaker (1999) and Wruck's (1990) financial failure definition. In fact, Wruck (1990) stresses that, although insolvency is different from financial failure; these two concepts are used interchangeably. Wruck (1990) and Ross et al. (2003) divide insolvency into stock based insolvency and flow based insolvency. Stock based insolvency occurs when the market value of the company's assets is less than the face value of its debts, which is defined as negative net economic value. A financially distressed company can be insolvent according to flow based insolvency; in another term, the company cannot generate liquidity to meet its current obligations, and this is called technical insolvency. While technical insolvency is frequently the cause of formal bankruptcy declaration, it may be a temporary condition (Altman and Hotchkiss, 2005).

Flow based insolvency gives financial restructuring rights to creditors whose debt covenants are violated. If a company is stock based insolvent but flow based solvent, then the creditors lose their bargaining power according to debt payments in due time (Wruck, 1990).

The definition of stock based insolvency initiates an insolvent company whose net present value is less than the face value of the debts, a company with negative net value. This situation resembles a chronic condition rather than a temporary condition. The valuation of the company needs a comprehensive evaluation process which is carried out when liquidation is planned (Altman and Hotchkiss, 2005). The companies in this situation try to reach a positive value by radical restructuring methods like exchange offer and divestitures. This kind of insolvency is generally a portent of legal bankruptcy (Kuhn and Morton, 1990).

Another financial concept, which is inescapably associated with financial distress, is default. Default can be described as a situation when a company cannot pay the debt or interest to creditors in due time, and consequently, violates a condition of an agreement with a creditor, which can be the reason for legal action (Altman and Hotchkiss, 2005). Gilson et al. (1990) and Altman and Hotchkiss (2005) separate the default concept into two categories, payment default on an interest or principal amount and technical default on debt covenant of the company. The major difference of default from insolvency is the reference of the date of maturity. A company can be insolvent for a long time. However, only on the date of maturity it can be classified as defaulted on its debt. When a company faces this event, it tries to renegotiate and restructure its debts before bankruptcy proceeding.

Bankruptcy is another financial concept that is associated with financial distress. One type of bankruptcy is described above and refers to the net worth position of a company. The other more observable type is a company's formal declaration of bankruptcy to the courts, accompanied by the petition either to liquidate its assets or attempt a restructuring program (Altman and Hotchkiss, 2005). Restructuring is a formal attempt to prevent legal bankruptcy; it involves very complex mechanism and many aspects of financially distressed company, such as its creditors, assets, shareholders, management, employees, and retirees (Datta and Datta, 1995). Liquidation involves sales of a company's assets in the framework of bankruptcy laws and distribution process of the revenues to the creditors and other stakeholders.

Neoclassic economists, as mentioned above, interpret corporate failure as equal to exclusion from industry. In this context, failure is an indicator of a natural selection mechanism of the market deciding between efficient and inefficient companies. According to advocates of neoclassic theory, the reason of inefficiency and the cause of market exclusion is insufficient profit. The companies operating with uncompetitive price-cost margins, encounter financial distress. Therefore, exclusion from market is accepted as a tool increasing welfare and an option for reallocation of industrial resources. On the contrary, a company can leave the industry with merger. Competitors can acquire the company because of its assets and expertise. In this aspect, this exclusion is caused by success rather than failure (Hunter, 2004).

In the empirical studies in the literature, bankruptcy, financial failure and financial distress are used interchangeably. The usage of financial failure or distress provides flexibilities in the research phase. Financial distress is a more flexible definition than bankruptcy and helps research to increase sample size; on the contrary, bankruptcy is a special form of financial distress. Bankruptcy constraint in researches decreases sample size. The usage of financial distress provides superiority not only in practice but also in theory, because not all of the financially distressed companies go bankrupt. Bankruptcy is the last choice for the companies which could not solve their financial problems. Shortly, usage of bankruptcy alone narrows the financial distress aspect (Aktaş, 1993).

Karels and Prakash (1987) in their empirical study about financial failure estimation, listed the definitions of financial failure, these definitions are negative net value, insolvency, default on capital and interest, issue of bad cheque, deferring in preferred stock dividend, control of government shift to creditors etc. Similarly Lin and McClean (2000) listed common financial failure and financial distress definitions as reorganization process, inability to cover interest payments, negative auditor’s report, liquidation process, operating losses, current year loss, consecutive two year loss, consecutive three year loss etc. Different definitions of financial failure lead different sample selection for the studies in this field. In this study, loss in consecutive three years, 2/3 asset value loss, negative equity figure and bankruptcy are taken into consideration as financial failure criteria.

2.2.1 Causes of Business Failure

The success or failure of any business is a result of the interaction of two sets of main factors. Firstly, the performance of a company is affected by external factors, which are beyond the control of business managers. The growth rate of the economy, inflation, exchange rates, interest rates, preferences, attitudes and changes in consumer behaviour, change in the characteristics of market activities; such environmental conditions clearly affect profitability of business and its market power (Sharma and Mahajan, 1980).

The other set of main factors affecting the performance of a business entity is the set of its internal factors, which are the factors existing in the company and under control. Among the factors related to company, insufficient equity to finance growth and excessive use of leverage, failures in location selection, inability to meet customer expectations, excessive fixed assets investments and so on, can be considered as internal factors affecting business performance.

According to another classification, it is possible to classify financial distress as the financial distress caused by economic hardship result of complications in the industry, which resembles external reasons of financial distress, and financial distress as a result of bad management that resembles internal reasons of financial distress (Wruck, 1990).

Poor management alone can cause economic failure and then cause financial distress. On the other hand for example, excessive leverage can also cause financial distress before economic failure. Therefore, the performance fall resulting from internal causes and excessive leverage can be considered as managerial incompetence (Whitaker, 1999).

According to the study conducted by the international rating agency, Dun & Bradstreet, in 1987, business failure is connected to the following five basic factors.

- Economic factors,
- Management experience,
- Impaired sales,
- Increasing costs,
- Other miscellaneous factors.

According to the subject report, the most important reason for business failure is displayed as the economic factors; management experience is in second place. External and internal causes of business failure are described below.

2.2.1.1 External Causes of Financial Distress

The companies are the economic units and they are affected by and have impacts on the environment in which they operate. Therefore, some of the environmental factors causing business failure are beyond the control of the business. Although it is not possible to prevent this kind of factors, it is possible to take some measures to reduce the adverse effects. Environmental factors that lead businesses to failure are described below:

Social environment

One of the external reasons causing business failure is the social environment in which company operates. A combination of economic conditions and behavioural patterns adopted by the population shapes the activities of the business enterprises (Büker et al., 1997).

Businesses, in order to be successful, are obliged to know the expectations of society and to continue their activities in accordance with these expectations. Avoidance of monopolistic practices, respect for consumer rights, and environmental consciousness are some of the social environments' expectations (Türko, 1999).

Rebellion and other social events and tense international relations, changes in the social and political situation of a society are said to be social and political risks affecting companies and their decision mechanism. In recent years, many businesses fell in distress caused by tense international relations and negative changes in social psychology. For example, after the approval of a law of Armenian Genocide in the French Senate, French companies in Turkey fell in distress. The stock price of French Alcatel dropped to one third (Tezcan, 2002). Another tragic example, September 11, 2001 the plane suicide attacks to the World Trade Center in New York, affected many leading airway and insurance companies badly. Their stock prices fell significantly and the companies came to border of bankruptcy. Swissair, one of them, stopped its flights and filed bankruptcy petition; on the contrary, the value of defense and weapon industry companies increased.

Industrial Environment

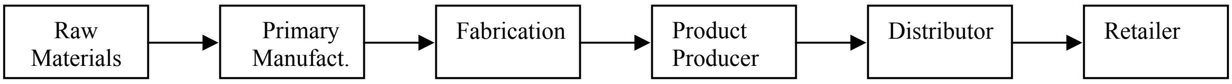
In the sector, in which distressed companies operate, some ascent and descent can occur. These sectoral waves can affect many companies; therefore, companies come across with financial distress, the repetition of these waves leads the companies to failure. For example; frequent strikes in a sector lead companies to financial distress and distort their production decisions. Another most recent example can be given concerning the agriculture sector; in Turkey, unorganized farmers have losses from time to time due to their crops. How? They cultivate the same crops, which results in excess supply; therefore, prices decrease. Considering this, farmers should found an association or society which coordinates farmers what to cultivate resulting in appreciation of farmers' economic welfare. We do not touch demographic factors distort agriculture sector.

Sector is a dimension, in which balance is never sustained and there are always some fluctuations; that is why, businesses ought to make and consider sectoral analysis. Uncertain conditions of this environment lead companies to face some danger and risks. By the way, companies are mostly affected by sectoral risks, which are related to the external environment of the company. Some of the sectoral risks are mentioned below.

Fashion Risk, that is incapability of companies to adapt to the choices and delights of the consumers, leads companies to failure.

Value Chain Risk, a value-chain is a linked set of value-creating activities beginning with basic raw materials coming from suppliers, moving to a series of value-adding activities involved in producing and marketing a product or service, and ending with distributors getting the final good into the hands of the ultimate consumer (Thomas L. Wheelen, 2000).

Figure 1: Hypothetic Value Chain Process



Source: Galbraith, J. R. (1991). Strategy and Organization Planning, in The Strategy Process: Concepts, Contexts, Cases, 2nd ed. Edited by H. Mintzberg and J.B. Quinn, Prentice Hall, p. 316.

A problem arisen in the supplier or the distributor of a company which can also harm the center company. For example, defected or low quality raw materials sent by the supplier can also affect the quality of the production, and these low quality products would ruin the company's reputation and decrease the sales, resulting in poor profits and financial distress. Vice versa, a problem in the distribution channel can also result in failure. Think of a company which is producing high quality products, but cannot market them. Unsold products mean loss; a sustained loss results in failure as well.

Just-in-time inventory systems are designed to reduce the level of an organization's inventory and its associated costs, aiming to push to zero the amount of time that raw materials and finished products remain in the factory, being inspected, or in transit (Beard and Butler, 2000). The concept is that suppliers deliver materials only at the exact moment needed, thereby reducing raw material inventories to zero. Moreover, work-in-process inventories are kept to a minimum, because goods are produced only as needed to service the next stage of production. Finished-goods inventories are minimized by matching them exactly to sales demand. Indeed management and coordination problems must be solved, scheduling must be scrupulously precise and logistics tightly coordinated (Daft, 2003). A problem in communication among adjoining links results in insufficient production and sales, therefore the risks mentioned in the above paragraph will be triggered.

Price Risk, ascent and descent in general price level or significant price changes in the sector can present difficulties for companies.

Inflation results in unstable economies in most of the developing countries as in Turkey. Inflation means disequilibrium in supply and demand and results in a steady increase in general price level; furthermore, inflation causes distortion in income distribution, weak savings, increase in monopoly, balance of payments disequilibrium all of which lead to an unstable economy. As a result, companies fall in distress easily in this kind of economy (Eren, 1995).

In Turkey and other developing countries, the demand for financial capital is mainly satisfied through capital markets not by banks due to high interest rates as a result of high inflation; because, inflation increases interest rates and results in decrease in money supply, which is essential for long-term investments. High interest rates increase the cost of funding, all of these affect investment decisions; under these circumstances, most of the companies neglect to invest and get weak. That is why most of the companies fail or become distress in an inflationary economy.

Competition Risk, is another failure reason in a sector. The aim of businesses, institutional and individual investors is investing for growing, developing and expanding in the sector; therefore, competition conditions are vital when sectoral analysis is studied. Competition density, antidumping law and existence of barriers to entry of a sector ought to be considered (Berk, 1999).

Telecom crisis can be given as an example of this situation. Since 1996 giant investors who invested in telecom sector were disappointed due to having many competitors resulting from the decrease in prices. Meanwhile, telecom companies preferred to cover capital needs through issuing bonds instead of issuing stocks; as a result their debt to equity ratio reached to 5-10. After then, two giant firms, Motorola and Ericsson, have chosen to retrench; Motorola fired 22000 workers and Ericsson declared 500 million dollars loss. One of the largest internet server company, PSINet, declared 3.5 billion dollars loss, too. Besides all of these events, most of the large companies' market value depreciated by nearly 60%-90% (Aydan et al., 2000).

Economic Environment

Businesses are part of the economic system and affected by the economic conditions in the country, in which they operate.

Economic factors that can cause business failure can be listed as follows; a sudden increase or decrease in interest rates, unexpected changes in inflation rate, exchange rate fluctuations, changes in import and export regime and monetary policies (Büker et al., 1997).

To meet society's needs, businesses supply goods and services to the market, on the other hand in order to continue its activities, they demand inputs like labour, capital, natural resources from the same market. Therefore, businesses stay in demand and supply side at the same time. This is the rule of economic cycle (Demir, 1997).

In most cases, government has determining roles in the functioning of state economy. Although under the free market economy, the role of government is declined, the macroeconomic policies that lead the future of the country are settled by government. With import-export regime, interest rates, tax regulations, financial assistance and support activities governments affect activities of businesses (Demir, 1997).

The change in value added tax rate (increase from 17% to 18% on 15 May 2001 in Turkey), foreign trade policy, changes in custom tariffs, changes in export tax rates, precautions of investment incentives, government intervention to foreign exchange rates, determination of minimum wages and seniority compensation, import restrictions, devaluation and other macro-economic factors can effect companies' financial situations positively and reverse (Akgüç, 2000). All sectors in Turkey were seriously affected by the devaluation during the financial crises in November 2000 and February 2001.

Natural Environmental

Natural environment implies natural resources used in production. Development and evolution of natural environment bears some opportunities that lead success in business operations and on the contrary bear some difficulties causing business failure as well. Depletion of natural resources and environmental pollution has impacts on business activities

(Türko, 1999). Moreover, natural disasters like earthquake, flood, fire, epidemic animal diseases etc. can be listed as sample natural factors affecting business activities.Unfortunately, estimation and taking measures against natural disasters is so hard.

Technological Environment

Depreciation of machineries and other production equipments can be given as an example of technological reasons of failures. Especially, rapid changes in technology and production techniques increase the intensity of competition and the uncertainty of economic direction. Therefore, incapability of adaptation to changes and wrong estimation of the direction of economy can easily move companies toward failure. Investing in wrong technology can easily overthrow the company. Other types of risks arising from technology are: accidents caused by machines and production method, production losses caused by wear and tear of machineries, unexpected effects; such as pollution, chemicals, radiation of used technology to the environment and human health.

Legal and Political Environment

There are some laws (commercial law, tax law, code of obligations, bankruptcy law, and so on) that businesses have to obey. The businesses that violate these laws are subject to various penalties and lose their reputation; hence, these negative events can be the cause of business failure (Türko, 1999).

2.2.1.2 Internal Factors

Internal factors, which are under the control of the business, affecting business performance can be listed in general terms under the following headings (Keskin, 2002):

1) Poor management,
2) Dissonance to the environmental developments,
3) Insufficient communication,
4) Unbalanced growth,
5) Failure in the main projects.

Quality of Management

The main internal reason of business failure is managerial incompetence. In a survey that was hold out by Buccino&Associates, a Chicago based turnaround consultant, in 1991 it was found that by 88% of the respondents the quality of management was identified as the primary difference between success and failure. In an earlier survey by D&B in 1980, over 44% of all failures were attributed to lack of experience and knowledge, or just plain incompetence (Altman, 1993). Furthermore, Gitman (1992) supports D&B by stating, that more than 50% of failures were connected with managerial incompetence. Managerial incompetence may cause to failure during investment and operations stages:

For all firms, investment process starts with construction or with developing and expanding operating facilities, followed by preparing an investment project pass through economic, technical, financial, and legal feasibility studies; whereas, managerial incompetence in this phase leads business into difficulties.

Yükçü et al. (1999) summarize some initial factors that lead to business failures;

- Incapability of forming optimal capital structure due to scarcity of equity capital,
- Inappropriate market analysis,
- Losing competitive power in early stage of operation due to high level of costs,
- Choosing wrong production methods,
- Choosing production technology which leads to high production costs,
- Choosing a wrong place for production facilities,
- Ineffective logistics,
- Dependency to the externalities due to patent, license, franchise etc. agreements,
- Incapability of sustaining optimal production capacity in addition having idle capacity due to heavy investments to fixed assets,
- Inappropriate settlement of production equipments and machineries,
- Forming business by insufficient investment project or misapplication of investment project.

After forming business, inexperienced management brings some incompetence with defeats in organization when business operates. Some main aspects of incompetence are listed below:

- High leverage composition and scarcity of equity capital due to unplanned growth,
- Insufficient financial planning, imbalance between fund resources and usage,
- High level of fixed costs over planned costs,
- Inability in collecting receivables on due time; therefore, uncollectible receivables and worthless receivables increase,
- Unstable inventory policy,
- High level production costs, and incompetence of controlling them,
- Insufficient sales,
- Inconsideration of market researches and market positioning,
- Inability to create a harmony among managers,
- Poor technical knowledge of managers,
- Incapability of utilizing appropriate techniques to decrease costs,
- Inadequate coordination among organization departments,
- Inability to introduce new product or service,
- Imbalance between authority and response.

Dun&Bradstreet compiled an interesting statistics about the age of the failing firms that supports the relationship between inexperienced management and failure. It is clear that failure probability of inexperienced, young and undercapitalized firm is greater than its older counterpart. That statistics showed that over 50% of all failures occur in the first five years of the companies. After the fifth year, the failure rate decreases as firms become more stable, experienced, and have better access to capital (Altman, 1993).

Table 1: Age of Failed Businesses

	Proportion of total failures (%) 1980	1990
1 year or less	**0.9%**	**9.0%**
2	9.6	11.2
3	15.3	11.2
Total in 3 years	**25.8%**	**31.4%**
4	15.4	10.0
5	12.4	8.4
Total in 5 years	**53.6%**	**49.8%**
6	8.9	7.2
7	6.3	5.3
8	5.2	4.5
9	4.3	3.8
10	3.4	3.5
Total in 10 years	**81.7%**	**74.1%**
Over 10 years	18.3	25.9
TOTAL	**100.0%**	**100.0%**

Source: Altman E. I. (1993). "Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting from Bankruptcy", 2.Edition, John Wiley& Sons Inc., p.18.

Dot-Com companies can be given as an example of failure by managerial incompetence. In the early 90's, dot-com companies introduced themselves to our lives through internet. These companies operate through internet and they differ from other classic type of companies in their strategies via utilizing opportunities that internet offers. In 1998, Amazon.com, which is one of the best in dot-coms, had value of 25 billion dollars; whereas Ford, world leading automotive manufacturer, took over industry gigantic Volvo at a 6,5 billion dollars and a web site named eXcite was sold at 6,7 billion dollars (Tezcan, 2002).

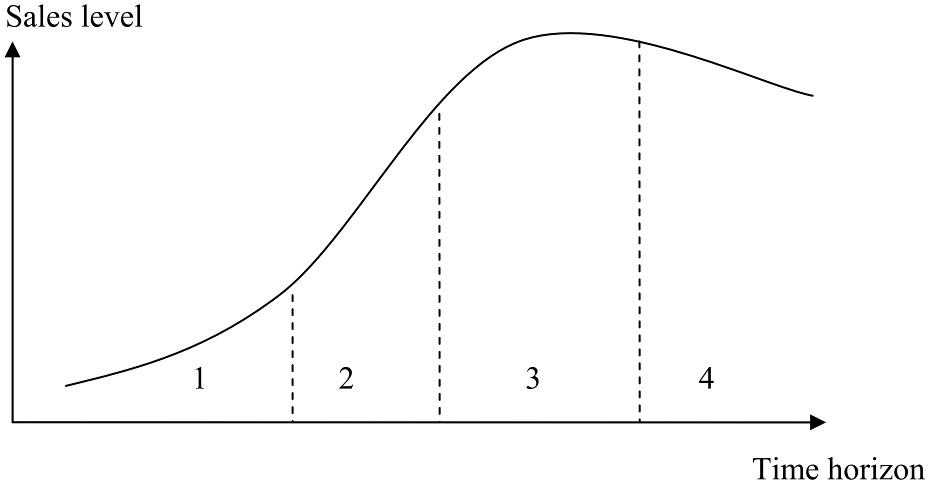
These dot-com companies were traded heavily in stock exchange market (NASDAQ), their stock prices reached peak levels; afterwards, these companies spent their money in unrelated fields and disappointed the investors, then their stock prices fell dramatically. Furthermore, these dot-com companies were erased from business area. The reason of their corrosion was inexperienced young management; on the contrary, Amazon.com still operates steadily and appreciated by authorities. The reason behind Amazon.com's success is the good management.

2.2.1.3 Business lifecycle

Business lifecycle is another aspect that is directly affected by external and internal factors, remarks the other side of business failures. Conceptually, companies are thought to operate eternally, but in real sense this is not valid. Businesses can be thought of as living organisms as they are born with investments done; they die when they get old and lose their effectiveness. We can classify business lifecycle in four phases; introduction, growth, maturity, and decline, like a new product introduced into market place.

That is why the shape of business lifecycle looks like the letter S due to the sales revenues, profits, and production (amount) progress in the time horizon. Also, this progress is named model S, displayed below.

Figure 2: Hypothetic Life Cycle of a Company



1. Introduction,
2. Growth,
3. Maturity,
4. Decline.

Although this model is simplified, this shape is a helpful framework for analyzing a company.

We can shortly mention business lifecycle as forward; in the phase of introduction, the company newly settles and gets in the industry, and aims to introduce itself. Sales volume is low and profit is next to nothing. In the phase of growth, the sales volume increases accelerated; therefore, profits grow significantly and come to maximum level. In the maturity phase, the number of competitor increases and due to the tense competition the profit level slightly shrinks. The maturity period is longer than the other periods. Sales level increases slightly and reaches peak level; whereas, after a while, sales and profit are next to decline. In the declining phase, the company loses its effectiveness, sales volume and profits become too weak for the company to survive further.

Defining, when these phases start and when they end involves subjective judgment, but some researchers developed objective criteria to define these phases (Mucuk, 1994).

Lifecycle hypothesis implies an effective management in the growth phase, but an insufficient management in the phases of maturity and decline can be modeled according to lifecycle. Therefore, the main purpose of the management should be to carry forward the growth phase and to prevent the declining phase.

Business management, when business is in the growth stage, should take environmental conditions into consideration to take optimum decisions to introduce new products or sustain growth; therefore, business would be held in the growth stage for a longer time. If the business is in the maturity or decline stage, business should be sold out to another firm or should be liquidated (Wheelen, 2000).

2.3 Consequences of Financial Distress

The failure of a business occurs in a while. Financial structure of the financially distressed company starts to weaken and worsen. Stock prices of the firm depreciate and the relationship with credit agencies starts to deteriorate due to increase in credit risk level and over drafted credit limit. The occurrence of financial distress has negative impacts not only on the company itself but also on related industry and the country's economy.

If a company is financially distressed, two things can happen. The company loses its technical liquidity, or it comes to the edge of bankruptcy.

2.3.1 Loss of Technical Liquidity

Loss of technical liquidity means that the company is not able to pay its current liabilities or debts when they are on due (Gönenli, 1988). Sometimes, although a company's total assets exceed total liabilities; the company may not be able to cover its debts. In such a situation, a company can start to pay a part of its debts; but cannot cope with further debts coming one after another. In such a case, financial distress is inevitable.

Mostly, loss of technical liquidity is caused by temporary problems such as deferred collection periods and inability of fulfillment of short-term liabilities. Measures, taken against the loss of technical liquidity, change from company to company.

It is mostly impossible for a company to fail suddenly in this kind of situation. A company, on the way to failure, gives some signals before failure; negative results of financial analysis based on financial ratios, a steady decline in stock price, exceeding credit limits of banks and inactivity of receivables, minimum level of deposit accounts, delays in payments. All of them are main indicators of a coming default or failure (Akgüç, 1998).

2.3.2 Bankruptcy

Bankruptcy of a firm or becoming bankrupt can be defined as the inability of the firm to pay its debts; obviously, being bankrupt is much worse than losing technical liquidity (Gönenli, 1988).

Although, bankruptcy comes out with a steady decline of asset value below liabilities, deciding to put an end to the life of a business may be a better decision than trying to survive (Wheelen, 2000).

The need to saving businesses or of reorganization was firstly perceived in the U.S. The first reorganization attempt was applied to railway sector. Although, the railway sector was almost bankrupt, it was protected by the U.S. Bankruptcy Law, article 77, in 1898 due to the crucial importance of the transportation sector to the economy (Üstündağ, 1998).

Bankruptcy is a legal proof of inability of a company to fulfill its liabilities; therefore, the aim of a bankruptcy process is to prevent frauds of company in order to protect creditors' claims, and to provide opportunities to form a new business after the fulfillment of all liabilities.

As we mentioned before, the main reason of bankruptcy or business failure is incompetence and unsuccessfulness of managers. With low sales and high production costs, the companies tend to meet their short-term cash needs by short-term debts only. This financing policy in turn, increases the risk of failure in future.

Bankruptcy risk is not a systematic risk and this aspect has been subject to many researches. Altman (1968) and Ohlson (1980), in their bankruptcy prediction studies, state that bankruptcy risk is not a risk correlated with market risk. Dichev (1998) mentions that the companies with high bankruptcy risk, earned low returns below average return in the same industry since 1980.

If a company comes to edge of bankruptcy, it would negotiate with its creditors or claim credits from banks, or file a bankruptcy petition to the court. If bankruptcy decision was taken, the company would act in two ways:

1. The company may engage in a reorganization process,
2. Or it takes liquidation decision.

Both actions require that, the company files a bankruptcy petition to the court. Necessary procedures after the petition would be handled by a committee assigned by the court for claims. In Turkey bankruptcy results in liquidation (Hatiboğlu, 1996).

In Turkey, liquidating the assets is the only choice. In the liquidating process, the company's assets are sold and the money is used to pay off debts. The investors taking the least risk are paid first; shareholders are the last people to get paid. Secure creditors always get first grabs at the proceeds from liquidation.

In the U.S. firms file bankruptcy in Federal District courts. There are two types of bankruptcy processes: liquidation and reorganization. The bankruptcy judge decides to liquidate the firm or attempt a reorganization program. Chapter 7 of the Federal Bankruptcy Act provides for liquidation of the company. Under liquidation process, a court-appointed trustee (an attorney or a business person) takes the control of the firm's assets to manage the bankruptcy process. The trustee is in charge of liquidating the assets by auction of private sale and distributing its proceeds according to absolute priority (Krishnamurti and Vishwanath, 2008).

In the order of the creditors receiving the proceeds of the liquefied assets of a firm, government's claims come first. Next, the claims of secured creditors come, such as bonds backed by specific assets of the firm. Next in line are employees' claims on wages, claims on the firm's pension plan, and the claims of unsecured or general creditors. Next to last come the claims of preferred stock holders and common stockholders.

In contrast to liquidation, the firm may instead seek to be reorganized, which is governed by Chapter 11 of the Federal Bankruptcy Act. Reorganizations are usually more complicated than liquidations, and are usually more in the interest of shareholders and creditors. Reorganization means that the firm is permitted to continue operations while working on a plan for turning the business around.

During reorganization, the firm is operated either by existing management or a court-appointed trustee (Altman and Hotchkiss, 2005). The plan of reorganization must be accepted by the creditors and the court before it can go into effect. The reorganization plan specifies how the creditors' claims will be satisfied by the reorganized firm. Reorganizations make sense if the firm is worth more than the pieces (Brouwer, 2006).

2.4 Costs of Bankruptcy

Costs of Bankruptcy can be classified in 2 types as;

- Direct Costs of Bankruptcy
- Indirect Costs of Bankruptcy

2.4.1 Direct Costs of Bankruptcy

Direct bankruptcy costs are legal and administrative costs of bankruptcy. Legal, auditing and administrative costs are the examples of direct bankruptcy costs. A financially distressed firm will need specialized legal and accounting assistance. It may also need to hire professionals with financial distress expertise, such as investment bankers, appraisers, auctioneers, and actuaries as well as those with experience in selling distressed assets. These experts generally charge substantial fees. While such professionals may well be used in more normal times, their use is almost certain to increase when a firm gets into serious financial difficulty (Branch, 2002). So, we can say that the direct cost of dealing with financial distress is largely in the form of fees paid to professionals (especially lawyers and accountants).

2.4.2 Indirect Costs of Bankruptcy

Most of the work on bankruptcy cost, other than the direct costs of bankruptcy administration, has been focused on what are termed indirect costs. Loss in market share can appear when a firm goes bankrupt or is financially distressed. Then, the interests of the firm tend to lose value because the firm's own value declines and the instruments tend to lose further value to the owner because of their reduced marketability.

Indirect costs of bankruptcy are the costs of avoiding bankruptcy filing incurred by a financially distressed firm. Losing sales, managerial distraction, the costs of a short-run focus, loss in market share, and loss of best personnel can be given as examples of indirect costs of bankruptcy.

Indirect costs of bankruptcy reflect the difficulties of running a company while it is going through bankruptcy. Direct costs of bankruptcy are relatively small compared to indirect costs, associated with bankruptcy related to managerial limitations, and efforts to correct the economic problems may be significant.

According to Gilson (1989), after filing for bankruptcy, managers suffer large personal costs and that more than half of the sampled managers are fired. Gilson and Vetsuypens (1994) find that managers that survive after a bankruptcy filing receive significantly lower salaries and bonuses; on average, managers receive only 35% of their previous gross income.

According to a study conducted by Branch (2002), direct cost of bankruptcy is about 4.45% - 6.35% of the market value before financial failure, indirect cost of bankruptcy appears between 5% - 10% of the market value before financial failure.

Altman (1984) found that the total direct and indirect costs of bankruptcy amount to about 15% of the pre-distress firm value for industrial firms and around 7% for retailers. More recently, Franks and Torous (1994) concluded that the average incremental cost of a bankruptcy exceeds that of an informal workout by at least 4.5%.

Some of the researchers underline that opportunity cost, which is caused by empirically immeasurable managerial loss time, should be considered under direct cost of bankruptcy. Some other researchers mention that opportunity cost should be considered under indirect cost of bankruptcy. Another indirect cost is decrease in profit caused by loss of sales due to probable bankruptcy and rising credit costs dependent to rising risk (Aktas, 1997).

2.5 Impacts of Bankruptcy on Industry and National Economy

Bankrupt businesses have a significant role in national economy. Unemployment rate, one of the most important macro-economic problems, will increase by reason of layoffs of bankrupt companies. Meanwhile, goods and services, which were formerly produced, are not produced any longer; therefore revenue loss will occur and capacity usage of industry decreases. Similarly, the investors, who invested in a bankrupt company, will be reluctant to transfer their savings through capital market to the businesses that need capital for expansion.

Enterprises conduct their business in a dynamic environment, for this reason impacts of cost of financial distress is not only limited by managers and owners of the company; also the connected business people and organizations in related industry are vulnerable to that impact.

In a study conducted by Buehler et al. (2006), it is mentioned that in the regions and the industries where high rates of bankruptcies occur merger activities are scant. On the other hand, another finding of that study is that mergers between large enterprises are more usual rather than among small enterprises. Moreover, company age is another significant factor on merger and bankruptcy. They found that occurrence of bankruptcy and merger in companies has a reverse relation with the age of the company. In the periods of macro-economic growth, while merger activities increase, bankruptcies or voluntary liquidations decrease.

The influence of the bankruptcy announcement of a rival company on the other companies operating in the same industry is another challenging subject. Lang and Stulz (1992) termed positive and negative effects of bankruptcy announcement of a rival company on the same industry as competitive effect and contagious effect respectively.

2.5.1 Competitive Effect

Bankruptcy of a rival company can be seen as a positive event for the competitors of the bankrupt firm. This event is termed as competitive effect in literature. According to competitive effect, by the bankruptcy of the rival firm, competitors are affected positively and their market share increases and their stock prices are appreciated by the market (Lang and Stulz, 1992; Ferris et al., 1997; Iqbal, 2002).

Iqbal (2002) in his study covering 1991 - 1996 periods in the USA found that competitors are influenced positively on return on equity by the financial failure of a company.

2.5.2 Contagion Effect

The news about the bankrupt rival company could indicate some problems common to other companies in the industry as well (Caton et al., 2008). According to contagion effect, competitors are influenced negatively by the formation of pessimistic thoughts about the industry caused by bankruptcy announcement of a rival company. While financial failure weakens the trust in the subject company, it could also reduce the credibility of the other companies in the same industry (Ferris et al., 1997; Iqbal, 2002).

In their studies, Ferris et al. (1997) found that the stock returns of the competitor companies of a financially distressed firm depreciated at about 4.68% in the first three days. This finding is a proof of negative information circulation about the industry.

Kanas (2004) examined the effects of the failed multinational banking group BCCI on banking industry in the UK, the USA, Spain and Switzerland. Kanas found that failure of the banking group had contagion effects on the British and Spanish banking sectors. In other words, according to findings of the study, the other banks in the national banking sector were influenced negatively.

Another study investigating contagion effects of financial distress was conducted by Gay et al. (1991). In this study, the effects of three failed Hong Kong banks on stock prices of the Hong Kong banking sector were investigated. It was found that other banks in the sector were negatively affected and stock prices reacted negatively within the industry due to unexpected failure of the three banks.

Financial failure of companies has the potential to affect negatively the whole society. Therefore, establishment and development of an early warning system for the companies carries a great importance. In this way, probable failures can be averted and as a result companies can find opportunities for restructuring.

Chapter 3
Resolution of Financial Distress

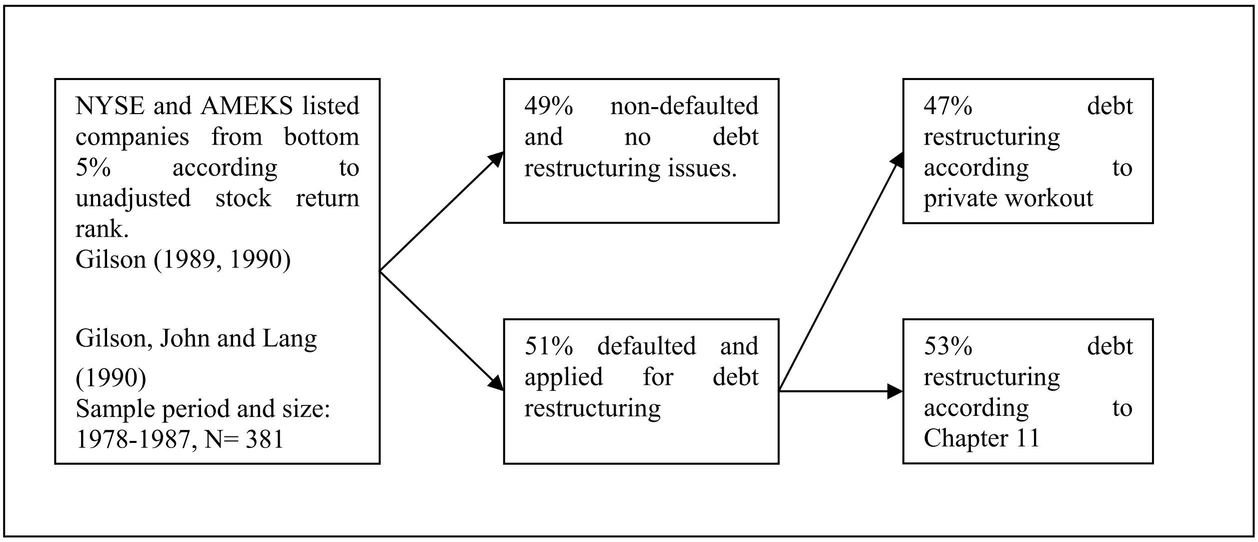
Resolution of financial distress takes place in an environment of interest conflicts and asymmetric information. Asymmetric information represents the problem of genuine information gain needed by stakeholders to define whether the company flow-based distressed or stock-based distressed (Wruck, 1990).

According to their interests, right holders have motive to provide biased and inaccurate information as accurate. Moreover, equity holders have motive to insist on flow-based distress in order to avoid their investments on stocks and increase the probability of protecting the value of investment. On the other hand, creditors have motive to claim stock-based insolvency. Executives of the company tend to hold the side which is less likely to damage their position. These interest conflicts can cause resource shortage and value loss (Wruck, 1990).

Findings related to the issues that the company can encounter through its business life prove that financial distress and death of the company are not synonyms. There are different approaches to resolve financial distress; one possibility is private workout, which is the negotiation between distressed firm and the creditors for debt restructuring, other possibilities are reorganization under bankruptcy law and liquidation under bankruptcy law.

According to the study conducted by Gilson (1989, 1990) and Gilson et al. (1990) for the selected NYSE and AMEX listed companies, from the bottom 5% of companies ranked according to their three-year unadjusted stock returns. 47% of financially distressed companies carried out private workout for debt restructuring and 53% of financially distressed companies carried out debt restructuring under Chapter 11 (see Table 2).

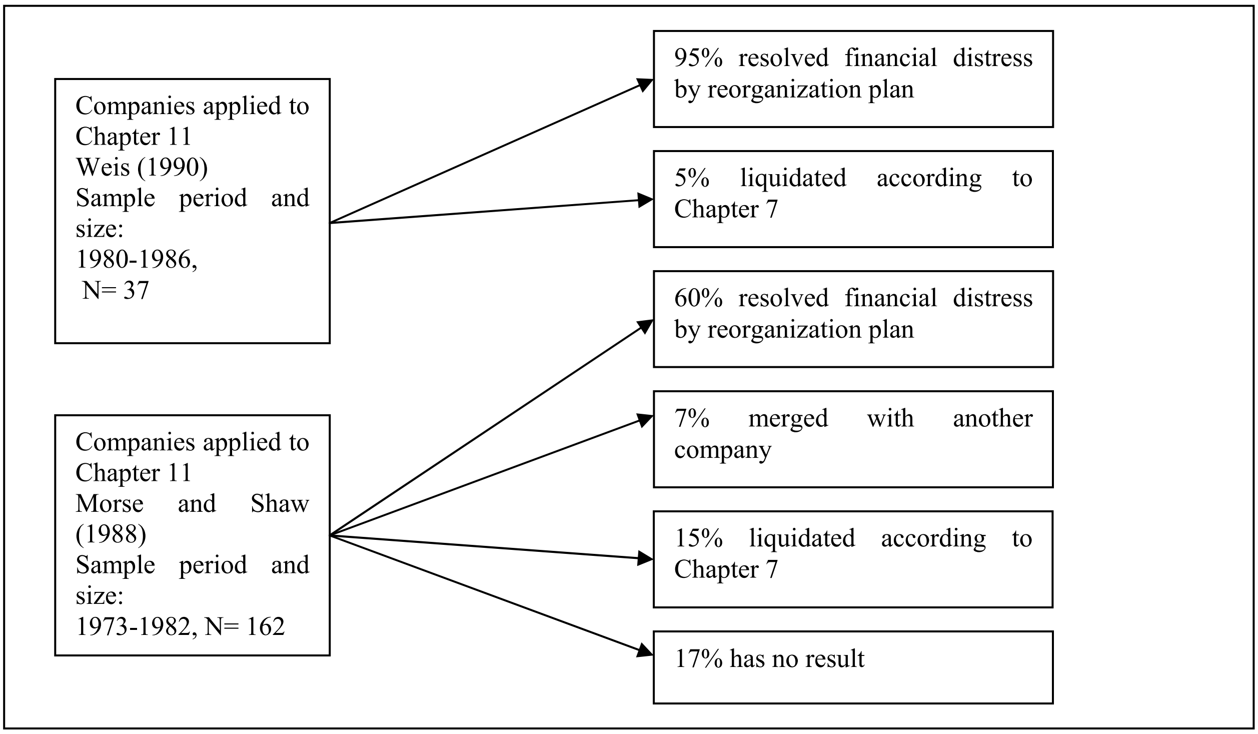
Table 2: Debt Restructuring



Source: Wruck, K. H. (1990). "Financial Distress, Reorganization and Organizational Efficiency", Journal of Financial Economics, 27 , p. 426.

The studies conducted by Weiss (1990), and Morse and Shaw (1988) examined the companies which applied for legal bankruptcy process. While 95% of the companies in Weiss' sample were rescued within the framework of a reorganization plan, 5% of the companies in the sample were liquidated. Results of Morse and Shaw's study showed that 60% of the sample companies were rescued by a reorganization plan, 15% of the companies were liquidated, 7% of the companies merged with another company, and 17% of the companies did not yet come to a decision (see Table 3).

Table 3: Bankruptcy Reorganization under Chapter 11



Source: Wruck, K. H. (1990). "Financial Distress, Reorganization and Organizational Efficiency", Journal of Financial Economics, 27 , p. 426.

There are three alternative ways that financially distressed companies can follow. These are: i) negotiations for restructuring of debts out of courts, ii) reorganization in the framework of legal bankruptcy process, iii) liquidation. But, while the reorganization process is applied, some similar measures can also be taken into consideration, for example; divestitures of some of the assets, merging, measures to increase savings in operational expenses etc. Below, these three alternatives and the factors affecting their selection are explained.

3.1 Out of Court Restructuring

Principally, a debtor company tries to renegotiate with creditors on the payment plan out of court. This situation is called as special payment plan or private workout (Brealey et al., 2001). There are many issues that can be subject to private workout. For example, a debtor company might like to renegotiate on credit term extension or credit composition with the creditors. In this aspect, private workout is somewhat different from prepackaged bankruptcy, which is one of the restructuring methods designed under Chapter

11. In private workout, the debtor would try to convince creditors about that the financial situation of the company expected under private workout would be much better than the financial situation under legal bankruptcy process (Gaughan, 2011).

Out of court restructuring process involves negotiations on several alternatives. These are alterations of the term of the original debts, composition of the debts, exchange offer, tender offer, etc. (Chatterjee et al., 1996). In addition, supportive measures like providing cash by means of asset sales or enhancing company performance can be taken. So, out of court restructuring attempts can be listed as financial claims restructuring methods, assets restructuring methods, and creation of new partnership relationships.

Recent studies showed that in voluntary restructuring various and significant operational changes were enforced in exchange for the company to continue its activities. According to those studies, in comparison with the pre-distressed situation significant asset sales and employee lay-offs are detected. Moreover, CEOs of many financially distressed firms are replaced during a restructuring process (Padilla and Requejo, 2000). The study of Gilson and Vetsuypens (1994) supports also these findings stating that many CEOs were replaced after a restructuring process. Asquit et al. (1994) found out financially distressed companies sold approximately 12% of their assets during a restructuring process. In their study they examined 112 junk bond issuer companies, which were defined as financially distressed according to their interest coverage ratio.

Advantages of private workout are bearing less cost compared to formal bankruptcy and requiring less time. Whereas, the more complex capital structure and the greater the size the company, the less the chance of renegotiation under framework of private workout (Brealey et al., 2001). On the other hand, in a private workout, parties will not be bound to rules and regulations of a formal bankruptcy process and they can establish their own rules as far as they negotiated. Therefore, out of court restructuring activities are much more flexible. Moreover, these activities provide debtors to continue their operations without interruptions, which prevent employment loss and ease the psychological stress of the company. However, the holdout problem can arise in such activities; if the risk of holdout cannot be avoidable then restructuring under legal bankruptcy process will be the better alternative (Gaughan, 2011).

3.2 Restructuring under Bankruptcy Law

Restructuring, emerging as an alternative to liquidation, helps the company to continue its operations. Generally, creditors' claims are secured by distribution of new security. This kind of restructuring is in favour of stockholders who have nothing else to lose and everything to gain if company survives (Brealey et al., 2001).

Restructuring under the framework of bankruptcy law exists in most countries, although there are differences in processes and responsibilities. For example, in the USA, legal restructuring is ordered under Chapter 11 of bankruptcy law. Applications for restructuring under the framework of bankruptcy law have a significant place in this country. While the asset value of the companies applied to restructuring under chapter 11 amounted to 95 billion dollars in 2000, the asset value of the companies was over 160 billion dollars in 2001 (Gaughan, 2011).

In recent years, large companies applied for restructuring under bankruptcy law. Among them WorldCom Inc. applied with an active value 103 billion dollars in 2002, Enron Corp. applied with an active value 63 billion dollars in 2001, Conseco Inc., from the insurance field, applied with an active value 62 billion dollars, etc. (Wetson et al., 2003) and during the economic crisis of 2001, many companies in Turkey applied for restructuring under bankruptcy law in the framework of Istanbul approach, which underlines the importance of this process.

The main objective of the restructuring process is finalizing the restructuring agreements, keeping the company as going concern and retaining its value. In this period, all actions against the company are suspended and the company continues its activities with the current management or a trustee assigned by the court. In this process, a restructuring plan is established. The restructuring plan is a table showing essentially who and how much each creditor will receive and each creditor gives up receivables in exchange for new securities. The important point in creation of restructuring plan is the establishment of payment plan that satisfies creditors and establishing a new capital structure that releases the problems causing financial distress. The restructuring plan comes into force after acceptance of creditors and approval of court (Brealey et al., 2001).

Restructuring under bankruptcy law provides some advantages to the debtor company; these are (Gaughan, 2011):

1. Prevention from takeover by creditors or cancellation of probable beneficial contracts and providing stand of legal follow up (automatic stay) against a debtor company,
2. Facilitates an effective way to continue to operate without creditors interferences,
3. Allows debtor to remain in possession (debtor in possession - DIP) of property upon which a creditor has a lien or similar security interest. The DIP status provides a debtor exclusive 120 days to prepare a reorganization plan, which can be extended by the court approval (Altman and Hotchkiss, 2005),
4. Stops the interest yield of the unsecured debts from the date of application,
5. Forces creditors to stick to the legal reorganization plan.

A special version of restructuring under bankruptcy law is prepackaged bankruptcy, which is a pre-made reorganization framework. This USA tailored prepackaged bankruptcy involves negotiations on the reorganization plan between debtor and creditor companies before actual Chapter 11 filing. In prepackaged bankruptcy, parties try to fulfil the terms of the reorganization plan that was previously agreed on. This type of restructuring is different from the traditional Chapter 11 reorganization process by providing time and cost saving in plan development and faster approval process. The first prepackaged bankruptcy was carried out by Crystal Oil Coo. The company completed the process in three months and reduced its debts from 277 million dollars to 129 million dollars by negotiations on new capital structure. In such debt restructuring processes, creditors receive convertible debt and warrants and equity in exchange for reduction in the original debt (Gaughan, 2011).

Prepackaged bankruptcy process provides a significant advantage by saving both time and resources. For the debtors, who want to protect financial resources and stay in Chapter 11 and also want to spend less time for bankruptcy issues, prepackaged bankruptcy features a great advantage. In addition, this method minimizes the holdout problem associated with voluntary non-bankruptcy agreements. In such an agreement, debtor needs approvals of all creditors. This situation is very difficult in an environment of many small creditors. The way to achieve this, is meeting 100% of credits of small creditors and paying the main creditors at an agreed lower amount (Gaughan, 2011).

3.3 Liquidation

The liquidation process is seen as the last option for a distressed company. Usually, it is preferred when the parties could not set a reorganization process through voluntary restructuring of bankruptcy law. In a liquidation process, the firm's assets are sold and the revenue distributed according to absolute priority rule, and the remaining, if any exists, is distributed to shareholders. If the asset value of the company exceeds its operating value, creditors will have motive to liquidate the company, because running a failed company causes value loss (Weston et al., 2003). The method of liquidation is usually the auction, but creditors can decide on a bargaining method of liquidation as well (Pekcanitez et al., 2005).

3.4 Juridical Structure of Bankruptcy and Reorganization in the USA and major European Countries

One of the significant differences between bankruptcy laws of the United States of America and European countries is how and when bankruptcy begins. Bankruptcy filings can be initiated voluntarily by managers or involuntarily by creditors or other parties. US bankruptcy law discourages involuntary filings by requiring that at least three creditors together initiate an involuntary filing. Therefore, most of the bankruptcy filings in the USA are voluntary filings. In contrast, European bankruptcy laws encourage creditors and other stakeholders to initiate involuntary bankruptcy filings (White, 1996). Moreover, regarding to bankruptcy requirements, while insolvency is a requirement for bankruptcy in Britain; in the USA, insolvency is not a condition for bankruptcy filings (Franks and Torous, 1996).

Table 4: Comparison of bankruptcy laws in the United States versus three European countries

	USA	European Countries
How is bankruptcy initiated?	Voluntary filings by managers	Involuntary and voluntary filings
Timing of bankruptcy	No sanctions for delay in filing	Sanction for delay in filing
Is an outside official appointed?	Normally not	Always
Who decides between liquidation and reorganization?	Existing managers (during exclusivity period)	Outside official or bankruptcy judge
How are the firm's assets distributed in liquidation?	Absolute priority rule	Absolute priority rule
Is there an "automatic stay" of secured creditors in reorganization?	Yes	France: yes Germany: no Britain: yes under admin. order
Who proposes the reorganization plan?	Managers during period of exclusivity	Outside bankruptcy official
How is the reorganization plan adopted?	Majority rule by creditors' classes and equity	France: bankruptcy court Germany: majority vote by creditors Britain: vote by creditors' committee

Source: White,M. J. (1996). The cost of corporate bankruptcy: A U.S.- European Comparison, Corporate Bankruptcy, *Ed: Jagdeep S. Bhandari, Lawrence A. Weiss, Cambridge University Press, p. 468.*

Table 4 indicates the comparison of bankruptcy law of three European countries (Germany, France, and Britain) and the USA and presents the significant similarities and differences between them.

Concerning timing of bankruptcy, in three European countries bankruptcy laws threaten managers and others with sanctions if they delay bankruptcy filing past a certain point. For example, in Germany, managers are personally liable for delay in filing later than three weeks before the company becomes insolvent (Brouwer, 2006). In France, managers are obliged to file bankruptcy within fifteen days of the date when the company becomes unable to pay its due debts. In Britain, managers, who know when the company will be insolvent, can be personally liable for additional incurred losses until bankruptcy filing. On the contrary, in the USA there is no clear policy for bankruptcy delays (White, 1996).

Timing of bankruptcy filings is closely connected with financial distress, bankruptcy process and cost of this process. In this context, early initiation of bankruptcy is a desirable situation; because, the earlier a company enters bankruptcy process, the less financially distressed it is. The approach in three European countries encourages early initiation of bankruptcy process by penalizing managers and banks for delay in filing and by helping creditors and others to initiate involuntary bankruptcy. The approach in the USA, in contrast, encourages early initiation of voluntary bankruptcy by being tolerant toward managers (White, 1996). The delay effect plays a significant role among the factors affecting financial failure cost.

The other important issue after bankruptcy initiation is the question, who decides liquidation or reorganization of the distressed company. In three European countries, bankruptcy court assigns a bankruptcy professional, who takes the governance of the company or has the authority to control the existing management (Brouwer, 2006). In contrast, in the USA existing managers have the right to choose between filing for bankruptcy under Chapter 7 or Chapter 11 (White, 1996). But, filing for bankruptcy under Chapter 11 means that the company continues operation with the existing management. From the perspective of creditors, it is a shortcoming of Chapter 11 process that the same management that brought the company in the state of financial distress also prepares a reorganization plan (Gaughan, 2011). Most of the European countries see bankruptcy as a personal failure of management; therefore they are not willing to allow them a second chance (Brouwer, 2006).

To sum up, the USA and European countries have different approaches to the case of bankruptcy. Company executives of the financially troubled companies in the USA are encouraged for early initiation of bankruptcy filings by providing flexible decision time. On the contrary, the executives of the failed European companies are punished for delaying bankruptcy filings. The other significant difference between the USA and the three European countries is that managers in the USA continue their control over the company but in European countries an outside official is assigned to manage or control the bankrupt company.

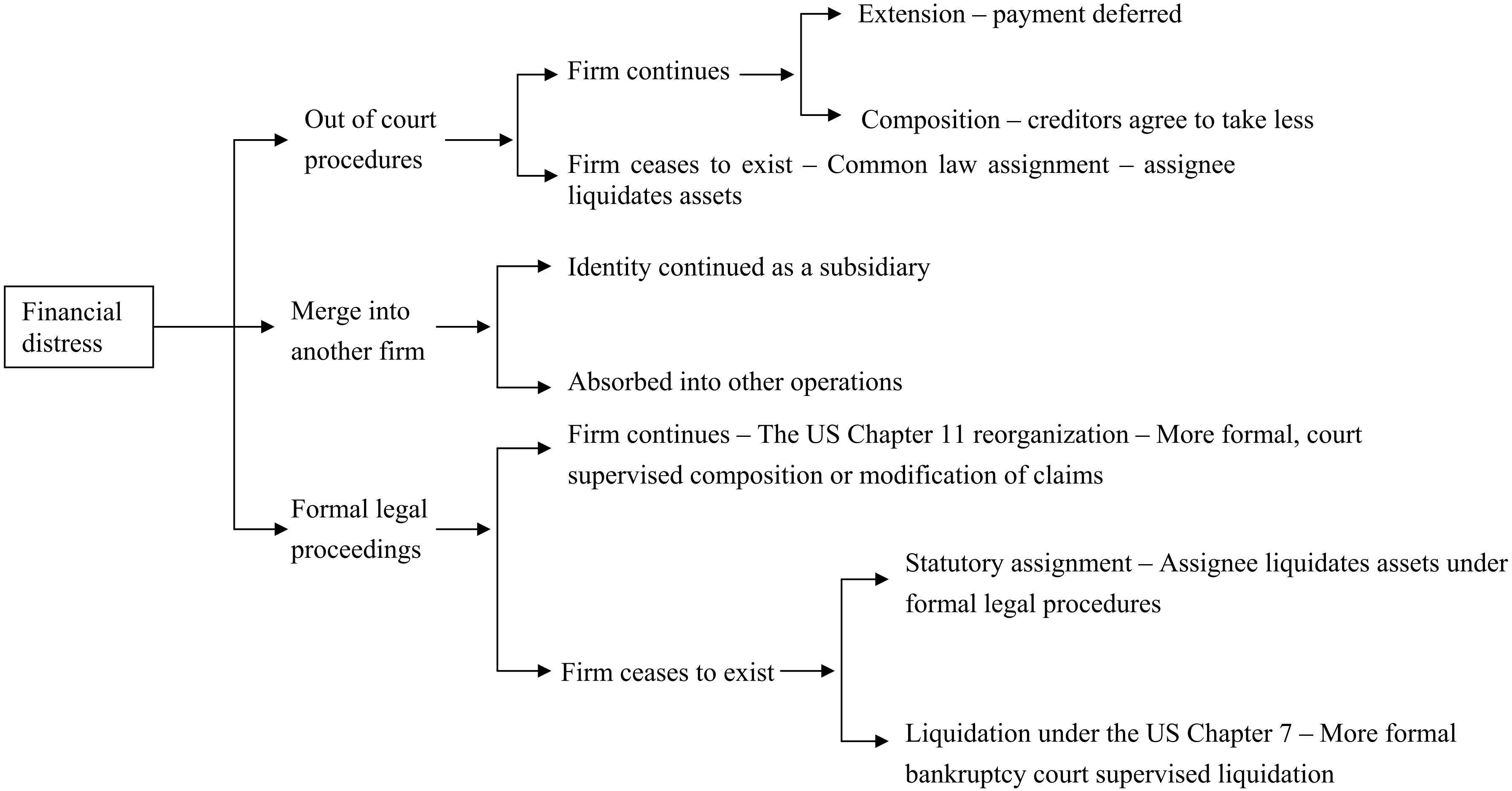
3.5 Juridical Structure of Bankruptcy and Reorganization in Turkey

Bankruptcy is defined as a procedure of foreclosure to charge creditors' claims by liquidation of all assets of the debtor (Pekcanitez et al., 2005). This definition is related to liquidation, which is one of the two basic regulations of bankruptcy law. The other regulation which has been in force for quite a while is concordat (composition of debts). Except concordat, Turkish bankruptcy law accepted two new regulations, which are closely related to financial failure costs and losses, which are adjournment of bankruptcy and negotiated reorganization.

The concept of debt restructuring of equity companies and cooperatives was taken into consideration in the phase of the recent economic crisis. In this context, after 2001 economic crisis, corporate debts were adjourned (payment moratorium) for three years with the approval of creditors, which is also called as Istanbul approach. At the end of the envisaged three years process of Istanbul approach and due to forces of the World Bank, in the context of 2003 and 2004 bankruptcy law amendments, concordat per abandoned assets and restructuring of debt payments, and adjournment of bankruptcy are included in the Turkish bankruptcy law (Öztek, 2006).

In Turkish bankruptcy law, there are two ways to declare bankruptcy; follow-up bankruptcy and direct bankruptcy. In the follow-up bankruptcy, creditor sends a legal order of payment and if the debtor cannot pay, the creditor initiates bankruptcy. In the direct bankruptcy, debtor, creditor, or inheritor can apply directly to bankruptcy court and initiate bankruptcy.

Table 5: Alternative Adjustments to Financial Distress



Source: Weston, J. F. and Copeland, T. E. (1992.) Managerial Finance, 9th edition, Dryden Press, p. 1147.

3.6 Reorganization and Reorganization Process

3.6.1 Reorganization

Reorganization is one of the two decisions that can be taken by a firm on the verge of bankruptcy, and it is a process prior to liquidation which is the ultimate option.

A firm should enter the reorganization process if its operating economic value is greater than its liquidation value. The goal of reorganization is to ensure the continuation of the firm's activities by altering the firm's capital structure. Business managers in real life mostly tend to enter the reorganization process before liquidation.

Reorganization can happen voluntarily by the firm or by the demand from the creditors, with or without legal procedures. The way to carry on the reorganization process is to be decided by the condition of the firm and its relationships with the creditors (Gallinger and Healey, 1991).

The following points are worth paying attention to in this process (Weston and Copeland, 1992):

- The firm, by not making payments at due dates, and because its liabilities have exceeded its assets, has gone bankrupt. Thus, some modifications should be made in the amount or structure of the firm's liabilities. Such modifications can be decreasing fixed payments or changing short term debt into long term debt.
- There is a necessity to invest new capital for improvement and working capital.
- The reasons that created the current hardship that might have originated from the management and activities should be identified and eliminated.

Hotchkiss's (1995) in his study concerning 197 public companies, which were on the edge of bankruptcy, investigated recovery from financial troubles and pointed out that the best option is reorganization. The study could not prove the necessity of liquidation. It was argued that the businesses would lose more value as a result of liquidation.

Initiation and application of a reorganization process can be examined in five steps. These steps are; applying to court for the initiation of the reorganization process, the meeting between the creditor and the debtor, preparation of the reorganization plan, approval of the reorganization plan and finally the meeting of the costs that appear during the process regardless of the approval of the plan.

Clearly, the most important step in this process is the preparation of the reorganization plan. A reorganization plan actually is a compilation, in other words, it is a reduction of demands. A plan has to meet two criteria:

- The plan has to be correct and just; shrinkage has to be applied equally to all departments.
- The plan should yield the best results; future activities of the firm should have good chances of being successful and profitable.

These two conditions can be named as standard of correctness, and standard of application, respectively (Weston and Copeland, 1992).

Standard of Correctness: In the foundation of correctness, there lies the lawfulness of the rights and the implication of the advantages by agreements. The creditors with small claims supply additional cash for reorganization and stretch the term of their credits. In order to accomplish this aspect of correctness, the below process should be carried out.

- A forecast of future sales should be made.
- The activities should be analyzed in order to forecast future revenues and cash flows.
- The varying amount of capital should be determined so that it can be applied to future revenues.
- In order to calculate the present value of varying amount of capital, the amount should be applied to the forecasted cash flow.
- In order to guarantee the safety of the reorganizing firm, the creditor persons or organizations should be identified.

Standard of Application: The primary condition of suitability is that the fixed costs, which appear after reorganization, must be met by the current cash flow. Usually, the amount of fixed payments, which the business has to make, can be supplied either by increasing operational cash flows or decreasing payments, or both. These activities are summarized below.

- The term of debt is usually stretched out. The interest should be decreased, if possible, and some debt should be exchanged with stocks.
- If the registered products have expired or are out of stock, they should be renewed.
- Before the firm restarts its activities the factory and equipment should be modernized.

The activities that shall be done in the reorganization process are explained below in detail.

3.6.1.1 Extending the Term of Debt or Debt Consolidation

A company can fundamentally have a strong financial structure but at the same time be in a situation when it temporarily cannot pay its debt for various reasons. In such a situation, claims of bankruptcy or liquidation from creditors will not be a beneficial solution. Because throughout this period, legal difficulties, unnecessary losses of time and money, and most importantly the losses resulting from the sale of goods at lesser value than they are worth are undesired situations. To allow the company to pay its debt by extending the term of the credits is also beneficial for the creditors.

If the company has more than one creditor, the majority of the creditors should be in favor of the process. If not, the term of the debt cannot be extended. The company and major creditors must reach an agreement and either figure out a payment plan that fits the interests of both sides or make up a committee that will take mutual decisions.

The term extension measure can be diversified in various ways. Consolidation of debt, (turning short term debt into long term debt), borrowing with better terms in order to pay off existing debt and creating new payment plans are examples of the diversifications.

3.6.1.2 Debt Composition

One of the measures that can be taken in the reorganization process is debt composition. For the creditors, giving up their claims for a partial repayment can be beneficial. That is because, if the creditor continues with legal action forcing bankruptcy and liquidation, in the end he might have to settle with a lower amount then before, since this process has its own costs and liquidated goods lose cash value. Thus, the best option for both the creditor and the debtor is coming to an agreement. Financial esteem is established and the debtor benefits by avoiding bankruptcy. For instance, with an agreement, 25% of the debt can be paid upfront and 60% of it can be paid in 6 installments, totaling in 85% of the debt.

This situation is explained in the Turkish tax regulation law under article number 324 "Giving up a portion of claims in agreement". Since for the creditor, the uncollected claim has no value, the creditor can write it off as a loss and can be deducted from the taxes. On the other hand this uncollected amount is a profit for the debtor. If the claims are not amortized in three years with losses, they are counted as profit in the fourth year. Thus, the taxation of the difference is postponed and the company is given a chance to improve its financial standing.

3.6.1.3 Concordat

Concordat is a different application of debt composition or term extension measures. It is in many ways similar to giving up claims by agreements.

Concordat is an application, which was prepared by the law makers in order to save or improve the situations of companies or debtors in financial troubles resulting from various reasons despite all their good will. With this application, the troubled business is protected from creditor take-over.

According to this arrangement, the debtor reaches an agreement with the majority of the creditors to pay a portion of the debt; the creditors give up the remaining portion. The important aspect of this arrangement is that not only the creditors who sign the agreement, but also the creditors, who decline the terms of the agreement, are bonded by it.

If a comparison is made between bankruptcy and concordat, it is seen that both are actually types of collective liquidation but they differ in their purposes. The purpose of bankruptcy is to liquidate the assets of the debtor and protect the interests of the creditor. On the other hand, the purpose of concordat is to save the debtor from financial trouble, and in contrast with bankruptcy, the debtor still manages the business.

According to the articles 285 and 305 of Turkish bankruptcy law, the debtor can ask for concordat by applying to legal organs. In Turkey, the following conditions should be met in order for the concordat to be accepted and applied:

- The debtor company should offer to pay a proportionate amount not less than 50% of total debt
- The Claims Examination Authority should find the offer genuine and accept it
- 2/3 of (both as number and as amount of debt) creditors have to accept the concordat offer.
- Approval of the Court of Trade

With concordat, the debtor company can be given an additional period of time to pay its debt, the debt can be spread into a new payment plan or it can be decided that no interest will be paid starting from the date of the concordat.

3.6.1.4 Management Takeover by the Creditors Committee

If the company is not managed efficiently and effectively by the existing management, the creditors can accept to financially aid the company on the condition of taking over the management of the company (Schall and Haley, 1980). According to the reached agreement, the management of the company can be left to a committee consisting of the representatives of the creditors. The committee stays in control until the financial situation of the company gets better, and although it might fail to solve some fundamental problems, and liquidation remains the final option, they take all the necessary measures to delay liquidation and keep the company in business.

3.6.2 Recapitalization

The key part of the reorganization plan usually deals with the firm's capital structure. The firm can try to change its capital structure by reaching an agreement with stockholders and bondholders, giving them new ones instead of the old. This is called reorganization of the capital structure, or recapitalization. Recapitalization strategy involves exchange of debts for equity or the extension of the maturities of existing debts. Building an optimum mixture of debt and equity would allow the firm to pay its debts and provide a reasonable level of earnings. Recapitalization is frequently planned to increase the equity and the control of the existing management (Gitman, 2009).

The reorganization of the capital structure can be examined under various headings such as measures including the common stocks, bonds and other measures.

3.6.2.1 Shareholders' Contribution Ratio

The indebted company can offer its creditors or the major creditor to give Shareholders' Contribution Ratio or stocks if the firm has an incorporate status. This increases the firm's equity capital and decreases debt.

Giving Shareholders' Contribution Ratio or firm's stocks can be done in different ways. Increasing the capital of the firm will create some capital to be given to the creditors to erase some debt. In this case the debt will be erased and the capital of the firm will increase. Alternatively, the owners or partners of the firm can give their shares to the creditors to compensate for the debt. In this case, the nominal capital of the firm does not change, but the debt decreases. To apply this measure, the creditors must be hopeful about the future of the firm and believe that they will get their receivables this way.

3.6.2.2 Arrangements Regarding Common Stocks

The first measure that can be taken for this issue is related to preferred stocks. This type of stock provides some privileges to its holders in dividend payments, using subscription privileges, having a say in the managing of the firm, and board membership candidates. The business, by replacing these types of stocks with common stocks can save itself from future burdens.

If the company is a corporation, it can lower the nominal values of the stocks according to Turkish trade law article 399; it can even price them lower than the base price. After this, the difference between the new price and the old price is added to the capital reserve account.

Another application is that; the company offers bonds to common stock holders instead of the common stocks. Here, the goal is to increase the income of the firm per share.

Another arrangement regarding stocks is to divide them. A stock is divided into two, three, or more stocks and all are given to the stockholder. Total capital of the firm does not change but the capital is now divided into more stocks. The goal here is to decrease the market value of each stock so that they are bought by more people. This might result in an increase in the price of the shares.

3.6.2.3 Arrangements Regarding Bonds

Here are the major arrangements that can be applied:

The business can offer the bondholders to exchange bonds with stocks. The goal is to decrease long term debt of the company and increase its capital. Turkish Trade Law article 430 applies to this arrangement.

Another application is to change the fixed rate bonds into participating bonds. Now the business owner pays the bond holders only when the company is making profits. As a part of this application, with the holders' permission, the interests on bonds can be lowered, and the business owner minimizes the costs in this issue.

3.6.3 Other Measures

In addition to all the measures mentioned above, the companies have other options to prevent financial troubles or to improve their financial situation. Since they are not in the scope of the study, only the topics are listed below:

- Finding new partners to the firm,
- reevaluating assets and using the increase in value to minimize losses,
- selling or leasing fixed assets,

- to transform debt into equity via creditor banks,
- merging,
- selling collective properties.

If all the reorganization efforts to recover the firm's financial situation or prevent financial troubles fail and no hope is left for the future of the company, the most suitable way is liquidation.

Under normal circumstances, the reorganization process starts with the creditor applying to the court. If the process was not started with the court or was denied by it, or if the application was approved but the reorganization plan was not, the business should be liquidated.

The decision is taken in special courts, under the authority of a judge with a formal procedure. With this decision a company can be legally shut down and the creditors' claims can be fully met.

Turkish trade law points to separate liquidations of companies. Articles 441 – 450 of this law arranged for the finalization and liquidation of incorporate partnerships. The people working on liquidation are assigned by the Bankruptcy Administration in accordance with the Bankruptcy Law. Liquidation staffs try to meet the debts of the company by selling the assets. After the full payment of the debts, the remaining portion of the money is divided among the partners in respect of the capital they have paid and the shares they used to hold. After the liquidation has ended, the liquidation staff demands the trade rights of the company to be revoked and the company ceases to exist.

Chapter 4
Importance of Default Prediction and Accuracy

Business enterprises share the information about gains or losses from the activities, assets structure and its source that they are obtained from, by providing financial statements. Genuine information based financial statements along with market information resemble the situation of the company and provide clues for future prospects of the company with the help of necessary analysis. Therefore analysis of financial statements and market information provides information about financial distress as well. Early estimation of financial distress facilitates a course of recovering remedial activities and avoiding activities from adverse effects.

Studies in the literature proved that it is possible to foresee financial distress earlier by using financial statements and market information. Ratio analysis is a rather frequently used method in financial distress prediction studies. Financial ratios revealed from financial statements make possible to evaluate a company's health. In those studies, it is aimed to find a financial ratio or ratios that provide significant information long before the occurrence of financial distress. The starting point of these studies is the deterioration of financial statement information of the financially distressed firm and pessimistic market prognosis about the company.

In such an environment assessing the financial strength of companies has traditionally been the domain of internal and external parties; such as, company managers, investors, creditors, auditors, government regulators, and other stakeholders.

4.1 Importance to the Management

A modern corporation is a team effort involving a number of players, such as managers, employees, shareholders, and bondholders. For a long time, economists used to assume without question that all these players acted for the common good, but in the last 30 years they have had a lot more to say about the possible conflicts of interest and how companies attempt to overcome such conflicts. These ideas are known collectively as agency theory.

Consider, for example, the relationship between the shareholders and the managers. The shareholders (the principals) want managers (their agents) to maximize firm value. In the United States the ownership of major corporations is widely dispersed and no single shareholder can check on the managers or reprimand those who are slacking. So, to encourage managers to pull their weight, a firm seeks to tie the managers' compensation to the value that they have added. For those managers who persistently neglect shareholders' interest, there is the threat that their firm will be taken over and they will be fired.

In some other countries, corporations are more likely to be owned by a few major shareholders and therefore there is less distance between ownership and control. For example, the families, companies, and banks holding large stakes in many companies can review top management as insiders (Brealey and Myers, 2003).

The role of the managers in the corporation is shortly maximizing shareholders' wealth. On this path, managers should review the company's position among its competitors in the sector, compare the company's actual situation with past performance, etc. If a company is on the way, i.e. if there is no danger at the door, management can follow growth or stability strategies.

If the recent performance is worse than earlier, the bell tolls for something bad. Acquisition or takeover by another firm can be inevitable. Takeovers generally occur because of changing technology or market conditions requiring a major restructuring of corporate assets. In some cases, which is essential for our topic, takeovers occur because incumbent managers are incompetent. When the internal process for change in large corporations is too slow, costly and clumsy to bring about the required restructuring or management change in an efficient way, the capital markets are doing so through the operation of the market for corporate control (Jensen, 1988). In this sense, the market for corporate control is best viewed as a major component of the managerial labor market in which different management teams compete for the rights to manage corporate resources (Jensen and Ruback, 1983).

Moreover, profitable activities of enterprises, protection, or expansion of market share, strength and expansion of competitive power are shaped according to decisions taken by managerial staff. By using a financial distress prediction tool management can recognize financial distress in an earlier phase and take remedial measures against adverse effects of financial distress.

The use of such prediction models provides managers with enough time to find necessary fund, set up new collaborations, search transfer opportunities without losing market value. Managers can use prediction tools for their companies' customers and supplier companies, and they can review their relationships with the companies having probable financial distress risk.

4.2 Importance to the Shareholders

Prediction models may be used by the shareholders in choosing between the opportunities open to them, divestment of the company, merging with or takeover by other companies. If the results are not satisfactory, then shareholders can choose the option to sell out the company at a price over real value, because the company still has a bargaining power to be sold over real value. If shareholders wait in the hope of curing (in reality, there is nothing to be taken into consideration to acquire past success) the company, they may face substantially low market values. Moreover, defining weak companies to takeover is much cheaper and easier through prediction studies.

Also, financial distress prediction models can be considered by the holding companies. Since, failure of a member company would ruin the reputation of the group and will affect investment decisions and credit decisions; therefore, holding companies can monitor what is going on through estimation tools and of course can takeover other distressed firms that would be beneficial for them. This doesn't mean that all the acquired companies would be operated; some takeovers are done for expanding the market share.

4.3 Importance to the Vendor and the Company

Modern corporations use just-in-time (JIT) methodologies to reach minimum production cost and zero defect. JIT methodologies provide a basis for managing inventory and stock in order to minimize waste, as does the effective development and use of quality management standards. Vendor relationships are therefore critical to the effective management of on-line quality.

JIT involves forecasting material requirements and organizing vendor shipments to ensure timely and effective supply. So it means lower inventory and in some cases no inventory at all. Feedback from operations is required in such a time as the vendor can supply the part when it is needed. This feedback is sustained through computer connections between the vendor and the company (James, 1996).

Quality doyen Deming stated "buy materials only if the supplier has a quality process. End the practice of awarding business on the basis of price tag alone" here we see; Deming strongly mentioned that companies should build long-term relationships with suppliers. But suppliers will only accept this if they see through practice and experience that policies will not change when the purchasing manager is replaced (Rao et al., 1996).

Think of such a vendor and a company relationship, they work together and enhance quality. They trust each other, therefore they just do business with each other; it is obvious that a problem arising in one can affect the other as well. Thus, supplier and the company should make distress prediction for controlling each other to be far from the danger. A financial problem in supplier would affect its business decisions and its product quality and production quantity. Less quality and less quantity would harm company's production and its sales resulting in losses and losing reputation in the mind of the customers. On the contrary, the problem in the company could harm the vendor as well; a financial distress in the company would be reflected in the payments to the vendor, so the vendor would fall in distress caused by the company.

To avoid such occurrences, vendor and company should monitor each other through these prediction tools. And if the circumstances are against them; they should find a new supplier or a company to supply.

4.4 Importance to the State

States, to cover public expenses, meet a large part of the income by taxes. Furthermore, tax revenues are more stable than other state incomes, therefore protection of this stability and expansion of taxpayers are vital issues that governments need to sustain. Since instability between expenses and incomes constitutes budget deficit that would be covered by debt financing. This situation results as folding public debts due to increase in interest expenses. In order to avoid this circle government considers actions increasing public savings. This is a difficult decision to be taken by government.

Increase in tax revenues depends on profitable enterprises in an operational efficient economic environment. Governments can expect an increase in revenues as far as they are successful in the task of providing a stable economic environment in which companies carry out their activities. Therefore, how far and in which direction companies are affected by the monetary and fiscal policies of government constitutes a vital role in economy. For example, what kind of results bears the decision of tax increase in order to raise state revenues? After such a decision the state’s revenues can increase but some of the companies may have to terminate their operations. However, a significant level of company shutdowns may cause reduction in state revenues. In this case, government would fail to reach its target. Government can utilize financial failure prediction methods in order to turn the incidents to favours. Because the government, by reducing tax rates can increase tax revenues. In order to achieve this target, companies need to be affected by this decision in a positive way and increase their activities. At the same time, from this situation, project owner entrepreneurs may be influenced in a positive way and they could reach the opportunities to implement their projects.

Before taking such decisions, government can predict probable employment problems. Because of closed companies, due to government policy, state can experience a loss of revenue and can encounter a growing unemployment problem. Unemployment problem does not only have an economic dimension but also political and social dimensions. Therefore, governments, by using business failure models, can avert disadvantages and turn them into advantages.

4.5 Importance to the Investors

Individual and institutional investors can utilize prediction methods and tools in their investment decisions. With the help of the prediction tools, investors can identify the poor stock or stocks in their portfolios and take actions to sell them before these stocks' value evaporate. In addition, investors can identify new valuable stocks to get them into portfolio as well. Fund managers would appreciate the performance of the funds that they operate. Financial failure prediction models provide significant advantages to the investors seeking high returns. An investor can reshape his portfolio by prediction tools, i.e. if the financially distressed company is expected to recover from its problems, then investing on this company's low priced stocks can bring high returns later, when the company resolves.

Default risk can show changes over time from company to company, and for the same company too. Credit rating companies rate companies according to their capability to satisfy their credits. According to these agencies' credit rates, investors take decision to sale or buy. For example, Standard and Poor's (S&P) assessed credit ratings of Chrysler, one of the world leading automotive corporations through 1980 and 1991. The credit rate BB in 1980 was decreased to CCC in 1981 and 1982. Afterwards, credit rate was increased firstly to B and then to BBB due to increased profits of Chrysler. In the year 1990, the company fell in distress and gained poor profits, and the credit rate was decreased again (Levy, 1999). Individual and other investors follow credit ratings announced by the credit agencies, for their investment decisions.

On the other hand, modern portfolio management indicates that secured investments bring low returns whereas risky investments bring high returns, but insisting on high returns bears the risk of losing a significant part of investment either.

Dichev (1998) in his study suggested that, bankruptcy risk of companies was not appreciated with high returns. In this study it was indicated that companies having high bankruptcy risk provided significant lower returns than the market.

Clark and Weinstein (1983) conducted a study to assess the stock performances of the financially distressed companies listed on the American stock markets. They calculated the abnormal and cumulative abnormal returns of related companies and found out that raw and market adjusted returns of subject stocks had negative values from 3 years prior to bankruptcy. Another study about stock return performances was conducted by Aharony et al. (1980). They investigated stock return performances of 110 bankrupted and 110 financially successful counter companies. They underlined that risk of bankrupt companies tends to increase. Stock returns of bankrupt companies were started to depreciate from 4 years prior to bankruptcy and that the negative course continued exponentially till bankruptcy.

The study of Iqbal and Shetty (2002) supports that the stock returns of financially failed companies tend to decrease in early periods of financial distress. They indicated that the investors, who had the information about the company earlier than the market, sold the stocks and therefore avoided possible losses. Another study about insider trading was conducted by Ma (2001), who investigated 89 financially failed companies in the years 1982 - 1990. In this study, it is underlined that insiders of Chapter 11 bankruptcy firms purchase significantly fewer shares than insiders of the control firms before the bankruptcy announcement. Moreover, only insider traders were ascertained decreasing their positions on the subject company coming closer to financial failure. This evidence underlines how important the prediction tools are for investors.

Usage of prediction models will increase the success in sale and purchase decisions of investors. Everyday capital markets are improved and investment areas are diversified. An individual investor may not have enough time for and experience in evaluation of investment tools. Especially, individual investors may not manage effectively the funds due to lack of experience. In such a situation, wrong decisions would be taken according to poor foresight and therefore the expected return on investment cannot be achieved.

Financial failure models do not only provide necessary time an investor needs but also resolve the experience deficits. Thus, investors achieve their objectives by investing in the right areas, and companies have the opportunity to be strong by rational distribution of funds. Resolution of difficulties in funding lets the opportunities for new investments and provides business to grow and grasp competitive advantages.

4.6 Importance to the Creditors

A creditor is a person or company who makes loan to the debtor company, or to whom the money is owed (Seyidoğlu, 2001). Default risk is considered in every kind of credit agreements by the creditors in order to protect themselves from the distress that they would encounter due to insufficient payments or even no payments of the debtors. That is why credit management is so important for credit organizations, companies, banks, and other financial institutions.

Credit management involves five main steps; these are defining the length of the payment period, defining the form of the contract, assessing each customer's creditworthiness, defining sensible credit limits, and the last step is to collect.

Assessing creditworthiness of the borrower is the vital step in credit management. There are a variety of sources of information about the customer; the creditor's own experience with the customer, the experience of the other creditors, the assessment of a credit agency, a check with the customer's bank, the market value of customer's securities, and an analysis of the customer's financial statements. Furthermore, with the help of a financial failure prediction model, credit institutions benefit from choosing the right company to loan. Evaluation and analysis of loan applications by such a model provide more successful and faster results. Rejecting loan application of a company which is predicted as financially distressed by the model, saves time and increases the effectiveness of human experts' credit rating success. Thus, the funds will be used in the right areas, and in this case, the country's economy and the credit institutes can gain great benefits.

4.7 Importance to the Labor and Labor Organizations

Labor is one of the important production factors and plays a significant role in success of a company. Employed labors, labor and employer's unions are directly affected by activities of enterprises. Businesses that achieved their objectives can rise in the market, so the labors would like to get their fair share from this situation.

Prediction models can be used by labor organizations to reveal information about the financial health of the company, from which labor organizations can define the pay rise and insist on other labor rights. On the other hand, labors of financially distressed predicted company can work harder to recover the company or seek another job for themselves.

4.8 Accuracy of Early Warning Systems

Accuracy of prediction models depends on certain fundamental factors; reliability of financial statements, knowledge and experience of the analyst, sectoral knowledge, anticipating economic trends during the analysis period, and awareness of the management's policies. Accurate prediction models would be beneficial for businesses, but inaccuracy or a possible error in prediction can lead to losses. For this reason prediction studies require seriousness from the beginning to the end.

It is known that some companies tend to deceive authorities by cosmetic financial tables (Anıl, 1997); therefore, an analyst should avoid selecting these kinds of financial statements in his/her study and work with audited financial statements only.

Interpreting and analyzing financial statements require knowledge and experience in this field. Experienced and acquainted analyst can see the missing and deceiving points in the statements, and can make better interpretations.

Sectoral analysis comes after macro-economic analysis in the establishment of early warning models; therefore, macroeconomic and sectoral information give clues about the external environment of the company or companies which are subject to the study.

Of the companies included in the analysis, past production, price, capital budgeting, and dividend payment policies are valuable sources of information for the health of the study. If it was possible to attain the future policies of subject companies then the accuracy of early warning study would increase. Comparison of past and current or future policies would light up the study in the right way.

Part II

Default Risk Assessment

Chapter 5
Default Risk Assessment Models

The question how to assess distress risk or estimate bankruptcies is of interest for various parties and has a long history in the finance literature. The most interested party in this matter has been credit institutions. Many academic studies were conducted in this area and are continued to be performed. The studies in the field of credit risk scoring were conducted frequently in the late 1960s and 1970s, and have become a significant field of application by evolving within time.

The pioneering studies in the field of bankruptcy prediction were introduced by Beaver (1966) and Altman (1968). Later on, various studies from academia followed these studies in the USA and other countries. The demand of finance industry on this field contributed to extension of these studies to advanced levels.

There are various possibilities to classify existing forecasting models; chronological classifications, methodological classifications like statistical or mathematical approaches, classical or theoretical approaches, static or dynamic approaches can be given as examples.

Altman and Hotchkiss (2005) classified all methods of bankruptcy or financial distress prediction studies chronologically in the following order:

- Qualitative (Subjective)
- Univariate (Accounting/Market Measures)
- Multivariate (Accounting/Market Measures)
    - Discriminant, Logit, Probit Models (Linear, Quadratic)
    - Nonlinear Models—for example, Recursive Participating Analysis (RPA) and Neural Networks (NN)
- Discriminant and Logit Models in Use
    - Consumer Models (e.g., Fair Isaacs)
    - Z-Score—Manufacturing
    - ZETA Score—Industrials

Private Firm Models (e.g., Risk Calc [Moody's], Z″-Score)

EM Score—Emerging Markets, Industrial

Other—Bank Specialized Systems

- Artificial Intelligence Systems

Expert Systems

Neural Networks (e.g., Credit Model [S&P], Central dei Bilanci [CBI], Italy)

- Option/Contingent Claims Models

Risk of Ruin

KMV Credit Monitor Model

- Blended Ratio/Market Value Models

Moody's Risk Calc

BondScore (CreditSights)

Z-Score (Market Value Model)

Modern rating systems and the studies conducted to assess credit risk, default risk or bankruptcy risk are heavily based on financial ratios and non-ratio financial information. According to a study conducted by Hossari (2006) 79% of the studies used financial ratio information, 15% of the studies used non-ratio financial information, and 6% of the studies used non-financial information for corporate collapse modelling. The study covers 208 studies between 1966 and 2004. Although, fundamentally different models are applied, the majority of the applied models use the same financial information for assessment of default risk.

Rating systems are in the process of transition from qualitative towards quantitative methods according to historical development. This process heavily benefits from computer systems and programs. Due to advent of personal computers, the analysis of default risk has gained acceleration.

In this chapter, historical evaluation of bankruptcy prediction and the models, which are used for modelling, are introduced. For modelling purpose, Discriminant Analysis (DA) and Logit Analysis (LA) from classical (traditional) statistical models; KMV model from market based structural models; Naïve Bayes (NB), Bayesian Network (BN), k-Nearest Neighbour (k-NN), Artificial Neural Network (ANN), Support Vector Machine

(SVM), C4.5, Chi-Square Automatic Interaction Detector (CHAID), Classification and Regression Tree (CRT) from machine learning models are used.

5.1 Bankruptcy Prediction Studies

The early studies of bankruptcy prediction, which are known, were conducted by Ramster and Foster (1931), Fitzpatrick (1932), Winakor and Smith (1935), and Merwin (1942) (Uğurlu and Aksoy, 2006). At the beginning of the research period of failure prediction there were no advanced statistical methods or computers available for them. So they were comparing the values of financial ratios in failed and non-failed firms with each other and found that the financial ratios were poorer for failed firms.

Later in the 1960's, the researches of predicting bankruptcy began to evolve. In 1966, the pioneering study of Beaver presented the discriminant analysis. The only point where Beaver was mostly criticized was that his study was dependent on univariate analysis and considered certain groups (a limited number) of financial ratios. In 1968 Altman expanded this analysis to multivariate analysis. Until the 1980's discriminant analysis was the dominant method in failure prediction.

5.2 Classical Statistical Models

5.2.1 Beaver's Financial Ratios as Predictors of Failure (1966)

Beaver selected 79 failed companies, which were bankrupt or had defaulted on payment of interest or preferred stock dividend or had an overdrawn bank account, among industrial public corporations whose financial tables presented in Moody's Industrial Manual during years 1954 to 1964. The asset size range was 0,6 million to 45 million dollars and the mean asset size was 6 million dollars. Beaver followed paired sample method to select non-failed companies, in his terms *"for each failed firm in the sample, a nonfailed firm of the same industry and asset size was selected."* The motivation behind this method was to control for the effects of factors (asset size and industry) on financial ratio and failure.

Beaver used three criteria to select 30 financial ratios for each of 5 years prior to failure:

1) popularity of financial ratios in the literature,
2) performance of the financial ratios in previous studies,
3) definition of the financial ratios in terms of a "cash-flow" theory.

Beaver conducted three type of empirical analysis to show the predictive ability of the financial ratios:

1) comparisons of mean values,
2) dichotomous classification tests,
3) analysis of likelihood ratios.

Beaver's comparison of means of financial ratios for failed companies exposed that their financial ratios were substantially worse and showed deterioration than that of non-failed companies as the year of failure approached.

The second empirical analysis was conducted to test the predictive ability of the financial ratios. The companies were randomly divided into two subsamples. For a given ratio an optimum cutoff point, which minimizes the percentage of incorrect classification, was found for each subsample. The optimal cutoff points were used for classification of own subsample and other subsample. However, Beaver realized that among 30 financial ratios only 6 of them were particularly significant in predicting failure. Significance of financial ratios was measured in terms of lowest misclassification rate. The best financial ratio was cash flow to total debt ratio with 10 % misclassification rate for five years prior to failure. His best six classifiers are:

1) cash flow to total debt,
2) net income to total assets,
3) current plus long-term liabilities to total assets,
4) working capital to total assets,
5) current ratio,
6) no-credit interval.

Nevertheless, Beaver was not satisfied with the findings, because classification test involved dichotomous choice and therefore, the important information about the probability of failure provided by the difference between the magnitude of the financial ratio and the cutoff point was not considered. The second limitation of the test was that the cutoff points obtained from sample cannot be optimal for population. To overcome these limitations, Beaver carried out the last experiment, analysis of likelihood ratios. This analysis involved preparation of histograms and inspection of overlap, skewness and normality of financial ratio distributions. Analysis of likelihood ratios supported that the financial ratios could be useful indicators of business failure at least five years prior to failure.

5.2.2 Altman's Model, Z-Score (1968)

Altman challenged univariate analysis and used multivariate discriminant analysis (MDA) to find the linear function of financial ratios that discriminates bankrupt and non-bankrupt companies best. He chose 33 bankrupt manufacturing firms during the years 1946 to 1965. Like Beaver, he selected 33 non-bankrupt manufacturing firms using paired sample method where industry and size were the matching criteria.

Altman chose 22 financial ratios according to their popularity in the literature and potential relevancy to the analysis and grouped them into five standard ratio categories: liquidity, profitability, leverage, solvency, and activity. Among them 5 financial ratios did the best overall job together in classifying bankrupt and non-bankrupt firms.

The final combination of ratios best discriminates between groups was as follows:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

Where,

X_1 = working capital to total assets,
X_2 = retained earnings to total assets,
X_3 = earnings before interest and taxes to total assets,
X_4 = market value equity to book value of total liabilities,

X_5 = sales to total assets,

Z = overall index or score.

The companies with lower Z-Scores than cutoff point are classified as bankrupt or vice-versa. The lower Z-Scores indicate higher distress risk. With this function, Altman classified the groups with 95% success 1 year prior to failure. A company with a Z-Score greater than 2.99 was classified as non-bankrupt; on the contrary, a company with a Z-Score below 1.81 was classified as bankrupt. The area between these two scores was labeled as *"zone of ignorance"* or *"gray area"* where misclassifications were observed.

Table 6: Classification Results, Original Sample (1968)

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

Source: Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy, Journal of Finance 23(4). p. 589.

Altman's model was more accurate than Beaver's univariate model. Produced type I and type II errors were 6% and 3% respectively and the overall classification accuracy was 95% in one year prior to failure.

In 1977, Altman, Haldeman and Narayanan aimed to integrate the previous Z-Score approach into recent developments with respect to business failures; therefore, they developed a second generation model of original Z-Score with several enhancements. This study incorporated advances in using statistical discriminant techniques at that time. The new model, which was called ZETA, was more accurate in classification of bankrupt companies than the original Z-Score up to 5 years prior to failure.

Altman et al. (1977) listed their 5 reasons to construct the ZETA model as follows:

- The increase in asset size and financial profile of business failures. The average asset size of the bankrupt company sample was approximately 100 million dollars. All of the companies in the study sample had asset size more than 20 million dollars.
- The new model ought to be as up-to-date as possible considering the temporal nature of the data.
- Previous studies focused on classification of manufacturers and specific industries. The retailing companies could also be analyzed with the appropriate analytical adjustments.
- Another vital feature of this study was that the data and footnotes to financial statements had been examined to consider the most recent changes in financial reporting standards and accounting practices.
- To test and evaluate some of the latest advancements and controversial aspects of discriminant analysis.

Altman et al. chose 53 bankrupt and 58 non-bankrupt companies during the years 1969 to 1975 for this study. One significant difference between Z-Score and the ZETA model was that the ZETA model provided classification statistics for non-bankrupt companies up to 5 year prior to failure; whereas, Z-Score provided only up to 2 year prior to failure. The ZETA model used 27 variables. The one year prior to failure classification accuracy for bankrupt companies was quite similar for both models (96.2% for ZETA and 93.9% for Z-Score) but the classification accuracy was consistently higher for the ZETA model in years 2-5 prior to failure. By the fifth year, the ZETA model was about 70% accurate, whereas the Z-Score's accuracy fell to 36%.

The ZETA model provided better results than the Altman’s (1968) Z-Score model. The table below compares the two models.

Table 7: Comparison of Zeta Model and Altman's 1968 Model

	Zeta Model		Altman's 1968 Model	
Years prior to Bankruptcy (1)	Bankrupt (2)	Non-Bankrupt (3)	Bankrupt (4)	Non-Bankrupt (5)
1	96.2	89.7	93.9	97
2	84.9	93.1	71.9	93.9
3	74.5	91.4	48.3	n.a.
4	68.1	89.5	28.6	n.a.
5	69.8	82.1	36	n.a.

Source: Altman E. I. (1993), Classification Results, Two Statements Prior to Bankruptcy

5.2.3 Ohlson's O Score (1980)

Ohlson introduced a logistic regression approach to the problem of corporate failure prediction literature. He argued against multiple discriminant analysis because of its restrictive constraints such as the requirement of identical variance-covariance matrices for both groups (failed, non-failed), and the requirement of normally distributed predictors. He found that the output of the MDA model, which is an ordinal ranking, provides nothing about the probability of default. Moreover, he criticized the matching procedure of applied MDA models, in which size and industry were used as matching criteria. He argued for the usage of variables as predictors rather than using them for matching. In order to ease these critical issues, he used conditional logit analysis for estimating probability of default.

Contrary to previous studies, Ohlson derived the failed firm data from 10-K financial reports which provides information about the financial condition of the firms; hereby, the researcher can check whether the firm went bankrupt before or after the date of release. He derived 105 bankrupt and 2058 non-bankrupt industrial firms in the period between 1970 and 1976. The predictors of the study were chosen according to frequency of appearance in literature in previous studies.

Ohlson's model has 9 variables with 2 dummy variables. These are:

1. SIZE = log (total assets/GNP price-level index),
2. TLTA == Total liabilities divided by total assets,
3. WCTA = Working capital divided by total assets,
4. CLCA = Current liabilities divided by current assets,
5. OENEG = One if total liabilities exceeds total assets, zero otherwise,
6. NITA = Net income divided by total assets,
7. FUTL = Funds provided by operations divided by total liabilities,
8. INTWO = One if net income was negative for the last two years, zero otherwise,
9. CHIN = $(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where NI_t is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income (Ohlson, 1980).

O-Score function:

$$\begin{aligned}\text{O-Score} = &- 1.32 - 0.407\ \text{SIZE} + 6.03\ \text{TLTA} - 1.43\ \text{WCTA} + 0.0757\ \text{CLCA} \\ &- 2.37\ \text{NITA} - 1.83\ \text{FUTL} + 0.285\ \text{INTWO} - 1.72\ \text{OENEG} - 0.521\ \text{CHIN}\end{aligned}$$

The above O-Score model is the model 1 of the study with 96.12% it has the highest accuracy compared with two other models. In total, Ohlson constructed three models: Model 1 was for prediction within 1 year, Model 2 was for prediction within 2 year and Model 3 was for prediction within 1 or 2 years.

Ohlson revealed four statistically significant factors for assessing probability of bankruptcy, these are:

1. Size of the firm,
2. Measure(s) of financial structure by a measure of leverage (TLTA),
3. Measure(s) of performance (NITA or/and FUTL),
4. Measure(s) of current liquidity (WCTA or WCTA and CLCA jointly).

Ohlson concluded that accuracy of the any model depends on the structure and the availability of the information and of the assumptions concerning misclassification costs. Significant improvements in prediction probably need additional variables.

5.2.4 Other Studies Employing Classical Statistical Methods

Deakin (1972) aimed at proposing a business failure model alternative to the models developed by Beaver and Altman. Deakin appreciated Beaver's empirical results for their predictive accuracy and Altman's multivariate approach. He planned to build a better failure prediction model by combining the best sides of Beaver's (1966) and Altman's (1968) studies. He used Beaver's 14 financial ratios to construct a discriminant function that produces highest classification accuracy. Deakin chose 32 failed companies over the period 1964 to 1970 and selected 32 non-failed companies using paired sample method where industry characteristics, asset size and year of financial statements were the matching criteria (Altman, 1993).

Deakin's first method was similar to Beaver's dichotomous classification test. To capture the order of the classification power of the financial ratios, he compared the average values of financial ratios and applied Spearman's rank correlation method. Except for the third year prior to failure, the correlation coefficients were significant in other years. The reason, why correlation coefficient in three years prior to failure was less significant, was found by the analysis of capital structure of the failed companies. It was observed that in those years the failed companies tried to expand and the required fund for expansion was obtained by getting into debt and issuing preferred stock. The failed company's cash flow was impaired by negative net income as failure approaches.

In his second method, Deakin applied discriminant analysis using the same 14 financial ratios and 32 failed companies, and the non-failed 32 companies were randomly drawn from Moody's Industrial Manual between 1962 and 1966. The misclassification rates were less than 5% in the first three years prior to failure for the original sample. The misclassification rates for the holdout sample consists of 11 failed and 23 non-failed companies drawn randomly from Moody's, were 22%, 6%, 12%, 23% and 15% respectively for the five years prior to failure. The statistics showed that the two groups were distinct in the first three years prior to failure and less distinct in four and five years prior to failure. Deakin underlined that discriminant analysis can be used to predict corporate failures three years in advance with a fairly high prediction accuracy.

Edmister (1972) aimed to develop a failure prediction model for small businesses. He defined small businesses as a company indebted to the Small Business Administration (SBA). Edmister computed 19 financial ratios, which were found significant in literature, from the financial statements of the indebted companies that were issued during years 1954 to 1969. He used two samples of companies to construct a multivariate discriminant analysis (MDA) model. The first sample consisted of 42 companies, due to the requirement of three consecutive financial statements prior to failure in order to test the predictive power of the model. The second sample consisted of 562 companies with one financial statement prior to failure. His methodological framework was based on testing four hypotheses:

1. A financial ratio's level as a predictor of failure,
2. The three year trend of a financial ratio as a predictor of failure,
3. The three year average of a financial ratio as a predictor or failure,
4. The combination of the industry level and industry relative trend for each financial ratio to predict failure (Altman, 1993).

Edmister's model was based on zero-one technique, the reason why he preferred this technique was that he wanted to diminish multicollinearity in the model. He transformed each ratio into zero-one variable based according to arbitrary cutoff points. Altman (1993) argued that this ratio transformation could lead an information loss ought to be avoided.

A total of 7 financial ratios out of 19 financial ratios constructed the prediction model below:

$$Z = 0.951 - \underset{(4.24)}{0.532X_1} - \underset{(2.82)}{0.293X_2} - \underset{(4.51)}{0.482X_3} + \underset{(2.61)}{0.277X_4} - \underset{(2.60)}{0.452X_5} - \underset{(1.68)}{0.352X_6} - \underset{(7.11)}{0.924X_7}$$

with $R^2 = 0.74$, $F = 14.02$, and $N = 84$.

where:
Figures in parenthesis are t-statistics.

Z = The zero-one dependent variable. It equals one for non-failed company and zero for failed company,

X_1 = Annual funds flow to current liabilities. It equals one if the ratio is less than 0.05, zero otherwise,

X_2 = Equity to sales. It equals one if the ratio is less than 0.07, zero otherwise,

X_3 = Net working capital to sales divided by the corresponding RMA average ratios. It equals one if the ratio is less than – 0.02, zero otherwise,

X_4 = Current liabilities to equity divided by the corresponding RMA average ratio. It equals one, if the ratio less than 0.48, zero otherwise,

X_5 = Inventory to sales divided by the corresponding RMA industry ratio. It equals one, if the ratio shows an upward trend, zero otherwise,

X_6 = The quick ratio divided by the trend in RMA quick ratio. It equals one if trend is downward and level just prior to the loan and is less than 0.34, zero otherwise,

X_7 = The quick ratio divided by RMA quick ratio. It equals one if the ratio shows an upward trend, zero otherwise.

The model produced an overall accuracy of 93% with 90% correct prediction of failed companies and 95% correct prediction of non-failed companies. He concluded that prediction power of the ratio based models hang on the selection of the variables and the method applied.

Libby (1975) used subset of Deakin's (1972) 14 financial ratios and 60 companies consist of randomly drawn 30 failed and 30 non-failed companies to capture the ability of the loan officers to interpret the prediction power of the financial ratio information in bankruptcy prediction context. Libby divided the sample into three subsamples contain random assigned 10 failed and 10 non-failed companies and calculated 14 financial ratios of the each subsample.

Using principal components analysis followed by varimax rotation, Libby determined five independent sources of variation within the 14 variables; profitability (net income to total assets), activity (current assets to sales), liquidity (current assets to current liabilities), asset balance (current assets to total assets) and cash position (cash to total assets).

Forty three loan officers, of whom 16 from small bank and 27 from large bank, participated Libby's study. Each officer evaluated 70 data sets of 5 financial ratios with prior information that half of the companies failed within three years.

Libby concluded that the loan officers interpreted the failures by utilizing financial ratio information. There was no significant difference found between large and small bank loan officer's decisions. There were no significant correlations between interpretation and loan officer's age and experience; no difference existed in short-term test-retest reliability between user subgroups, loan officers made relatively uniform interpretation of financial ratio information (Altman, 1993).

Altman (1993) criticized Libby's study about the fact that the loan officers informed earlier that one-half of the companies being analyzed failed. This type of information is, of course, not available to analysts. In another study conducted by Casey (1980) proved that loan officers who were not informed about failure density could only correctly predict 27% of a sample of bankrupt firms. Non-bankrupt prediction accuracy was much better.

Deakin (1977) extended his 1972 study to provide an indication of frequency and nature of misclassification of non-failed companies and to improve prediction power of the model. He used the sample of 63 failed companies, of which 32 companies were from his 1972 study and 31 companies were from the study of Altman and McGough (1974), failed in 1970 and 1971 and matched them with 80 non-failed companies randomly drawn from Moody's. For each of the companies he computed Libby's (1975) five financial ratios.

Accuracies of linear and quadratic classification models were 94.4% and 83.9% respectively. Deakin's validation tests were based on three decision rules classifying failed and non-failed companies: classify failed if linear and quadratic models classify failed, classify non-failed if linear and quadratic models classify non-failed, and investigate further if both models produce conflicting results.

Validation test conducted to 1780 companies of the Compustat 1980 file classified 290 companies as failed, 1317 as non-failed and 173 companies were assigned to further investigation. Deakin reserved 290 classified failed and 100 non-failed companies to evaluate the prediction power of the models. Based on the definition of the failure classification accuracy varies, if failure was defined as bankruptcy, liquidation and restructuring then only 18 (6.2%) of the 290 failed companies and all of the 100 non-failed companies were predicted accurately. If the failure definition was extended with mergers, dividend cuts or omissions then 224 (77.2%) of the 290 failed companies were predicted accurately and 35 (35%) of the 100 non-failed companies predicted as classified. To test the predictive power of the models further he selected 47 bankrupt companies between 1972 and 1974. 39 (83%) of the bankrupt companies classified accurately, 7 companies were assigned to further investigation and 1 bankrupt company classified as non-failed.

Scott (1981) in his study compared the studies of Beaver (1967), Altman (1968), Deakin (1972), Wilcox (1971, 1976), and Altman et al. (1977), in terms of their classification accuracies and their adherence to Scott's own conceptual bankruptcy framework. Scott's underlined that the variable selection approach could cause a classification error if the chosen predictive variables used for the companies in the periods different from the period initial model constructed. He concluded that "*of the multidimensional models, the ZETA model is perhaps most convincing. It has high discriminatory power, is reasonably parsimonious, and includes accounting and stock market data as well as earnings and debt variables. Further, it is being used in practice by over thirty financial institutions. As a result, although it is unlikely to represent the perfect prediction model,* *it will be used as a benchmark for judging the plausibility of the theories discussed in the following sections.*"

5.3 Discriminant Analysis

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

$$Z = \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \,, \qquad (1)$$

where Z = discriminant score,

β_i (i = 1, 2, ..., n) = coefficient (discriminant) weights;

x_i (i = 1, 2, ..., n) = independent variables, the financial ratios.

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

Discriminant analysis performs better when the variables follow a multivariate normal distribution and the covariance matrices for every group are equal. However, empirical studies have shown that especially failing firms violate the normality condition (Back et al., 1996). Moreover, multicollinearity among independent variables is often a serious problem, especially when stepwise procedures are employed (Hair et al., 1998). However, empirical studies have proved that the problems connected with normality assumptions do not weaken DA's classification capability, but DA's prediction ability.

In addition, Altman (2000) states that the multicollinearity aspect is not serious in DA, it usually motivates careful selection of the predictive variables (ratios). It also has the advantage of potentially yielding a model with a relatively small number of selected measurements which convey a great deal of information. This information might very well indicate differences among groups, but whether or not these differences are significant and meaningful is a more important aspect of the analysis.

The two mostly used methods in deriving the discriminant models are the direct and the stepwise methods.

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

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

5.4 Logit Analysis

Logit analysis investigates the relationship between binary or ordinal response probability and explanatory variables. The parameters of the model are estimated by the method of maximum likelihood. Like DA, this method weights the independent variables and assigns a Z-score in the form of failure probability to each firm in the sample. The advantage of this method is that it relaxes the assumption of DA. The first practitioner of logit analysis in failure prediction was Ohlson (1980). Most of the studies conducted after 1981 used logit analysis to relax the constraints of DA (Zavgren, 1985; Lau, 1987; Keasey and McGuinness, 1990; Tennyson et al., 1990). Logit analysis uses the logistic cumulative probability function to predict failure. The result of the function is between 0 and 1 and probability of failure in logit analysis can be written as:

$$\text{Probability of failure} = \frac{1}{1+e^{-z}} = \frac{1}{1+e^{-(\beta_1+\beta_2 x_2+\ldots+\beta_n x_n)}} \text{ (Gujarati, 2003)} \qquad (2)$$

where β_i (i =1, 2, ..., n) = coefficient weights,

x_i (i = 1, 2, ..., n) = independent variables, the financial ratios

5.5 Market-based Model (Option based Default Probability)

The static nature of the accounting models described above forced researchers to consider market information in their construction of models. The initial assumption of market based models is that market knows all the necessary information about the firms and reflects them in stock prices, so market based models predict default risk by combining firm's leverage structure and market value of its assets.

Dichev (1998), Griffin and Lemmon (2002), and Ferguson and Shockley (2003) examined the relation between the stock returns and bankruptcy risk of insolvent and risky companies by using Altman's (1968) Z-score and Olson's (1980) conditional logit model. Avramov et al. (2007) underlined the strong link between credit ratings and stock returns. Shumway (2001) criticized traditional ratio analysis to be static and its bankruptcy probabilities to be biased and inconsistent, by ignoring the fact that the firms change over time, and to overlook the causative indicators of bankruptcy. Therefore, Shumway established a dynamic logit based model that uses both accounting based and market driven variables to forecast bankruptcy more accurately. A recent study followed Shumway's approach is Chava and Jarrow's (2004) study that considers industry effects and monthly observation intervals to validate the superior forecasting performance of Shumway's hazard model, and Beaver et al. (2005) investigated robustness of predictive ability of financial ratios through time.

These mentioned studies focused heavily on classification accuracy and compensation of decreasing predictive ability of the models rather than causative indicators of financial failure. Beaver et al. (2005) stated that several forces over the last forty years potentially affect the ability of financial ratios to predict bankruptcy. Those factors could be summarized as development of accounting standards which has a positive effect on predictive ability of financial ratios; on the contrary, increase in relative importance of financial derivatives and intangible assets in financial statements, and increase in the degree of discretion entering financial statements impaired the financial statements' quality. So, this phenomenon underlined the importance of market driven data in financial failure prediction literature.

As Beaver et al. (2005) emphasized the spread of financial derivatives and corporate debt products in economy attracted academics' and practitioners' interest in structural models that forecast corporate defaults. Because, a deficiency of accounting based models is data limitations and explanatory variables are primarily limited to financial statements data, which are updated infrequently and are determined by accounting procedures that rely on book value rather than market valuation. And there is often limited economic theory as to why a particular financial ratio would be useful in default forecast. In contrast, modern structural default risk measurement models are more firmly grounded in financial theory. One of the popular innovative forecasting structural model stems from Black-Scholes' (1973) and Merton's (1974) seminal works on pricing options; this method was further developed by KMV corporation which was later acquired by Moody's. Consistent with Bharath and Shumway (2004), we refer to this model as the KMV-Merton model. This model was applied to various sectors by Vassalou and Xing (2004), Chan-Lau et al. (2004), Hillegeist et al. (2004), Van den End and Tabbea (2005), Gharghori et al. (2006), Ergin and Fettahoglu (2008), among others.

The main promises of KMV-Merton model can be summarized as follows:

- It has a strong theoretical structure. Its verification does not need discussion according to time and sample like empirically constructed accounting based models (Ergin and Fettahoglu, 2008). It provides theoretical determinants of default risk and the structure how to derive distress information from the market facts.

- There is definite number of variable in the model and the variables do not change as in accounting based models (Ergin and Fettahoglu, 2008).
- In contrast to accounting based models, it is forward-looking. Default information of the model is extracted from the market prices which contain the expectations about the future.
- It considers volatility of assets in the analysis and assessment of default risk. Volatility is a crucial variable in default prediction. It captures the possibility of asset value corrosion to the point, when a firm will not be able to meet its debts (Hillegeist et al., 2004).

However, this market based model relies on the efficient market hypothesis. This assumption is the main shortcoming of market based models. In reality, market does not reflect all the information about the financial situation of a firm, so this causes bias in the estimation of future market value of assets and the volatility of asset returns. The other shortcoming of market based models is that they only consider public firms listed on stock markets not the private firms (Berg, 2007). So this model also has some limitations.

5.5.1 The KMV-Merton Model

Black and Scholes (1973) and Merton (1974) developed an option pricing model that is also used for computing corporate default measures. An important observation in Merton's (1974) model is that the equity of a firm is viewed as a call option on the value of a firm's assets. The strike price of the call option is equal to the face value of the firm's debts and the option expires at time T, when the debt matures. Principally, the liability side of the balance sheet of a firm is composed of debt and equity. The equity holders have the right but not the obligation to pay back the debts to the creditors. When the debts of the firm mature, the equity holders would pay the debts to the creditors, if the market value of the firm's assets exceeds the face value of the debts. Otherwise, the equity holders would not pay the debts if the value of the firm's assets is not high enough to fully pay back the firm's debts. Then the firm files for bankruptcy and is assumed to transfer the ownership of the firm to the creditors without cost. Therefore, equity holders are the residual claimants on the firm's assets after all other obligations have been met and have limited liability, when the firm is bankrupt. Consequently, the payoffs to equity are similar to payoffs to the call option.

The Merton model has two important assumptions. The first assumption is that the market value (V_A) of a firm's underlying assets follows a Geometric Brownian Motion with an instantaneous drift (μ), volatility (σ) and standard Wiener process W.

$$dV_A = \mu V_A dt + \sigma_A V_A dW \qquad (3)$$

The second assumption is that the firm has issued just one discount bond maturing in T periods. Under the assumptions stated above, the equity of the firm is a call option on the underlying value of the firm's asset with a strike price equal to face value of the firm's debts expiring at time T. The face value of the debt at time t is denoted by X, which will mature at time T. The market value of a firm's equity (V_E) is a call option on V_A, and according to the Black-Scholes-Merton option valuation model their relationship is defined by the following equation.

$$V_E = V_A\, N(d_1) - Xe^{-rT}\, N(d_2) \qquad (4)$$

In the equation above, N(.) is the cumulative standard normal distribution, r is the risk free rate and the parameters d_1 and d_2 are related through the following equations.

$$d_1 = \frac{\ln(V_A / X) + (r + 0{,}5\sigma_A^2)T}{\sigma_A \sqrt{T}} \qquad (5)$$

$$d_2 = d_1 - \sigma_A \sqrt{T} \qquad (6)$$

As stated in Crosbie and Bohn (2003), default occurs when the market value of the firm's assets is less than the face value of debt (X) at the time of maturity. Alternatively, default happens when the ratio of market value of assets to book value of debt is less than one. Hence, the probability of default (PD) is the probability that the market value falls below the face value of debt at time T.

The BSM model assumes that the natural log of future asset values is distributed normally so the probability of default at t can be presented as follows:

$$\text{PD}_t = \text{N (-DD)} = \text{N}\left[-\frac{\ln\frac{V_{A,t}}{X_t} + (\mu - 0{,}5\sigma_A^2)T}{\sigma_A\sqrt{T}}\right] \tag{7}$$

where distance-to-default (DD)

$$\text{DD} = \frac{\ln\frac{V_{A,t}}{X_t} + (\mu - 0{,}5\sigma_A^2)T}{\sigma_A\sqrt{T}}, \tag{8}$$

shows which number of standard deviations from the mean is required for default to materialize.

Crosbie and Bohn (2003) state that, the weak point of the model hangs on the normality assumption of the model. Since the Moody's KMV model's empirical distribution of default rates has a much wider tail than the normal distribution. Unfortunately, we do not have the opportunity to employ an empirical distribution on default occurrences for Turkish firms.

5.6 Machine Learning Models

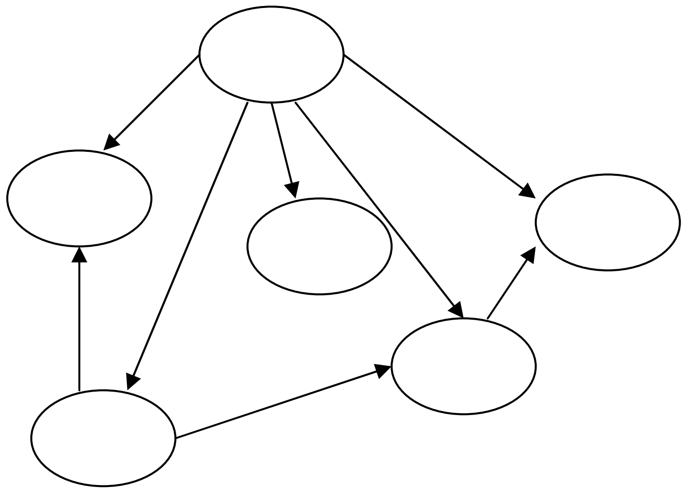
Statistical models have certain distributional hypotheses that financial statement data do not always fit. Hence some non-parametric techniques have been developed to overcome the constraints of traditional statistical models. Most of them belong to the data mining domain, such as artificial intelligence. Most of the researchers dealt with the issue of comparing data mining methods with traditional statistical models.

In this context, the present study can be included partly in this research line. The present research presents eight machine learning algorithms: Bayesian Network and Naïve Bayes from the Bayesian algorithms, k-Nearest Neighbor (k-NN) instance based learning, Artificial Neural Network (ANN) with Multilayer Perceptron (MLP), Support Vector Machine (SVM), C4.5, CHAID and CRT from decision tree algorithms for financial distress classification modeling.

5.6.1 Bayesian Models

The Näive Bayes Classifier method is based on the so-called Bayesian theorem, the term näive refers to independence. The Näive Bayes Classifier produces probability estimates rather than predictions. The probability estimate is the conditional probability distribution of the values of the class attribute based on the values of other attributes. In this way, Näive Bayes Classifier is just an alternative way of representing a conditional probability distribution and can only represent simple distributions (Witten and Frank, 2005). But Bayesian Network is a theoretically well-founded way of representing probability distributions concisely and comprehensibly in a graphical manner. The structure of Bayesian Network (BN) is represented by a directed acyclic graph (DAG), which is a network of nodes, representing attributes, connected by directed edges, expressing dependencies between attributes, in such a way that there are no cycles.

Figure 3: A Sample Bayesian Network

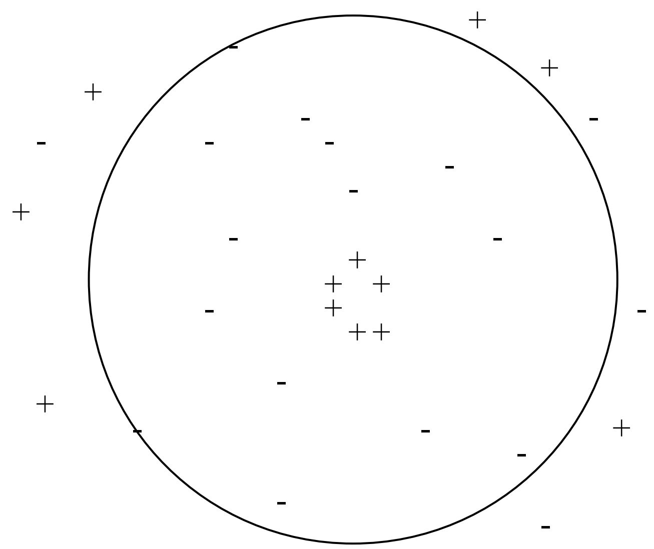


BNs do not depend on the underlying distributions of variables. BNs do not suffer from missing attributes of instances; instances with missing variables can be used to train or test BNs. In fact bankrupt and financially distressed firms tend to have missing variables for bankruptcy studies. BNs are dynamic and interactive. BNs can be updated with new information added to the training set and BNs are more transparent and intuitive compared to neural networks because the relationships among attributes are explicitly represented by the DAG (Sun and Shenoy, 2007).

5.6.2 K-Nearest Neighbor

K-nearest neighbor (k-NN) algorithm is one of the most fundamental and simple classification methods based on closest training examples in the feature space. K-NN is a type of instance based algorithm in the category of lazy learning algorithms (Aha, 1997). K-NN classifies an object based on its similarity to other objects. The logic assumes that similar objects are close to each other and dissimilar objects are distant from each other. So, an object is labeled according to the label of the majority of its neighbors. The similarity of objects is assessed by using a suitable distance measure; usually Euclidean distance is used as a distance metric for continuous variables. However, there is no common concept of defining the number of nearest neighbors, researchers decide on it in order to have good classification accuracy; but it intuitively makes sense to use more than one nearest neighbor, if the size of the training set is large.

Figure 4: A Sample k-NN

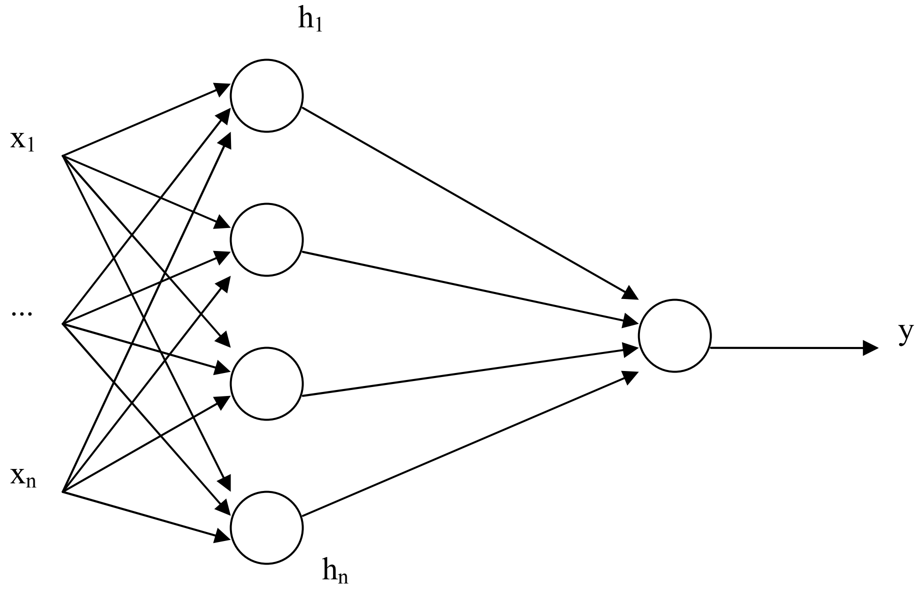


This simple method has some practical problems, it tends to be slow for large training set, it performs badly with noisy data and it performs badly with irrelevant attributes because each attribute has the same influence on the decision, just as it does in the Näive Bayes method (Witten and Frank, 2005). On the other hand, this simple method has an advantage over most of the other machine learning methods allowing adding new examples to the training set anytime.

5.6.3 Artificial Neural Networks

Artificial Neural Networks (ANN) is another machine learning tool based on computational models inspired from biological network of neurons found in the human central nervous system. The most prominent ANN algorithm in the financial distress prediction domain is Multi-Layer Perceptron (MLP), which is composed of three layers; input layer contains the predictors, namely attributes, the hidden layer contains the unobservable nodes, the output layer contains the responses, and there can be several hidden layers for complex applications. The most frequently used algorithm for learning MLP is the Back Propagation algorithm (BPA). BPA uses gradient descent which can find a local minimum. If the function has several minima, for MLP has many, it may not find the best one. This is a significant drawback for standard MLP compared with Support Sector Machine (SVM) (Witten and Frank, 2005).

Figure 5: Multi-Layer Perceptron with one Hidden Layer



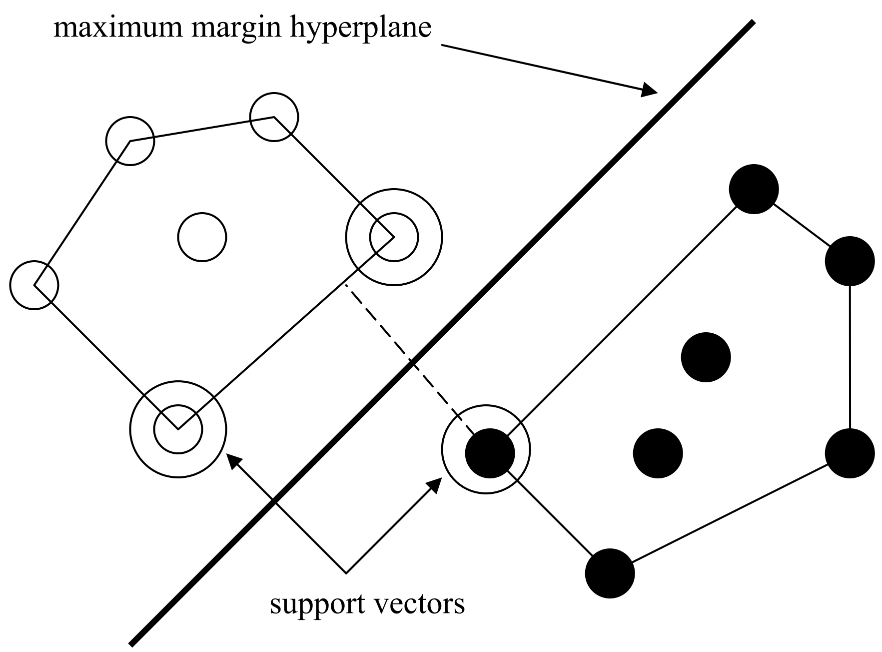
ANN is more adaptive to real world situations, it can discriminate non-linear patterns, so it does not suffer from the constraints of statistical models. However, ANN has several drawbacks, it is a black box procedure, and it is hard to interpret the results owing to lack of explanatory power and lack of feature selection, it needs too much time and efforts to construct a best architecture (Lee, 2006).

5.6.4 Support Vector Machines

Support vector machine (SVM) was introduced by Vapnik (1995). The support vector machine is a blend of linear modeling and instance based learning, it selects a small number of critical boundary instances called support vectors from each class and builds a linear discriminant function that separates each class as wide as possible. The system transcends the limitations of linear boundaries by making it practical to include nonlinear terms in the function, making it possible to form quadratic, cubic and higher order decision boundaries.

The basic idea of SVM is to use a linear model to implement nonlinear class boundaries through some nonlinear mapping the input vector into the high dimensional feature space. A linear model constructed in the new space can represent a nonlinear decision boundary in the original space. In the new space, an optimal separating hyperplane is constructed. Thus SVM is known as the algorithm that finds a special kind of linear model, the maximum margin hyperplane. The maximum margin hyperplane gives the maximum separation between the decision classes. The training examples that are closest to maximum margin hyperplane are called support vectors. All other training examples are irrelevant for defining binary call boundaries.

Figure 6: A Maximum Margin Hyperplane



Source: Witten and Frank (2005), Data Mining Practical Machine Learning Tools and Techniques, 2nd Edition. San Francisco - Elsevier, Morgan Kaufman Publishers, p. 216.

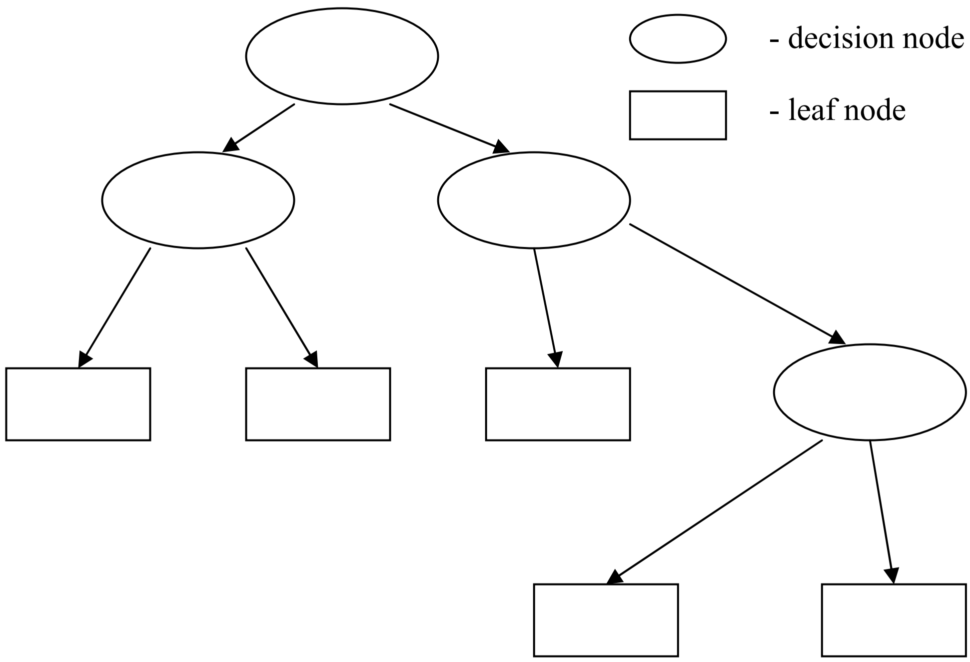
Support vector machines, like neural networks, do not suffer from constraints of statistical distributions. With support vector machines, overfitting is unlikely to occur and they often produce very accurate classifiers. On the other hand, the computation is very complex and they are slow compared to other machine learning algorithms when applied in a nonlinear setting.

5.6.5 Decision Trees

Decision tree is the implementation of the divide and conquer strategy to a set of independent instances to learn the problem. A decision tree is composed of root, internal decision nodes and terminal leaves. Each node in a decision tree represents a test of a particular attribute or a function of one or more attributes in the instance set to be classified. The outcomes of a test represent branches, so each branch represents the test value that the node can take. This process starts at the root and is repeated recursively until a leaf node is reached. Then the instance is classified according to the class assigned to the leaf.

There are different types of decision tree algorithms which are ID3, CRT (Classification and Regression Tree) and CHAID (Chi-Square Automatic Interaction Detector). ID3 was introduced by J. Ross Quinlan in 1979, ID3 was later enhanced in the version C4.5 and now C5.0. ID3 and enhanced algorithms split the attributes based on the gain in information that the split provides. CRT and CHAID are relatively new and popular non-parametric analysis techniques. The CRT algorithm builds a decision tree using the gini, twoing or ordered twoing criterion to choose the optimum split, whereas the CHAID algorithm uses chi square statistics for optimum splits.

Figure 7: A Simple Decision Tree



Decision tree is a non-linear architecture able to discriminate non-linear patterns and does not suffer from any distributional constraints. It does not require too much time for preparation of initial data and it performs well for large data, and results are easy to interpret.

5.6.6 Some Studies in Default Prediction Used Machine Learning Methods

The constraints of traditional statistics have always been a discussion point and criticized heavily, so this circumstance motivated practitioners to switch into structural financial forecasting models (explained previously in this chapter) and non-parametric models. Some of the non-parametric studies can be summarized as follows:

Marais et al. (1984) applied RPA (Recursive Partitioning Algorithm) for modeling commercial bank loan classification and compared the model with probit. They found that RPA was not significantly better than probit.

Frydman et al. (1985) used RPA and DA in financial distress prediction. A less complex RPA model was found to perform better than DA in terms of cross-validated and bootstrapped accuracies.

Messier and Hansen (1988) used inductive algorithm ID3 in loan default and bankruptcy prediction. The results were evaluated by comparing with the results of DA. ID3 outperformed DA on the other hand both models had partly common predictive attributes.

Odom and Sharda (1990) developed a neural network model for bankruptcy prediction and compared the results with that of DA in terms of classification accuracy. They asserted that neural networks might be used in bankruptcy prediction domain.

Cronan et al. (1991) applied RPA to datasets representing the mortgage, commercial, and consumer lending problems and compared the results with that of DA, logit, probit, and ID3. RPA provided results superior to that of ID3 and other statistical models while using fewer variables.

Tam and Kiang (1992) applied data mining in bank failure prediction and they used ANN as the main model and compared it with DA, Logistic regression, k-NN and ID3 in terms of prediction accuracy, adaptability, and robustness. Back propagation network outperformed the other models. Statistical models were found better than ID3 and k-NN, which was the least accurate model.

Coats and Font (1993) utilized a neural network to estimate the future financial health of firms. The neural network was used for identifying data patterns that distinguish healthy firms from distressed ones. Their results suggested that the neural network approach was more effective than DA.

Godwin Udo (1993) set up a neural network model to predict going concern of firms based on financial ratios. The results indicated that the neural network was more accurate than multiple regression analysis.

Wilson and Sharda (1994) compared the prediction capabilities of neural network model and DA model. They found out that the result of the NN model was significantly superior to the DA model in bankruptcy prediction.

Altman et al. (1994) applied a neural network on Italian Centrale dei Bilanci's dataset, consisting of over 1000 Italian firms, and compared the results with that of DA. The results indicated that both models provided balanced classification accuracy. They suggested that both models could be combined for predictive reinforcement.

Boritz and Kennedy (1995) examined two neural network approaches, Back-Propagation and Optimal Estimation Theory, for predicting bankruptcy filing. The model based on Optimal Estimation Theory had the lowest type I error and highest type II error while the traditional statistical techniques DA, logit, and probit had the reverse relationship. The model based on Back-Propagation had the intermediate level of type I and type II errors. The results indicated that performance of the models were sensitive to the selected variables.

Back et al. (1996) applied DA, logit and Genetic Algorithms to find out predictors of bankruptcy. The result revealed that all of the models chose a different number of variables as predictors. Logit analysis chose the same subset of variables of DA with an exception of one variable. Neural network chose relatively far more variables than logit and DA, whereas neural network was superior to both statistical models in terms of classification accuracy for one to three years prior to bankruptcy.

Henly and Hand (1996) used k-NN with an adjusted Euclidian distance metric in assessing a credit scoring problem. It was found that k-NN performed well in achieving lowest expected bad risk rate compared to linear regression, logit, decision trees and decision graphs. They asserted that k-NN was a prosperous tool for assessing credit score.

Etherige and Sriram (1997) used two ANN models, categorical learning NN and probabilistic NN, and compared them with statistical DA and logit models to examine financial distress one to three years prior to failure. In comparing overall classification error, DA and logit outperformed NN models. In fact, when relative error cost was considered, ANN models performed better than statistical models. The results indicated that ANN models' performance increases as the time period moves farther away from the eventual failure date.

Joos et al. (1998) compared the performances of decision tree and logit analysis in a credit classification environment. For this purpose, they used an extensive database of one of the largest Belgian banks. They asserted that logit models were consistent in a credit decision process, on the other hand for the qualitative and short scheme data, decision tree was better in terms of classification accuracy.

Varetto (1998) analyzed the comparison of genetic algorithm (GA) and Linear Discriminant Analysis (LDA). The analysis was conducted to 1920 sound and counterparty mate companies to assess insolvency risk. He concluded that GA was the effective method for insolvency diagnosis, although the result of LDA was superior to GA.

Yang et al. (1999) applied probabilistic NN instead of Back-Propagation NN for bankruptcy prediction and compared the results with that of DA. They asserted that probabilistic NN without pattern normalization and Fisher DA provided the best overall estimation, but DA produced outstanding results for bankrupt companies.

Lin and McClean (2000) used four classification models, DA, logit, NN, and DT, for prediction of financial distress. Each model was subject to three variable selection methods, human judgment, ANOVA, and factor analysis. They found that the variables selected by ANOVA provided better results and among the classifier models DT and NN outperformed statistical models in terms of classification accuracy.

Ko et al. (2001) used Liang's CRIS (composite rule induction system) model and compared it with NN and logit in the corporate financial distress prediction domain. They asserted that CRIS and NN outperformed the logit model; however, despite the higher performance of CRIS and NN, the extracted rules by CRIS are easier to understand for human auditors.

Atiya (2001) was inspired by Merton's asset value model, so he brought new variables, extracted from stock prices, in the domain of bankruptcy prediction. He showed that using market based variables in addition to traditional financial ratio variables resulted in significant increase of classification accuracy by 4% for three years prior to bankruptcy.

Sarkar and Siriram (2001) developed Bayesian Network (BN) models to help human auditors in assessing bank failures. Their Naïve Bayesian Network and composite attribute BN's performance in classification accuracy was comparable to DT algorithm C4.5. They underlined that the prediction power of BN increases when recent financial indicators are used in the models.

Park and Han (2002) introduced an Analytic Hierarchy Process weighted k-NN model, a derivative of the k-NN method, in the bankruptcy prediction area, and compared the performance of the new model with regression, logit, weighted k-NN and pure k-NN. The results were in favor of AHP weighted k-NN in terms of classification accuracy.

Yip (2003) introduced a hybrid Case-based Reasoning (CBR) model that uses statistical evaluation for automatically assigning attribute weights and nearest neighbor algorithm for case retrieval. Comparison with DA proved that the model would be a competitive alternative in the failure prediction context while it outperformed traditional statistical models.

Härdle et al. (2004) implemented SVM for corporate bankruptcy prediction and compared with DA. SVM outperformed DA slightly in terms of classification accuracy; however the difference was not significant at 5%. Moreover, they proved that SVM was capable to extract information from real life economic data sets.

Shin et al. (2005) used SVM with RBF (Radial Basis Function) for bankruptcy prediction on mid-sized Korean manufacturing firms' dataset. They asserted that a small value of the upper bound parameter C leads model to underfit the data, per contra large values of C indicates overfit, whereas small values of kernel parameter δ leads to overfit the data, on the contrary higher values indicate the inclination to underfit. Their best values for (C, δ) were (75, 25) and the classification accuracy was superior to that of BPN. They concluded that there was no systematic way to define optimum kernel function parameters.

Min and Lee (2005) applied SVM for bankruptcy prediction by utilizing 5-fold cross-validation and grid search for optimal parameters of the upper bound C and the kernel parameter δ for RBF. The optimal values found with cross-validation for (C, δ) were (2^{11}, 2^{-7}). They tested the model's classification accuracy by comparing with BPN, DA, and logit. The SVM model was found superior to other models. The authors underlined that there was no common way to define the values of the parameters and which kernel function to use.

Kotsiantis et al. (2005) investigated efficiency of machine learning techniques in the domain of bankruptcy prediction. In this regard, Naïve Bayes, C4.5, Local Decision Stump, Ripper, and RBF algorithms were trained using 150 failed and solvent Greek firms. The result indicated that machine learning algorithms could enable an analyst to predict bankruptcy with satisfactory accuracy long before bankruptcy.

Hu and Ansell (2006) studied financial distress prediction with five credit scoring techniques, NB, logit, RPA, ANN and SVM with SMO (sequential minimal optimization). They conducted the study considering the US, European and Japanese retail markets. All market models presented best classification accuracy for one year prior to financial distress. The US market model performed relatively better than the European and Japanese models for five years prior to financial distress. Regard to constructed composite model compared to Moody's credit ratings, SVM was the best performing model closely followed by ANN, logit model was the least performing model, similar to Moody's.

Lee (2006) introduced a Genetic Programming DT model, which is integration of GP and DT with C4.5 where functions to be used in GP are attributes of DT. This integration facilitates DT builder model to handle incremental training data, in other words, GP can be considered as DT breeder. GD-DT was found superior to CART, C5.0, ANN, and logit in terms of classification accuracy and AUROC (area under the ROC curve).

Kirkos et al. (2007) explored the effectiveness of data mining classification techniques in detecting firms issuing fraudulent financial statements. In connection with detecting fraudulent financial statements, DT, NN and Bayesian Belief Networks were employed. Bayesian Belief Network showed best performance in terms of classification.

Zheng and Yanhui (2007) used CHAID algorithm for corporate financial distress prediction and compared the results with that of ANN model. The results indicated that the CHAID decision tree model is capable to predict financial distress with providing interpretable classification figures.

Auria and Moro (2008) used SVM for solvency analysis and compared the prediction accuracy with that of logistic regression and DA. They mentioned that the performance of SVM model improved by integration of non-linearly separable variables to four financial variables based on SVM. Those four variables were used for company rating by Deutsche Bundesbank. The authors used company data provided by Deutsche Bundesbank. Their best model revealed with (C, δ) as (10, 4) and (10, 2.5) for the manufacturing and the trade sector, respectively. Their analysis also showed the lack of a systematic method to define the kernel function parameters.

Quintana et al. (2008) used Evolutionary Nearest Neighbor Prototype Classifier (ENPC), which is an evolutionary nearest neighbor algorithm, in the bankruptcy prediction domain and it received good results compared to the other machine learning algorithms NB, logit, C4.5, PART (builds partial C4.5), SVM, and ANN with MLP in terms of classification accuracy. They asserted that the ENPC algorithm could be considered an alternative method for bankruptcy prediction.

Lin et al. (2009) constructed a hybrid model using Rough Set Theory (RST), Grey Rational Analysis (GRA) and CBR for business failure prediction. They used RST as preprocessing for relevant attribute selection, then they used GRA to derive attribute weights for the CBR retrieval process. This hybrid model produced better classification accuracy than RST-CBR (with equal weights) and CBR itself.

Vieria et al. (2009) analyzed financial distress with SVM, NN with MLP (multi-layer perceptron) and Addaboost M1 using the DIANE database of small and medium size French companies. The constructed models were compared with logit analysis in terms of prediction accuracy. SVM achieved the highest accuracy, but all models showed comparable results. The authors stressed that large sets of input in classifiers can reduce both error types.

Aghaie and Saeedi (2009) aimed to construct a financial distress prediction model based on Bayesian Networks. They tested the model with the variables revealed by two different variable choosing methods, conditional correlation between variables and conditional likelihood, respectively. The model with variables chosen by conditional likelihood performed slightly better. On the other hand, the other BN produced the same classification accuracy as logistic regression did. The authors claimed that BN could be used as an alternative method for financial distress prediction. Moreover, they found that companies having lower profitability, more long term liabilities, and lower liquidity are more inclined to financial distress.

Derelioglu et al. (2009) used NN with MLP for Small and Medium-sized Enterprises' (SME) credit risk analysis. The conducted model was compared with k-NN and SVM. The variables of the models were chosen by DT, Recursive Feature Extraction (RFE), factor analysis, and principal component analysis. The NN model produced slightly better results than the other models.

Koyuncugil and Ogulbas (2009) aimed to construct a data mining model for detecting financial and operating risk indicators of financial distress, the chosen algorithm for modeling purpose was CHAID, of which result is supposed to be easy to understand, easy to interpret, and easy to apply by non-professionals of SME. Financial ratios derived from financial tables and the operational variables were extracted by a questionnaire distributed to SME's located in OSTIM, Organized Industrial Zone in Ankara. The study has not been completed yet. After completion of the study, the constructed model will be turned into software for SME's.

Chapter 6
Empirical Design

Financial failure of enterprises, in addition to the cost for related business groups, also involves social costs. Therefore, a large number of financial failure prediction models was developed using different methods. The absence of a perfectly valid model for any environment and condition motivates the researchers to exert themselves for developing new models in this field.

So far, various statistical and theoretical methods have been used to predict financial failure. In this study, the methods, most commonly used in financial failure prediction literature, will be used to construct some prediction models and the conducted methods will be compared with regard to prediction accuracy and ROC figures.

6.1 Data and Sample Selection

The initial sample of this study is composed of the listed industrial firms on the Istanbul Stock Exchange (ISE). The main reason of this preference is the difficulty in reaching the financial data of the other firms in Turkey. The listed firms have to provide audited financial statements on a regular basis. Those presented information are regularly updated and can be reached by the investors from the ISE's website. The advantage of the ISE data is that all the financial statements have to be independently audited, so they provide reliable trustworthy information. On the contrary, the disadvantage of ISE information is limited to the number of companies listed. The number of industrial companies doesn't exceed 200 over the years.

In this study, for modeling issues, the financial statements of failed and non-failed firms are derived from the same annual periods, in other words 1997, 1998 and 1999 year-end financial statements are in scope of this study to predict financial failures in 2000. In 2001, Turkey endured an economic crisis and the aftermaths of the crisis were influential in the following year either. Moreover, Capital Market Board of Turkey announced "Capital Market Accounting Standards" in accordance with International

Financial Reporting Standards (IFRS) in the Official Gazette No. 25290. The announcement underlines that all of the companies included within the scope of this notification have to prepare financial statements in accordance with IFRS from 01.01.2005 and the companies, if they wish, can prepare financial statements in accordance with IFRS from 31.12.2003. So, the financial statements of some companies are from the previous regulation and some of the financial statements are prepared according to the new regulation. In other words from year-end 2003 till year-end 2005, there are different types of financial statements. In order to avoid the problems can be caused by using the financial statements that were prepared according to different standards, it is preferred in this study to use the financial statements prepared according to previous standards.

The initial sample is consequently composed of 180 production industry firms quoted to ISE, with 150 non-distressed and 30 financially distressed firms. Financially distressed firms are defined by the criteria below:

- Firms applied for bankruptcy,
- Turkish bankruptcy law article 179 pursuant to Turkish trade law articles 324 and 434; business enterprises incurring 2/3 loss in capital stock can be defined as bankrupt.

Bankruptcy is a legal procedure, even though those companies selected according to this criteria did not go bankrupt, those companies can be classified as financially distressed.

- Negative equity figures,
- Firms with net loss in each of the preceding three years.

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

Table 8 provides summary statistics for industry failure rates based on individual firms for the year 2000. According to Table 8, 16.7% of industrial firms listed on ISE were defined as financially distressed. The failure rates vary considerably among industry groups. The iron and steel (50%); chemistry, plastic and dye (50%); paper and packaging (37.5%); cotton and wool (36.84%); synthetic (33.33%); home textile and carpet (33.33%); electronics, telecom and technology (28.57%); durable consumer goods (14.29%); food and beverage (13.79%); ready to wear and leather (12.5%); construction products (11.11%); and metal processing (10%) have experienced the highest rates of failure, measured as the percentage of firms in the industry that were defined as financially distressed according to above criteria for the study period 2000. On the contrary; none of the firms in the auto spare parts, automotive, cement, ceramics, fertilizer and pesticides, furniture, glass, media, petroleum products, pharmacy and health, stationary products, and tire and cords industries were defined as financially distressed for the study period.

Table 8: Summary Statistics of Industry Failure Rates

Industry	Number of Firms	Number of Distressed Firms	Percent of Distressed Firms
Auto Spare Parts	7	0	0.00
Automotive	7	0	0.00
Cement	16	0	0.00
Ceramics	5	0	0.00
Chemistry, Plastic and Dye	8	4	50.00
Construction Products	9	1	11.11
Cotton and Wool	19	7	36.84
Durable Consumer Goods	7	1	14.29
Electronics, Telecom and Technology	7	2	28.57
Fertilizer and Pesticides	4	0	0.00
Food and Beverage	29	4	13.79
Furniture	2	0	0.00
Glass	3	0	0.00
Home Textile and Carpet	3	1	33.33
Iron and Steel	4	2	50.00
Media (Press)	3	0	0.00

Metal Processing	10	1	10.00
Paper and Packaging	8	3	37.50
Petroleum Products	5	0	0.00
Pharmacy and Health	2	0	0.00
Ready to Wear and Leather	8	1	12.50
Stationary Products	2	0	0.00
Synthetic	9	3	33.33
Tire and Cord	3	0	0.00
Total	180	30	16.67

The empirical study was carried out by Microsoft Excel, SPSS 15 for windows, and WEKA 3.6 open source machine learning software developed at WEKA, the University of Waikato.

6.2 Variable Selection

After the initial groups were defined and firms were selected, balance sheet and income statement data are collected. 53 financial ratios were found useful for this study. 26 financial ratios of variable set have been used in discriminant models of Beaver's (1966) univariate analysis and the multivariate analysis of Altman (1968), Deakin (1972), Edminster (1972), Blum (1974), Altman et al. (1977), and El Hennawy and Moris (1983), which are representative examples of studies using the multiple discriminant analysis technique. Moreover, additional 27 financial ratios from the independent investment investigation company IBS Analysis (www.analiz.ibsyazilim.com) have been found useful for this study. These variables were classified into 6 standard ratio categories. In Table 9, aggregate financial ratios, their codes, and ratio categories presented.

Table 9: Aggregate Financial Ratios Found to be Useful

Ratio Category	Ratios	Ratio Code	Analysts
Liquidity Ratios	Current Ratio	Lq1	B, D, A-H-N
Liquidity Ratios	Quick Ratio	Lq2	D
Liquidity Ratios	Cash Ratio	Lq3	E, D
Liquidity Ratios	Working Capital to Total Assets Ratio	Lq4	B, A, D
Liquidity Ratios	Current Assets to Total Assets Ratio	Lq5	D, E-M
Liquidity Ratios	Quick Assets to Total Assets Ratio	Lq6	D, E-M
Liquidity Ratios	Quick Assets to Inventory Ratio	Lq7	B*
Liquidity Ratios	Cash to Total Assets Ratio	Lq8	D
Liquidity Ratios	Cash Flow to Short Term Debts Ratio	Lq9	E
Liquidity Ratios	Cash Flow to Total Assets Ratio	Lq10	E-M
Liquidity Ratios	Cash Flow to Total Debts Ratio	Lq11	B*, B, D
Liquidity Ratios	Working Capital to Equity Ratio	Lq12	IBS
Leverage Ratios	Total Debts to Total Assets Ratio	Lv1	B, D
Leverage Ratios	Short Term Debts to Total Assets Ratio	Lv2	IBS
Leverage Ratios	Short Term Debts to Total Debts Ratio	Lv3	IBS
Leverage Ratios	Long Term Debts to Total Assets Ratio	Lv4	IBS
Leverage Ratios	Financial Debts to Total Assets Ratio	Lv5	IBS
Leverage Ratios	Interest Coverage Ratio	Lv6	A-H-N
Leverage Ratios	Long Term Debts to Equity Ratio	Lv7	E-M
Leverage Ratios	Short Term Debts to Equity Ratio	Lv8	E
Leverage Ratios	Total Debts to Equity Ratio	Lv9	IBS
Fiscal Structure Ratios	Tangible Fixed Assets to Long Term Debts Ratio	Fs1	IBS

Fiscal Structure Ratios	Equity to Fixed Assets Ratio	Fs2	IBS
Fiscal Structure Ratios	Fixed Assets to Long Term Debts Ratio	Fs3	IBS
Fiscal Structure Ratios	Financial Fixed Assets to Fixed Assets Ratio	Fs4	IBS
Fiscal Structure Ratios	Financial Fixed Assets to Long Term Debts Ratio	Fs5	IBS
Fiscal Structure Ratios	Retained Earnings to Total Assets Ratio	Fs6	A, A-H-N
Activity Ratios	Account Receivable Turnover Ratio	A1	IBS
Activity Ratios	Inventory to Net Sales Ratio	A2	E
Activity Ratios	Payables Turnover Ratio	A3	IBS
Activity Ratios	Net Working Capital to Net Sales Ratio	A4	E, D
Activity Ratios	Current Assets to Net sales Ratio	A5	D
Activity Ratios	Tangible Fixed Assets Turnover Ratio	A6	IBS
Activity Ratios	Total Assets Turnover Ratio	A7	A
Activity Ratios	Long Term Debt Turnover Ratio	A8	IBS
Activity Ratios	Equity to Net Sales Ratio	A9	E
Activity Ratios	Quick Assets to Net Sales Ratio	A10	D
Activity Ratios	Cash to Net Sales Ratio	A11	D
Profitability Ratios	Gross Profit Margin	P1	IBS
Profitability Ratios	Net Profit Margin	P2	IBS
Profitability Ratios	Operational Profit Margin	P3	IBS
Profitability Ratios	Operating Profit Margin	P4	IBS
Profitability Ratios	EBIT Margin	P5	IBS
Profitability Ratios	Taxes to Net Sales Ratio	P6	IBS
Profitability Ratios	Taxes to Profit Before Taxes Ratio	P7	IBS
Profitability Ratios	Return on Equity	P8	IBS
Profitability Ratios	Return on Long Term Debts	P9	IBS

Profitability Ratios	Return on Assets	P10	B, D
Profitability Ratios	Financial Expenses to Inventories Ratio	P11	IBS
Profitability Ratios	EBIT to Total Assets Ratio	P12	IBS
Profitability Ratios	Operating Income to Total Assets Ratio	P13	A, A-H-N
Market Value Ratio	Market to Book Ratio	M1	IBS
Market Value Ratio	MV of Equity to Book Value of Debts Ratio	M2	A, A-H-N

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

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

The variables, the financial ratios to be used in the analysis, were selected through two variable elimination stages. In the first stage, one-way ANOVA test was conducted. The aim was to define financial ratios of distressed and non-distressed groups that differentiate at 5% significance level. In the second stage the remaining variables were input to the attribute selection algorithm, which is embedded in the WEKA platform, for further elimination.

The outcome of stage 1, the ANOVA test statistics, mean, standard deviation, F-test statistic and its significance level for distressed and non-distressed firms are presented in Table 10. Small significance level indicates group mean differences. In our case, the selected 35 financial ratios with a significance level of less than 5% indicate that one group differs from the other group. The ratios are ordered according to their significance level.

Table 10: ANOVA Test Statistics

Ratios	**Non-Distressed**		**Distressed**		**Test Statistics**	
	Mean	Std. D.	Mean	Std. D.	F	Sig.
Lv1	0.571	0.203	1.614	1.245	94.560	**0.000**
P10	-0.012	0.092	-0.578	0.689	93.894	**0.000**
P13	0.004	0.111	-0.539	0.696	82.706	**0.000**
Fs2	1.410	1.341	-1.090	2.096	79.951	**0.000**
Lv5	0.271	0.206	1.075	1.101	69.781	**0.000**
Lq4	0.170	0.181	-0.701	1.238	68.102	**0.000**
Lv2	0.441	0.185	1.217	1.112	65.519	**0.000**
Lq1	1.657	0.927	0.641	0.443	41.890	**0.000**
Lv4	0.131	0.112	0.397	0.476	38.156	**0.000**
Lq2	1.099	0.738	0.401	0.352	31.250	**0.000**
P12	0.135	0.104	0.002	0.239	25.828	**0.000**
Lq10	0.082	0.101	-0.039	0.240	21.685	**0.000**
Lq11	0.170	0.214	-0.003	0.153	21.475	**0.000**
Lq9	0.220	0.269	0.005	0.190	21.083	**0.000**
P9	0.200	5.402	-5.898	16.480	14.248	**0.000**
P5	0.288	0.350	-0.996	4.210	13.535	**0.000**
M2	2.305	2.550	0.717	1.330	13.386	**0.000**
Lq8	0.096	0.111	0.029	0.047	13.227	**0.000**
P3	0.112	0.257	-0.858	3.336	12.330	**0.001**
Lq3	0.341	0.571	0.042	0.088	10.034	**0.002**

A9	0.376	0.468	2.420	8.109	9.371	**0.003**
A4	0.379	0.983	-66.019	278.229	8.510	**0.004**
P8	-0.154	0.422	0.793	3.959	8.167	**0.005**
Lq6	0.400	0.160	0.312	0.204	7.948	**0.005**
P2	-0.029	0.277	-27.368	122.974	7.386	**0.007**
Lq5	0.611	0.169	0.516	0.261	7.305	**0.008**
P4	0.011	0.355	-27.024	122.641	7.262	**0.008**
A3	6.494	7.867	2.950	3.228	7.181	**0.008**
P6	0.034	0.080	0.000	0.000	6.499	**0.012**
Lv7	0.510	0.761	-0.819	6.193	6.485	**0.012**
A5	1.329	1.269	3.224	9.194	5.891	**0.016**
P7	0.230	0.584	0.000	0.000	5.712	**0.018**
A2	0.363	0.292	1.281	4.757	5.485	**0.020**
P11	1.156	2.510	9947.342	60477.586	4.042	**0.046**
Lq7	4.362	10.866	199.541	1196.698	3.974	**0.048**
A8	14.699	35.687	3.473	4.838	3.630	0.058
Fs6	0.074	0.066	0.049	0.097	3.492	0.063
A7	0.595	0.373	0.469	0.434	3.137	0.078
Lv9	2.184	2.289	-0.919	22.403	2.751	0.099
A1	2.613	1.637	3.210	4.134	1.904	0.169
P1	0.290	0.163	0.236	0.383	1.724	0.191
Fs4	0.106	0.164	0.148	0.239	1.571	0.212
Lv8	1.674	1.784	-0.100	16.954	1.566	0.212
A10	0.895	1.172	1.223	2.254	1.517	0.220
M1	0.961	0.804	0.786	1.314	1.045	0.308

Fs1	6.174	10.480	4.170	12.420	1.001	0.318
Fs3	7.380	12.060	5.285	14.961	0.806	0.370
Lv3	0.773	0.159	0.746	0.208	0.722	0.397
Lq12	3.739	3.640	1.493	32.029	0.698	0.404
A11	0.264	0.894	0.157	0.604	0.479	0.490
Lv6	401.854	4248.338	-5.653	35.442	0.339	0.561
A6	4.135	13.480	4.930	12.253	0.107	0.745
Fs5	0.956	2.577	0.821	2.457	0.083	0.774

In this study, it is assumed that misclassification errors are not equally important. Cost of type I error is higher than the cost of type II error to a credit institution. For example, if the model classifies a financially distressed company as non-distressed, this is referred to type I error. The cost of this type of error to a credit institution is loss of interest and principle in case of default, and probable recovery costs in bankruptcy proceedings. On the other hand, if the model classifies a non-distressed company as distressed, this is referred to as type II error. The cost of this type of error to credit institution is loss of profit. As a matter of course, accurate estimation of distressed firms becomes important.

For the cost sensitive modeling purpose, in the second stage of variable elimination phase, the cost sensitive attribute evaluator algorithm, which is embedded in WEKA platform, was employed. The reliefF (recursive elimination of features) attribute evaluator is the selected base evaluator of cost sensitive evaluator algorithm, which evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different classes. This evaluator can operate on both discrete and continuous class data. The used cost matrix, which is an essential parameter in cost sensitive attribute evaluation, is depicted in Table 11, where the algorithm weights misclassification of a distressed company 10-fold more than misclassification of a non-distressed company.

Table 11: Cost Matrix

	Non-distressed	Distressed
Non-distressed	0	1
Distressed	10	0

Cost sensitive attribute evaluator ranks the attributes according to their individual evaluations, the selected 10 best cost sensitive variables used for classification modeling are listed below.

Lq8 Cash to Total Assets Ratio,
Lq6 Quick Assets to Total Assets Ratio,
Lv5 Financial Debts to Total Assets Ratio,
A2 Inventory to Net Sales Ratio,
Lq5 Current Assets to Total Assets Ratio,
Lv1 Total Debts to Total Assets Ratio,
Lv2 Short Term Debts to Total Assets Ratio,
P10 Return on Assets,
P13 Operating Income to Total Assets Ratio,
Lq10 Cash Flow to Total Assets Ratio.

The majority of the selected variables belongs to liquidity and leverage ratio groups.

Given the limited sample size available for the study, it is preferred to employ all the data for training and validation. Nevermore, to avoid probable over-fitting problem, a 10-fold cross-validation process is applied. Eventually, there is no unique way to define the number of folds to be formed; however 10-fold cross-validation is frequently preferred by the practitioners (Witten and Frank, 2005).

For modeling the KMV-Merton model consistent with Vassalou and Xing (2004), short term debt plus one half of long term debt were considered as book value of firm's debt (X). As risk free rate (r), yearly compounded interest rate of treasury discounted auctions figures for the period 2000, which is about 36%, was taken into analysis.

6.3 Traditional Statistical Models

6.3.1 Discriminant Analysis Model

The purpose of DA is to summarize the information contained by independent variables into an index value (dependent variable). The set of variables was chosen by stepwise selection to enter or leave the model using the significance level 0.05 of an F-test from analysis of covariance. The variables of 1 annual period prior to failure constituted the model sample of this study and prediction ability of developed discriminant model of 1 annual period prior to failure was tested through the variables of 2 and 3 annual periods prior to failure.

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

The linear discriminant function is in the form of;

$$Z_a = C + ß_1 A2 + ß_2 Lq5 + ß_3 Lv1$$

In the function, Z_a stands for discriminant score of firm a; C stands for the constant term; $ß_1$, $ß_2$ and $ß_3$ stand for estimated weights of inventory to net sales ratio, current assets to total assets ratio, and total debts to total assets ratio, respectively. Briefly, these 3 cost sensitive financial ratios are the selected characteristics, which best discriminate distressed firms from non-distressed ones.

Table 12: Discriminant Model Weights

Characteristics	Weights
A2	2.275
Lq5	-1.914
Lv1	3.739
(Constant)	-1.709

Table 12 presents the estimated weights of the discriminant function. Discriminant model is obtained by putting the estimated weights into related places and the outcome of the model takes the form below.

$Z_a = -1.709 + 2.275\ A2_a - 1.914\ Lq5_a + 3.739\ Lv1_a$

Among the variables two of them have a positive sign and one has a negative sign; hence decrease in positive signed characteristics (ratios) and increase in negative signed characteristic of a firm reduce its probability of failure.

Table 13: Test Statistics of the Estimated Discriminant Function

Eigenvalue	Canonical Correlation	Wilks' Lambda	Chi-square	df	Sig.
0.910	0.690	0.524	114.178	3	0.000

Table 13 presents the test statistics of the estimated discriminant function. Eigenvalue is the ratio of the between group sum of squares to the within group sum of squares for the discriminant scores. The largest eigenvalue corresponds to the eigenvector in the direction of maximum spread of the group means, in other words, the largest eigenvalue indicates the efficiency of the discriminant function. The eigenvalue of the estimated discriminant function is quite large.

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

Wilks' lambda is the proportion of total variance in the discriminant scores not explained by differences among the groups. Values close to 0 indicate that the group means are different. The value of Wilks' lambda is transformed into Chi-square to be used along with the degrees of freedom to determine significance. The significance level of the estimated discriminant function is 0.000, indicating that the group means differ.

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

$$Z = \frac{N_D Z_D + N_{ND} Z_{ND}}{N_D + N_{ND}} = 0.00006 \cong 0$$

Z : Cut-off score
N_D : Number of distressed firms
N_{ND}: Number of non-distressed firms
Z_D : Discriminant scores mean of distressed firms
Z_{ND}: Discriminant scores mean of non-distressed firms

Therefore;

If $Z_a > Z$, firm is classified as distressed,
If $Z_a < Z$, firm is classified as non-distressed.

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

6.3.2 Logit Analysis Model

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

For the logit analysis, variables were selected using the logistic regression procedures available in SPSS 15. In logistic regression, the dependent variable (Y) gets the value "1" for distressed firms and "0" for the non-distressed firms. Therefore, if $P_a \geq 0.50$ the model classifies a firm as distressed. As in the discriminant analysis model, stepwise (forward conditional) selection is used and the same significance level of 0.05 was set for variables to enter or leave the model. The variables of 1 annual period prior to failure constituted the model sample of this study and the prediction ability of developed logit model of 1 annual period prior to failure was tested through the variables of the 2 and 3 annual periods prior to failure.

Table 14: Estimated Variables and Their Coefficients for the Logit Model

	B	S.E.	Wald	df	Sig.	Exp(B)
A2	6.005	2.125	7.986	1	0.005	405.484
Lv2	6.591	2.313	8.121	1	0.004	728.240
P13	-19.111	4.683	16.656	1	0.000	0.000
Constant	-8.001	1.845	18.811	1	0.000	0.000

Table 14 presents the estimated variables and their coefficients and test statistics for the logit model. B is the estimated coefficient with its standard error S.E., Wald statistic is equal to the square of the ratio of B to S.E. If the Wald statistic is significant (less than 0.05), then the parameter is useful to the model. All of the three parameters are useful to the model, as indicated by their respective significance levels. Exp(B) is the predicted change in odds for a unit increase in the predictor (ratio). If Exp(B) is less than 1, increasing values of the variable correspond to decreasing odds of the event occurrence and vice versa, if Exp(B) greater than 1. Therefore, a unit increase in A2 and Lv2 can be interpreted as an increase in failure probability and a unit increase in P13 can be interpreted as a decrease in failure probability.

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

$$P_i = \frac{1}{1 + e^{-(-8.001 + 6.005A2 + 6.591Lv2 - 19.111P13)}}$$

6.3.3 Evaluation of Models

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

In previous parts, DA and logit models and each technique were presented. It was noticed that the underlying assumptions of DA and logit models concerning the relationships among the independent variables, affect the model selection process in an outstanding way. The two alternative models use only one common characteristic information. To find out if there are differences in their prediction ability, the models were tested through one, two and three annual periods prior to failure date. The constructed models were compared in terms of classification accuracy along with misclassification rates and AUROC (area under receiver operating characteristic curve). Classification accuracy is a straightforward method considering the ratio of true estimates, which is employed widely by practitioners (Lee, 2006). ROC curve is the plot of the true positive rate against the false positive rate. That is to say, the value of the AUROC is usually between 0.5 and 1, the value close to 1 represents a good classification whereas diagonal line with a value of 0.5 represents the test with no discriminating power. In this study, for calculation of AUROC for all models, predicted group membership results were used instead of probability scores used. Table 15 presents the prediction accuracy results and AUROC values for each technique.

Table 15: Prediction Results for DA and Logit Analyses

Model	Performance Measures	-1	-2	-3
Discriminant Analysis Model	Classification Acc. (%)	75.6	78.3	80.6
	Type I Error (%)	6.7	13.3	30
	Type II Error (%)	28	23.3	17.3
	AUROC	**0.827**	**0.817**	**0.763**
Logit Analysis Model	Classification Acc. (%)	95	90.6	84.4
	Type I Error (%)	23.3	53.3	93.3
	Type II Error (%)	1.3	0.7	0
	AUROC	**0.877**	**0.730**	**0.533**

For one annual period prior to failure, the logit model performed better than the DA model. It produced only 23.3% type I errors (classifying the distressed firm as non-distressed) and 1.3% type II errors (classifying the non-distressed firm as distressed), while the DA model produced 6.7% type I errors and 28% type II errors. The overall errors amount to 5% for the logit model and 23.4% for the DA model, the overall prediction accuracy amounted to 95% for the logit model and 75.6% for the DA model. The AUROC results of Logit and DA models are 0.877 and 0.827, respectively.

For two annual periods prior to failure, both models were superior to each other in overall prediction accuracy and AUROC values. The highest prediction accuracy and the fewest type II errors were produced by the logit model and the fewest type I errors were produced by the DA model. The logit model produced 53.3% and 0.7% type I and type II errors, respectively, and the DA model produced 13.3% and 23.3% type I and type II errors, respectively. The overall errors amounted to 9.5% for the logit model and 21.7% for the DA model. The overall prediction accuracy amounted to 90.6% for the logit model, and 78.3% for the DA model. The AUROC results of DA and logit models are 0.817 and 0.730, respectively.

For three annual periods prior to failure, according to prediction accuracy the logit model outperformed the DA model, but indeed this is deceiving, because logit model predicted only 2 distressed firms correctly and the rest of the firms are predicted as non-distressed. The overall prediction accuracies amounted to 84.4% for the logit model and 80.5% for the DA model. Type I errors of logit and DA models are 93.3% and 30%, respectively and type II errors of DA and logit models are 17.3% and 0% respectively. The AUROC results of DA and logit models are 0.763 and 0.533 respectively.

As a result, with respect to overall errors and prediction accuracy, the logit model performed better than the DA model. On the other hand, it is noticed that the DA model performed better in regards to type I errors, which remained constantly below those produced by the logit model for three periods. On the contrary, the logit model had a tendency to produce less type II errors while departing from the failure occurrence period.

Both models reach their best results for one annual period prior to failure according to AUROC values. When the performance evaluation is considered in the scope of type I errors and AUROC results, the DA model outperforms the logit model. For each period, the DA model produced the least type I errors compared to the logit model. Except for one period prior to failure the DA model had the highest AUROC values in the other two periods. Another remarkable point is that the overall prediction accuracy of the DA model decreased by the period closing to failure occurrence point. The AUROC value 0.533 of the logit model for three annual periods prior to failure shows that the logit model had a very low discriminating power for this period.

6.4 Market Based Model

6.4.1 KMV-Merton Model

In this section of the empirical study, three KMV-Merton models are constructed and the produced results are compared with those of the DA and the logit models found in the previous section. However, this comparison is limited to only one annual period prior to failure occurrence. The reason is the absence of daily stock prices prior to 1999. The existing monthly average stock prices can cause bias in asset value and volatility estimation; therefore daily stock prices after 1999 were used for modeling.

Financial data generally have leptokurtosis, volatility clustering and leverage effects. For this reason, in the study, normality assumption of the model is also replaced by heavy-tailed alternatives, which are student's t-distribution and asymmetric student's t-distribution. So, in this way, two additional models are established and they are compared with the traditional accounting based models from the previous section.

For estimation purposes, this study follows a procedure similar to the one used by Hillegeist et al. (2004) in order to obtain the unobserved parameters of the model. First, the initial values are determined by setting V_A equal to the book value of liabilities plus the market value of equity and $\sigma_A = \sigma_E V_E / (V_E + X)$. σ_E is defined by the of standard deviation of log changes of daily stock prices. Then by using equations through (4) and (6), new values for V_A are estimated and based on these new V_A values, a new σ_A is computed. The new σ_A is used as a new input in the equations to estimate new V_A. This iterative procedure is repeated until the new σ_A converges to the previous one. The tolerance level for convergence applied here is 10^{-6}. Values satisfying this condition gave us the estimated values of market asset value and asset volatility. The mean log changes in implied asset values (V_A) were used as an estimate of the drift term (μ) in equation (3), since Crosbie and Bohn (2003) provided no description of how to estimate the drift term. In the calculations consistent with similar studies, term structure of debts was assumed mature in one year (T = 1).

The above estimation process was repeated two more times by substitution of the normality assumption of the model by student's t- and asymmetric student's t-distributions. Asymmetric student's t distribution can be summarized as follows:

Asymmetric student's t distribution:

$$t(x|\gamma)=\frac{2}{\gamma+\frac{1}{\gamma}}\left[t\left(\frac{x}{\gamma}\right)I_{\{X\geq 0\}}+t(x\gamma)I_{\{X<0\}}\right], \tag{9}$$

where $I_{\{X\geq 0\}}$ is 1 if $X \geq 0$ and 0 if $X < 0$, (Rachev et al., 2008)

Consistent with Vassalou and Xing (2004), short term debt plus one half of long term debt are considered as book value of firm's debt (X). As risk free rate (r), yearly compounded interest rate of treasury discounted auctions figures for the period 2000, which is about 36%, was taken into analysis.

Comparison of the five different models begins with presenting their average financial failure probability rates for non-distressed and distressed firms and results are tabulated below.

Table 16: Average Financial Failure Probability Rates of the Models

Model	Non-Distressed(%)	Distressed(%)	Total(%)
KMV-Prob (Normal Dist)	5.6	43.9	12
KMV-Prob (T-Dist)	5.6	44	12.1
KMV-Prob (Asym. T-Dist)	8.3	52.6	15.7
DA-Prob	9.5	71.1	19.8
Logit-Prob	5.4	72.6	16.7

According to Table 16, the average failure probability rates of non-distressed, solvent firms are much closer to zero than the average failure probability rates of distressed firms. For classification purpose, the cut-off value for the probabilities is set to 50%. The average rate for distressed firms is 43.9% in the KMV-Prob (Normal Dist) model and 44% in the KMV-Prob (T-Dist). These values are close to each other and moderately lower than 50%. On the other hand, the average rate for distressed firms is 52.6% in the KMV-Prob (Asym. T-Dist) model, that is slightly higher than 50%. These figures can be interpreted as KMV-Prob (Normal Dist) and KMV-Prob (T-Dist) estimating (classifying) distressed firms as solvent. Therefore, type I error produced by KMV-Prob (Normal Dist) and KMV-Prob (T-Dist) will be high compared to KMV-Prob (Asym. T-Dist) and accounting based models. On the other hand, type II errors produced by these five models will be more or less close to each other.

If results of accounting based models are left aside and concentration is focused on KMV-Prob models, then asymmetric t-distribution assumption based KMV-Merton model's figures are significantly different and better than those of other assumptions based KMV-Merton models. This difference could indicate that substitution of normal assumption by the asymmetric t-distribution assumption strengthens the KMV-Merton model.

Table 17: Correlation Matrix

	Distressed	KMV-Prob (Normal Dist)	KMV-Prob (T-Dist)	KMV-Prob (Asym. T-Dist)	DA-Prob	Logit-Prob
Distressed		0.495	0.492	0.523	0.777	0.817
KMV-Prob (Normal Dist)	0.404		0.999	0.965	0.594	0.603
KMV-Prob (T-Dist)	0.409	0.981		0.965	0.591	0.601
KMV-Prob (Asym. T-Dist)	0.433	0.800	0.822		0.597	0.603
DA-Prob	0.583	0.519	0.519	0.530		0.884
Logit-Prob	0.602	0.556	0.562	0.545	0.875	

In the correlation summary Table 17, Pearson correlations are presented above the diagonal and Spearman correlations are presented below the diagonal. All of the correlations are significant at the 1% level (2-tailed). Distressed is an indicator variable equal to 1 if the firm is defined as financially distressed, and 0 otherwise. Spearman correlation is a non-parametric version of Pearson correlation.

According to the correlation matrix table, the Pearson correlations and Spearman correlations show that all of the probability measures are positively correlated. KMV-Prob (Asym. T-Dist) and KMV-Prob (Normal Dist) have the highest correlation coefficient of 0.603 with Logit-Prob, while KMV-Prob (T-Dist) has a coefficient of 0.601 with Logit-Prob. KMV-Prob (Normal Dist) and KMV-Prob (T-Dist) has the highest correlation coefficients of 0.999 with each other and 0.965 with KMV-Prob (Asym T-Dist). These higher correlation coefficients among KMV-Prob measures were foreseeable, because all of the variables of the models are derived from the same data basket, only the distribution assumptions of the models differ from each other and this difference shows itself by 0.034 below deviance produced by the asymmetric t-distribution assumption. Besides, DA-Prob and Logit-Prob also have a higher correlation value of 0.884. These five models' correlation coefficients with distressed indicator could be ranked from highest to lowest as Logit-Prob, DA-Prob, KMV-Prob (Asym. T-Dist), KMV-Prob (Normal Dist) and KMV-Prob (T-Dist) according to their coefficients of 0.817, 0.777, 0.523, 0.495, 0.492, respectively. While the market based KMV-Prob measures and accounting based traditional ratio models of DA-Prob and Logit-Prob have positive correlations, the moderate magnitudes of the correlations suggest that KMV-Prob measures may be reflecting different information content about the probability of financial failure. On the other hand higher correlation values of DA-Prob and Logit-Prob could refer to the fact that these two accounting based models represent the similar information content. Their initial distinction from KMV-Prob is that they do not include a measure of volatility, which is a key component of KMV-Prob measures.

Next, to see which model performs better solely with regard to classification accuracy and AUROC figures, the estimation accuracies of these five different models are presented in Table 18. In the table, type I error rate stands for estimating a distressed firm as solvent and type II error rate stands for estimating a solvent firm as distressed.

Table 18: Prediction Results for Market Based Models and Accounting Based Models

Model	Type I Error (%)	Type II Error (%)	Overall Accuracy (%)	AUROC
KMV-Prob (Normal Dist)	56.67	4.67	86.67	0.693
KMV-Prob (T-Dist)	53.33	4.67	87.22	0.710
KMV-Prob (Asym. T-Dist)	46.67	4.67	88.33	0.743
DA-Prob	6.6	28	75.6	0.827
Logit-Prob	23.3	1.3	95	0.877

Table 18, demonstrates that Logit-Prob model outperforms DA-Prob model and KMV-Prob models. Logit-Prob model produced 23.3% type I errors and 1.3% type II errors, while DA-Prob model produces 6.6% type I errors and 28% type II errors. The overall estimation accuracies of Logit-Prob model and DA-Prob model were 95% and 76.6%, respectively. On the other hand, KMV-Prob models produced quite much type I errors than the other two accounting based models. KMV-Prob (Asym. T-Dist) model produced 46.67% type I errors and 4.67% type II errors, and the followers KMV-Prob (T-Dist), KMV-Prob (Normal Dist) produced 53.33%, 56.67% type I errors, respectively; their percentages of type II errors produced were equal to 4.67%, i.e. the three market based model produced an equal amount of type II errors. Regarding overall accuracy the Logit model outperforms all of the models with 95% and the DA model is the worst model with 76.6%. On the other hand, KMV-Prob (Asym. T-Dist) is the best performer among the market based models with 88.33% of overall accuracy, followed by KMV-Prob (T-Dist) and KMV-Prob (Normal Dist) models with 87.22% and 86.67% of overall accuracy, respectively. This demonstration proved that substitution of the normal assumption of market based models with fat-tailed alternatives increased the power of the model. But AUROC figures were in favor of the DA model against KMV-Prob models. The highest AUROC value belongs to the logit model with 0.877 and it is followed by DA model with 0.830. KMV-Prob models are ranked in consistent with overall accuracy as KMV-Prob (Asym. T-Dist), KMV-Prob (T-Dist), KMV-Prob (Normal Dist) and their AUROC values are 0.743; 0.710 and 0.693, respectively.

According to the above findings of estimation accuracies and AUROC values, these analyses suggest that KMV-Prob has no superiority over accounting based models, unlike the suggestion in Hillegeist et al. (2004) to increase the power of estimating bankruptcy by using KMV-Prob instead of accounting based models as a proxy for probability of bankruptcy. As Bharath and Shumway (2004) state, the most important inputs of the model are market value of equity, book value of debt, and the volatility of equity. When market value of equity declines the probability of failure increases, which is the strong and weak point of the model. In addition, amount of book value of debt is another aspect in the model. In the study, it was implicitly assumed that all of the firm's debts mature in one year. This assumption is violated in practice. Book value of debt (X) is set to current debts and one half of long term debts, which is the assumption of Vassalou and Xing (2004). The amount of long term debt in book value of debt is arbitrary; hence lowering the default point (X) reduces the probability of failure. In Turkey, relative high level of indebtedness of industrial firms, debt term structure and heavy foreign borrowing make firms fragile to global financial shocks (Özmen and Yalçın, 2007). This high level of indebtedness indicates that the amount of book value of debt should be considered carefully. For the model to perform better, as Bharath and Shumway (2004) state, both Merton model assumptions must be met and markets must be efficient and well informed.

Moreover, the performance of the market based model is correlated with the employed statistical distribution assumption. In this study, asymmetric t-distribution assumption increased the performance of the model compared to normal and t-distribution assumptions.

6.5 Machine Learning Models

This section of the study is designed to present and discuss the outcomes of 8 data mining classification models under 5 headings. These classification models are Naïve Bayes and Bayesian Network representing the Bayesian models family, k-NN, ANN with MLP, SVM with SMO, C4.5, CHAID and CRT from the decision trees family. These constructed models were compared in terms of classification accuracy along with misclassification rates and AUROC (area under receiver operating characteristic curve) as the previous models.

6.5.1 Bayesian Models

Naïve Bayes and Bayesian Network are the selected classifiers representing Bayesian models. Naïve Bayes classifier is a probabilistic classifier based on Bayesian theorem, often stumbling across the independence assumption, whereas Bayesian Network without independence assumption overcomes that block. In the study, both models are tested. For Bayesian Network, simple estimator is chosen as estimator and Look Ahead Hill Climbing Algorithm (LAGD Hill Climbing) was selected as search algorithm due to its better classification results. Classification and AUROC figures of both classifiers for each period are presented in Table 19 below.

Table 19: Prediction Results for Bayesian Network and Naïve Bayes

Model	Performance Measures	-1	-2	-3
Bayesian Network	Classification Acc. (%)	91.1	88.9	72.2
	Type I Error (%)	30.0	16.7	70
	Type II Error (%)	4.7	10	19.3
	AUROC	**0.827**	**0.867**	**0.553**
Naïve Bayes	Classification Acc. (%)	92.2	85.6	77.8
	Type I Error (%)	33	30	36.7
	Type II Error (%)	2.7	11.3	19.3
	AUROC	**0.820**	**0.777**	**0.720**

For one annual period prior to failure, Naïve Bayes model performs slightly better than Bayesian Network in terms of classification accuracy. It produced 33% type I errors and 2.7% type II errors, while Bayesian Model produced 30% type I errors and 4.7% type II errors. As a consequence, Naïve Bayes' and Bayesian Network's classification accuracy rates were 92.2% and 91.1%, respectively. In contrast to classification accuracy, the AUROC results are in favor of Bayesian Network. The AUROC values of Bayesian Network and Naïve Bayes were 0.827 and 0.820, respectively.

For two annual periods prior to failure, unlike the previous period above, the results are in favor of Bayesian Network in terms of both evaluation methods. It produced 16.7% type I errors and 10% type II errors, while Naïve Bayes produced 30% type I errors and 11.3% type II errors, classification accuracy of Bayesian Network and Naïve Bayes were 88.9% and 85.6%, respectively. The AUROC results of Bayesian Network and Naïve Bayes were 0.867 and 0.777, respectively.

For three annual periods prior to failure, Naïve Bayes performs better than Bayesian Network, unlike for the previous period. It produced 36.7% type I errors and 19.3% type II errors, while Bayesian Model produced 70% type I errors and 19.3% type II errors. The classification accuracies of Naïve Bayes and Bayesian Network amounted to 77.8% and 72.2%, respectively. The AUROC results of Naïve Bayes and Bayesian Network were 0.720 and 0.553 respectively.

Both models reached their best classification accuracy results for one annual period prior to failure; moreover, when the performance evaluation is considered in the scope of type I error and AUROC results, both models are superior to each other. With regard to type I error, Bayesian Network produced fewer errors than Naïve Bayes for one and two annual periods prior to failure, whereas Naïve Bayes is superior for three annual periods prior to failure. According to AUROC results Naïve Bayes is only superior for three annual periods prior to failure, while for the other two periods, Bayesian Network has the best results.

6.5.2 k-NN Instance Based Learning

K-Nearest Neighbor classifier's distance computation parameter was set to Euclidian metric with cross-validation. Distance weight parameter was set to weight by 1/distance and 3 was the selected number of neighbors to be used by the classifier for each period. Classification and AUROC results are presented in Table 20 below.

Table 20: Prediction Result for k-NN

Model	Performance Measures	-1	-2	-3
k-NN	Classification Acc. (%)	90.5	85	83.9
	Type I Error (%)	40	70	73.3
	Type II Error (%)	3.3	4	4.7
	AUROC	**0.783**	**0.630**	**0.627**

Classification accuracy of k-NN model for one annual period prior to failure is significantly better than the results for the other two periods that shows closer results.

Type I error results were 40%, 70% and 73.3% by order of periods from the closest to the farther period. It should be mentioned that the longer the period before failure, the greater the type I errors produced. For the same ordering of periods, type II error results are 3.3%, 4% and 4.7% respectively. The calculated classification accuracy values were 90.5%, 85% and 83.9%, respectively. Revealed AUROC values of the model are 0.783, 0.630, and 0.627, respectively. As it is noticeable that AUROC values have a reverse relationship with those of type I error, the higher the type I error, the smaller the AUROC values.

6.5.3 ANN with Multilayer Perceptron (MLP)

To apply ANN in classification multilayer perceptron (MLP) classifier, which uses back propagation algorithm for classification, was selected for training and validation. Classification and AUROC results are presented in Table 21 below.

Table 21: Prediction Results for MLP

Model	Performance Measures	-1	-2	-3
ANN	Classification Acc. (%)	90	90	80.6
	Type I Error (%)	40	36.,7	63.3
	Type II Error (%)	4	4.7	10.7
	AUROC	**0.780**	**0.793**	**0.630**

This ANN model shows best performance for one and two annual periods prior to failure in terms of classification accuracy, overall percentage of correct classification for these periods is 90%. Produced type I and type II errors for one annual period prior to failure were 40% and 4%, respectively. For the next period, the produced type I and type II errors were 36.7% and 4.7%, respectively. Moreover classification accuracy for three annual periods prior to failure was 80.6% which was its least rate, and the produced type I and type II errors were 63.3% and 10.7%, respectively. The AUROC value decreased significantly in three annual periods prior to failure. The AUROC values were, by order of periods from the closest to the farther period, 0.780, 0.793 and 0.630. The AUROC value for the period -3 is closer to the diagonal line, in other terms the model lost its classification power for this period.

6.5.4 Support Vector Machines (SVM)

For model construction, SVM classifier with John Platt's sequential minimal optimization algorithm was selected for training and validation process of the classifier. As explained in the synopsis part of the Weka platform for the classifier, this algorithm globally replaces all missing values and transforms nominal attributes into binary ones and it also normalizes all attributes by default. The preferred kernel function of the algorithm is the RBF kernel function and algorithm parameters C and γ vary through the periods. Prediction results and parameters are presented in Table 22 below.

Table 22: Prediction Results for SVM

Model	Performance Measures	-1	-2	-3
SVM	Classification Acc. (%)	92.7	88.9	85.6
	Type I Error (%)	30	46.7	60
	Type II Error (%)	2.7	4	5.3
	AUROC	**0.837**	**0.747**	**0.673**
	C	100	150	25
	γ	0.0001	0.2	1

SVM classifier achieves the best accuracy of 92.7% for one annual period prior to failure. For the other two and three annual periods prior to failure, shows 88.9% and 85.6% classification accuracies, respectively. Type I error productions for the same periods were 30%, 46.7%, and 60%, respectively, while type II error rates were 2.7%, 4% and 5.3%, respectively. It is remarkable that type I and type II error have the similar course of deterioration, in both cases, the error indicators of the -3 periods were almost twice that of the -1 period. AUROC value of the model for period -1 is 0.837 then for the earlier periods, the value decreased drastically to 0.747 and 0.673, respectively. All of the indicators were consistent with each other proving that the correct estimation of the distressed and non-distressed firms decreases gradually for the preceding periods.

6.5.5 Decision Trees

Selected decision tree algorithms Quinlan's C4.5, CHAID and CRT were used for model construction in this study. J48 algorithm of the Weka platform represents

Quinlan's C4.5. The CHAID and CRT algorithms were conducted by employing SPSS 15. Revealed results for the decision tree algorithms are presented in Table 23 below.

Table 23: Prediction Results for Decision Trees

Model	Performance Measures	-1	-2	-3
C4.5	Classification Acc. (%)	87.2	83.3	79.4
	Type I Error (%)	46.7	53.3	80
	Type II Error (%)	6	9.3	8.7
	AUROC	**0.737**	**0.687**	**0.557**
CHAID	Classification Acc. (%)	92.2	88.9	84.4
	Type I Error (%)	46.7	23.3	66.7
	Type II Error (%)	0	8.7	5.3
	AUROC	**0.767**	**0.840**	**0.640**
CRT	Classification Acc. (%)	96.7	97.2	97.2
	Type I Error (%)	20	0	16.7
	Type II Error (%)	0	3.3	0
	AUROC	**0.900**	**0.983**	**0.917**

At first glance, it is captured from the table above that the CHAID and CRT algorithms seem superior to C4.5. In one annual period prior to failure, CRT algorithm outperforms C4.5 and CHAID. It produced 20% type I errors while C4.5 and CHAID both produced 46.7% error. In contrast, the produced type II error significantly low for the classifiers; except C4.5, which produced 6% errors, CHAID and CRT classified non-distressed firms without error. The overall prediction accuracy amounts to 87.2%, 92.2% and 96.7% for the classifiers C4.5, CHAID and CRT, respectively. The best AUROC figure achieved by CRT at 0.900. The other models had significantly lower levels of AUROC amounting to 0.767 for CHAID and 0.732 for C4.5.

For the next period, CRT is again superior to both models and C4.5 is still worst in classification accuracy. Classification accuracy rates of the models were 97.2%, 88.9% and 83.3%, respectively. C4.5 had the highest type I errors at 53.3%, this followed by CHAID with 23.3% type I errors and CRT produced no type I error. In type II error production, CRT model had the fewer errors with 3.3% and C4.5 and CHAID produced 9.3% and 8.7% type II errors, respectively. The AUROC values of C4.5 and CHAID were 0.687 and 0.840, respectively. CRT had, with 0.983, the highest AUROC value for this period.

For three annual periods prior to failure, CRT model had the higher classification accuracy with 97.2% and the other models, C4.5 and CHAID had classification accuracies closer to 80% with 79.4% and 84.4%, respectively. The highest type I error with 80% reached by C4.5 and followed by CHAID with 66.7% type I error, CRT produced acceptable type I error of 16.7%. In type II error production CRT had no errors while C4.5 and CHAID produced 8.7% and 5.3% type II errors, respectively. C4.5 had the lowest AUROC value amounting to 0.557 and CRT and CHAID had 0.917 and 0.640, respectively. Among these models, CRT is the best performer in terms of each of performance evaluation indicators.

Moreover, decision tree algorithms are rule learner algorithms and the rules learned by the applied algorithms, which classified the companies, are listed as follows:

C4.5 Rules

Rule 1: Lv2 ≤ 0.792 and P13 ≤ -0.092 and A2 ≤ 0.109 then non-distressed.

Rule 2: Lv2 ≤ 0.792 and P13 ≤ -0.092 and A2 > 0.109 and Lv1 ≤ 0.686 then 80% non-distressed and 20% distressed.

Rule 3: Lv2 ≤ 0.792 and P13 ≤ -0.092 and A2 > 0.109 and Lv1 > 0.686 then 91.7% distressed and 8.3% non-distressed.

Rule 4: Lv2 ≤ 0.792 and P13 > -0.092 then 97.1% non-distressed and 2.9% distressed.

Rule 5: Lv2 > 0.792 and P13 ≤ -0.014 then distressed.

Rule 6: Lv2 > 0.792 and P13 > -0.014 then non-distressed.

CHAID Rules

Rule 1: Lq10 ≤ 0.085 and Lv1 ≤ 0.661 then non-distressed.

Rule 2: Lq10 ≤ 0.085 and Lv1 > 0.661 then distressed.

Rule 3: Lq10> -0.085 and Lq10 ≤ then 50% non-distressed. 50% distressed.

Rule 4: Lq10 > 0.011 and Lq10 ≤ 0.039 and Lv5 ≤ 0.471 then non-distressed.

Rule 5: Lq10 > 0.011 and Lq10 ≤ 0.039 and Lv5 > 0.471 then 50% non-distressed. 50% distressed.

Rule 6: Lq10 > 0.039 and Lv1 ≤ 0.896 then 98.4% non-distressed. 1.6%distressed.

Rule 7: Lq10 > 0.039 and Lv1 > 0.896 then distressed.

CRT Rules

Rule 1: P13 ≤ -0.147 and Lv1 ≤ 0.671 then non-distressed.

Rule 2: P13 ≤ -0.147 and Lv1 > 0.671 and Lq5 ≤ 0.829 then distressed.

Rule 3: P13 ≤ -0.147 and Lv1 > 0.671 and Lq5 > 0.829 then non-distressed.

Rule 4: P13 > -0.147 and Lv5 ≤ 0.711 and Lv1 ≤ 0.968 and A2 ≤ 1.118 and P13 ≤ -0.027 then 81.5% non-distressed. 18.5% distressed.

Rule 5: P13 > -0.147 and Lv5 ≤ 0.711 and Lv1 ≤ 0.968 and A2 ≤ 1.118 and P13 > -0.027 then 99.2% non-distressed. 0.8% distressed.

Rule 6: P13 > -0.147 and Lv5 ≤ 0.711 and Lv1 ≤ 0.968 and A2 > 1.118 then distressed.

Rule 7: P13 > -0.147 and Lv5 ≤ 0.711 and Lv1 > 0.968 then distressed.

Rule 8: P13 > -0.147 and Lv5 > 0.711 then distressed.

Classification accuracy of a model is valid for all of the rules that the model learned or the whole tree that is built. It is not possible to exclude any of the nodes. For classification of a new company, it is enough to satisfy any of the learned rules. Naturally, all of the rules should be coherent with each other, any conflict among rules damage soundness of the model. According to the above rules, CHAID and CRT algorithms learned much more detailed rules compared to C4.5 algorithm. All of the rules are consistent with each other.

Chapter 7
Summary and Conclusion

The search for a prediction method that forecasts financial failure accurately before it happens is an important research topic in finance area and a lot of research has been done on this issue. The conducted studies used various methods, among them traditional statistical models, market based models, and machine learning algorithms are still in use in the financial prediction area, because they suit well to the problem at hand and produce promising results.

The failure prediction research has suffered from the lack of a unified theory since the 1930's, when the first empirical studies on this subject were published. In spite of that, empirical prediction results were promising. Without theoretical background alternative models predicted the future of a firm usually correctly in 80% of the cases, in some studies the amount of correct classifications was even higher (Back et al., 1996). The problem is that even before the theoretical construction for the failing firms is settled, the prediction accuracy is dependent on the best possible selection of variables to be included in the prediction models and also on the statistical method used.

Until the 1980's, the prominent method in failure prediction was discriminant analysis. In the 1980's, logistic analysis replaced this method and today these traditional statistical models have some challengers. Some of these are theoretical market based models and the non-parametric members of the machine learning family like neural networks, lazy learners, decision trees, etc. All of these models seem to lead to high prediction accuracy.

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

The targets of the prediction models can be summarized as letting an analyst or any of the stakeholders act due to the results of the model and pre-intervene to the variables in order to affect the prediction results. In this sense, combining multivariate statistical analyses and structural models and considering them as a whole, it is possible to construct a multidimensional and objective early warning system that let analysts take course of action according to the results and pre-intervene to the variables to asses organizational strategies (Aktan, 2009b).

On the other hand, the efficiency of the early warning system, whether it is market based or accounting based, depends on two main aspects. One is the preparation of financial statements in accordance with accounting standards consistent with legal regulations and the second is the existence of a well informed and efficient market. In other terms, the efficiency of the early warning system increases with transparency of the financial statements and availability of information about the company in the market. Consequently, the early warning system is a worthwhile technique in predicting financial failure, perfection of the system depends on proper work of accounting and auditing firms in the economic system.

Absence of a perfect solid prediction model, which can be used in all kinds of environment and conditions, motivates the search for an appropriate model involving various applications on various data in the literature. In this respect, this study focused on application and evaluation of prediction or classification performances of different prediction methods on Turkish industrial public firms. These methods are discriminant and logit analysis from traditional statistical models, option pricing method from market based models and eight non-parametric methods from machine learning models.

In this study, it is not aimed to present or highlight a model's superiority over others. It is aimed to present the efficiency of each selected methods in the financial distress prediction field.

The group of original variables was formed by selecting from previous central studies 26 of those variables, which were found to be good predictors of failure, and 27 of the variables from the independent investment investigation company IBS. These variables were roughly divided into six categories, namely liquidity, leverage, fiscal structure, activity, profitability and market value.

Classification accuracies along with misclassification rates and AUROC values of representative models for each examined period are presented. For DA, leave-one-out cross validation and for machine learning algorithms, 10-fold cross validation preferred for avoiding overfitting problem, since all the data were used for the training and validation processes. All of the classification models, except the KMV-Merton model, used variables selected through ANOVA and cost sensitive variable election processes. In other terms, the variables minimizing type I error and maximizing overall classification are used in modeling.

For one annual period prior to failure, except DA, KMV-Merton and C4.5 all of the models produce more or equal than 90% classification accuracy with CRT algorithm having the highest accuracy with 96.7%, and the least value belonging to DA with 75.6%. This situation is consistent with the AUROC values only for the CRT algorithm, the least AUROC value was achieved by KMV-Prob (Normal Dist) with 0.693, whereas the highest value of CRT amounted to 0.900. Logit model produced the second best results in terms of classification accuracy and AUROC values with 95% and 0.877, respectively. The other models based on learning algorithms had AUROC values less than 0.900. KMV-Prob (Asym. T-Dist) produced better results than Quinlan's C4.5 algorithm.

For the next previous period prior to failure, DA shows the least performance in classification accuracy with 78.3%, while CRT reaches 97.2% accuracy in this term. The best AUROC value belongs to CRT with 0.983 and followed by Bayesian Network with 0.867. The least AUROC value was reached by k-NN algorithm with 0.630. The CRT algorithm produced no type I error, in other terms this algorithm classified all of the distressed firms correctly.

For three annual periods prior to failure, CRT had the best performance in classification accuracy and AUROC with 97.2% and 0.917, respectively. The worst performer in this term, regarding AUROC figures, was the logit model, although its promising 84.4% classification accuracy, it produced an AUROC value of only 0.533. Except 2 distressed firms' correct classification, the rest of the firms were classified as solvent. The moderately high classification accuracy of 84.4% is almost equal to the ratio of non-distressed firms 83.3% in the whole data set. On the contrary, type I error and AUROC figures indicate that this model is the worst in this period. If all the other indicators are neglected and only classification accuracy is considered then the logit model ranks in the 3rd place together with CHAID among 10 classification models. In fact, this is not the case here; this study uses AUROC and misclassification figures along with classification accuracy for evaluation of models. Therefore, together with AUROC and the type I error evaluation proves that the logit model is very poor in this term. It can be said that solely relying on one indicator or relying on classification accuracy alone can mislead the user.

For all periods CRT, is the absolute winner, but the promising results of CRT indicate an overfitting problem as a result of using the same data for training and validation.

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

Moderate lower performance of the KMV-Merton model can be caused by an arbitrary determination of book value of debt, statistical distribution assumption of the asset returns, and violation of efficient market assumption of the theory. However, recent studies proved that market based structural models can be used in estimating default risk. Thus, financial failure estimation models are grounded on a theoretical model for the first time. In addition, theory grounded market based structural models have some superior attributes compared to traditional accounting based models. These attributes can be summarized referring to the initial model of this study. KMV-Merton model has definite variables and these variables never change, on the contrary, in traditional accounting based models, variables vary according to researcher. Next, in an efficient market, equity prices valued according to future expectations, in other term, any new information in the market is immediately reflected in equity prices. But in traditional accounting based models, the data resources are based on historical data.

Therefore, in the light of the analysis findings, it is hard to recommend the KMV-Merton model solely. In contrast to Hillegeist et al. (2004), suggestion of using KMV-Merton model solely as a proxy for probability of bankruptcy, market based models should make contributions to traditional accounting based models until the Turkish stock market matures some more, hence there is some evidence of stock price manipulations in ISE (see Hürriyet, 02.04.2009).

More importantly, in spite of the promising results of the above reported classification models, this study has several limitations, some of which involve the need for additional research, others are absence of robust theoretical framework for selection of potential explanatory variables of financial distress, and the relatively small sample size of distressed firms.

In summary, four conclusions can be made. First, the differences between alternative model selection methods affect the number of independent variables to be selected. Second, not only the number of variables, but also the information content of the models, varies due to the variables that measure different economic dimensions of a firm. Third, connected with alternative failure prediction methods, also the prediction performance varies. Finally, each of the learning algorithms can be used along with other statistical and structural prediction models or as an alternative tool for financial distress prediction. But assessing corporate financial structure barely relying on learning algorithm outcomes can be misleading; therefore it should be underlined that the assessment should be made by collaboration of human judgment and prediction methods.

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Part III

Appendix

A. Discriminant Analysis SPSS 15 OutputSummary of Canonical Discriminant Functions

Table A 1: Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.910(a)	100.0	100.0	.690

a First 1 canonical discriminant functions were used in the analysis.

Table A 2: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.524	114.178	3	.000

Table A 3: Canonical Discriminant Function Coefficients

	Function
	1
A2	2.275
Lq5	-1.914
Lv1	3.739
(Constant)	-1.709

Unstandardized coefficients

Table A 4: Classification Results(b,c)

		Distressed	Predicted Group Membership		Total
			.00	1.00	.00
Original	Count	.00	144	6	150
		1.00	9	21	30
	%	.00	96.0	4.0	100.0
		1.00	30.0	70.0	100.0
Cross-validated(a)	Count	.00	144	6	150
		1.00	9	21	30
	%	.00	96.0	4.0	100.0
		1.00	30.0	70.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 91.7% of original grouped cases correctly classified.

c 91.7% of cross-validated grouped cases correctly classified.

B. Logit Analysis SPSS 15 Output

Table B 1: Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	82.521	1	.000
	Block	82.521	1	.000
	Model	82.521	1	.000
Step 2	Step	15.323	1	.000
	Block	97.844	2	.000
	Model	97.844	2	.000
Step 3	Step	10.272	1	.001
	Block	108.116	3	.000
	Model	108.116	3	.000

Table B 2: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	79.681(a)	.368	.619
2	64.358(b)	.419	.706
3	54.086(c)	.452	.760

a Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

b Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

c Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Table B 3: Classification Table(a)

Observed			Predicted		
			Distressed		Percentage Correct
			.00	1.00	.00
Step 1	Distressed	.00	147	3	98.0
		1.00	14	16	53.3
	Overall Percentage				90.6
Step 2	Distressed	.00	148	2	98.7
		1.00	11	19	63.3
	Overall Percentage				92.8
Step 3	Distressed	.00	148	2	98.7
		1.00	7	23	76.7
	Overall Percentage				95.0

a The cut value is .500

Table B 4: Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1(a)	P13	-15.873	3.071	26.715	1	.000	.000
	Constant	-2.440	.368	44.030	1	.000	.087
Step 2(b)	A2	5.406	1.927	7.870	1	.005	222.698
	P13	-17.024	3.657	21.670	1	.000	.000
	Constant	-3.944	.713	30.607	1	.000	.019
Step 3(c)	A2	6.005	2.125	7.986	1	.005	405.484
	Lv2	6.591	2.313	8.121	1	.004	728.240
	P13	-19.111	4.683	16.656	1	.000	.000
	Constant	-8.001	1.845	18.811	1	.000	.000

a Variable(s) entered on step 1: P13.

b Variable(s) entered on step 2: A2.

c Variable(s) entered on step 3: Lv2.

C. Correlation Outputs of SPSS 15 for KMV-Merton Models and Classical Statistical Models

Table C 1: Pearson Correlations

		Distressed	KMV-Prob (Normal Dist)	KMV-Prob (T-Dist)	KMV-Prob (Asym. T-Dist)	DA-Prob	Logit-Prob
Distressed	Pearson Correlation	1	.495(**)	.492(**)	.523(**)	.777(**)	.817(**)
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	180	180	180	180	180	180
KMV-Prob (Normal Dist)	Pearson Correlation	.495(**)	1	.999(**)	.965(**)	.594(**)	.603(**)
	Sig. (2-tailed)	.000		.000	.000	.000	.000
	N	180	180	180	180	180	180
KMV-Prob (T-Dist)	Pearson Correlation	.492(**)	.999(**)	1	.965(**)	.591(**)	.601(**)
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	180	180	180	180	180	180
KMV-Prob (Asym. T-Dist)	Pearson Correlation	.523(**)	.965(**)	.965(**)	1	.597(**)	.603(**)
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	180	180	180	180	180	180
DA-Prob	Pearson Correlation	.777(**)	.594(**)	.591(**)	.597(**)	1	.884(**)
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	180	180	180	180	180	180
Logit-Prob	Pearson Correlation	.817(**)	.603(**)	.601(**)	.603(**)	.884(**)	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	180	180	180	180	180	180

** Correlation is significant at the 0.01 level (2-tailed).

Table C 2: Spearman's rho Correlations

			Distressed	KMV-Prob (Normal Dist)	KMV-Prob (T-Dist)	KMV-Prob (Asym. T-Dist)	DA-Prob	Logit-Prob
Spearman's rho	Distressed	Correlation Coefficient	1.000	.404(**)	.409(**)	.433(**)	.583(**)	.602(**)
		Sig. (2-tailed)	.	.000	.000	.000	.000	.000
		N	180	180	180	180	180	180
	KMV-Prob (Normal Dist)	Correlation Coefficient	.404(**)	1.000	.981(**)	.800(**)	.519(**)	.556(**)
		Sig. (2-tailed)	.000	.	.000	.000	.000	.000
		N	180	180	180	180	180	180
	KMV-Prob (T-Dist)	Correlation Coefficient	.409(**)	.981(**)	1.000	.822(**)	.519(**)	.562(**)
		Sig. (2-tailed)	.000	.000	.	.000	.000	.000
		N	180	180	180	180	180	180
	KMV-Prob (Asym. T-Dist)	Correlation Coefficient	.433(**)	.800(**)	.822(**)	1.000	.530(**)	.545(**)
		Sig. (2-tailed)	.000	.000	.000	.	.000	.000
		N	180	180	180	180	180	180
	DA-Prob	Correlation Coefficient	.583(**)	.519(**)	.519(**)	.530(**)	1.000	.875(**)
		Sig. (2-tailed)	.000	.000	.000	.000	.	.000
		N	180	180	180	180	180	180
	Logit-Prob	Correlation Coefficient	.602(**)	.556(**)	.562(**)	.545(**)	.875(**)	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.
		N	180	180	180	180	180	180

** Correlation is significant at the 0.01 level (2-tailed).

D. Machine Learning Models

D.1 Bayesian Network Output Weka 3.6

=== Run information ===

Scheme: weka.classifiers.bayes.BayesNet -D -Q weka.classifiers.bayes.net.search.local.LAGDHillClimber -- -L 2 -G 5 -P 1 -S BAYES -E weka.classifiers.bayes.net.estimate.SimpleEstimator -- -A 0.5
Instances: 180
Attributes: 11
Lq5
Lq6
Lq8
Lq10
Lv1
Lv2
Lv5
A2
P10
P13
distress
Test mode: 10-fold cross-validation

Bayes Network Classifier
not using ADTree
#attributes=11 #classindex=10
Network structure (nodes followed by parents)
Lq5(1): distress
Lq6(2):
Lq8(2): Lq6
Lq10(2): P13
Lv1(2): distress
Lv2(2): distress
Lv5(3): distress
A2(3): distress
P10(3): distress
P13(3): distress

distress(2): Lq6
LogScore Bayes: -794.5540042498288
LogScore BDeu: -827.2552213941485
LogScore MDL: -842.62237319768
LogScore ENTROPY: -769.9209772852172
LogScore AIC: -797.9209772852172

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	164	91.1111 %
Incorrectly Classified Instances	16	8.8889 %
Kappa statistic	0.6712	
Mean absolute error	0.1132	
Root mean squared error	0.2863	
Relative absolute error	40.3716 %	
Root relative squared error	76.8158 %	
Total Number of Instances	180	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.953	0.3	0.941	0.953	0.947	0.901	Non-dist.
	0.7	0.047	0.75	0.7	0.724	0.901	Distressed
Weighted Avg.	0.911	0.258	0.909	0.911	0.91	0.901	

=== Confusion Matrix ===

```
   a    b   <-- classified as
 143    7 |   a = Non-dist.
   9   21 |   b = Distressed
```

D.2 Naïve Bayes Output Weka 3.6

=== Run information ===

Scheme: weka.classifiers.bayes.NaiveBayes
Relation: Financial_Distress-weka.filters.unsupervised.attribute.Remove-R1-4,7,9,11,14,16-17,19-30,32-33
Instances: 180
Attributes: 11
Lq5
Lq6
Lq8
Lq10
Lv1
Lv2
Lv5
A2
P10
P13
distress
Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Naive Bayes Classifier

Attribute	Class Non-dist. (0.83)	Distressed (0.17)
Lq5		
mean	0.6201	0.5014
std. dev.	0.1806	0.2527
weight sum	150	30
precision	0.0061	0.0061
Lq6		
mean	0.4062	0.2425
std. dev.	0.1692	0.1801

weight sum	150	30
precision	0.0053	0.0053

Lq8

mean	0.1049	0.0243
std. dev.	0.1165	0.0445
weight sum	150	30
precision	0.0047	0.0047

Lq10

mean	0.0892	-0.078
std. dev.	0.1268	0.2988
weight sum	150	30
precision	0.0122	0.0122

Lv1

mean	0.5586	0.9835
std. dev.	0.173	0.387
weight sum	150	30
precision	0.0129	0.0129

Lv2

mean	0.4338	0.7409
std. dev.	0.1721	0.3369
weight sum	150	30
precision	0.0125	0.0125

Lv5

mean	0.2469	0.6144
std. dev.	0.1771	0.3671
weight sum	150	30
precision	0.0132	0.0132

A2

mean	0.169	0.4894
std. dev.	0.1209	0.5867
weight sum	150	30
precision	0.0179	0.0179

P10

mean	0.0457	-0.3476
std. dev.	0.0984	0.4682
weight sum	150	30
precision	0.0174	0.0174

P13

mean	0.0797	-0.3355
std. dev.	0.1383	0.4313
weight sum	150	30
precision	0.017	0.017

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	166	92.2222 %
Incorrectly Classified Instances	14	7.7778 %
Kappa statistic	0.6957	
Mean absolute error	0.0837	
Root mean squared error	0.2655	
Relative absolute error	29.8233 %	
Root relative squared error	71.2409 %	
Total Number of Instances	180	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.973	0.333	0.936	0.973	0.954	0.934	Non-dist.
	0.667	0.027	0.833	0.667	0.741	0.934	Distressed
Weighted Avg.	0.922	0.282	0.919	0.922	0.919	0.934	

=== Confusion Matrix ===

a	b	<-- classified as
146	4 |	a = Non-dist.
10	20 |	b = Distressed

D.3 k-NN Output Weka 3.6

=== Run information ===

Scheme: weka.classifiers.lazy.IBk -K 3 -W 0 -X -I -A "weka.core.neighboursearch.LinearNNSearch -A \"weka.core.EuclideanDistance -R first-last\""
Relation: Financial_Distress-weka.filters.unsupervised.attribute.Remove-R1-4,7,9,11,14,16-17,19-30,32-33
Instances: 180
Attributes: 11
Lq5
Lq6
Lq8
Lq10
Lv1
Lv2
Lv5
A2
P10
P13
distress
Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

IB1 instance-based classifier
using 1 inverse-distance-weighted nearest neighbour(s) for classification

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	163	90.5556 %
Incorrectly Classified Instances	17	9.4444 %
Kappa statistic	0.625	
Mean absolute error	0.0982	
Root mean squared error	0.3048	
Relative absolute error	35.0055 %	

Root relative squared error	81.773 %
Total Number of Instances	180

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.967	0.4	0.924	0.967	0.945	0.912	Non-dist.
	0.6	0.033	0.783	0.6	0.679	0.912	Distressed
Weighted Avg.	0.906	0.339	0.9	0.906	0.9	0.912	

=== Confusion Matrix ===

```
  a   b   <-- classified as
 145   5 |   a = Non-dist.
  12  18 |   b = Distressed
```

D.4 ANN Multilayer Perceptron Output Weka 3.6

=== Run information ===

Scheme: weka.classifiers.functions.MultilayerPerceptron -L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H a
Relation: Financial_Distress-weka.filters.unsupervised.attribute.Remove-R1-4,7,9,11,14,16-17,19-30,32-33
Instances: 180
Attributes: 11
Lq5
Lq6
Lq8
Lq10
Lv1
Lv2
Lv5
A2
P10
P13
distress
Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Sigmoid Node 0
Inputs Weights
Threshold -9.946582152444398
Node 2 2.4851027395863596
Node 3 2.691613095561797
Node 4 1.6350957523813736
Node 5 6.133891013801015
Node 6 0.14120372143904267
Node 7 2.119693387599779
Sigmoid Node 1
Inputs Weights
Threshold 9.932049617807392
Node 2 -2.5738094240791787
Node 3 -2.667794236936317

Node 4 -1.6092399567051934
Node 5 -6.11205391247937
Node 6 -0.14737869490584124
Node 7 -2.081226264531114

Sigmoid Node 2
Inputs Weights
Threshold -3.9418496349397527
Attrib Lq5 0.8876388929880207
Attrib Lq6 0.26278905307702577
Attrib Lq8 4.699731466406317
Attrib Lq10 -0.63268314807809
Attrib Lv1 -1.2300491389778814
Attrib Lv2 -1.3973847198909397
Attrib Lv5 0.12527337701993121
Attrib A2 -2.033531421620472
Attrib P10 4.485966672830835
Attrib P13 6.433051263078948

Sigmoid Node 3
Inputs Weights
Threshold -3.317936648523849
Attrib Lq5 0.9450540284336768
Attrib Lq6 1.3502542378334157
Attrib Lq8 4.565702520447678
Attrib Lq10 -1.1622951513458906
Attrib Lv1 -1.296418225822775
Attrib Lv2 -1.2714096928067429
Attrib Lv5 0.7165642416638391
Attrib A2 -2.166923380000647
Attrib P10 4.674196364129472
Attrib P13 6.561711687762296

Sigmoid Node 4
Inputs Weights
Threshold -3.0490847818833156
Attrib Lq5 0.45834293195403036
Attrib Lq6 1.1869180366626046
Attrib Lq8 3.243829251215821
Attrib Lq10 -0.19428652255236803
Attrib Lv1 -1.3832926831854986
Attrib Lv2 -0.8301598369288893

Attrib Lv5 0.7026433084529695
Attrib A2 -1.6348626187208493
Attrib P10 3.318574951628465
Attrib P13 4.853176333188232
Sigmoid Node 5
Inputs Weights
Threshold -7.776669383094252
Attrib Lq5 -2.319885963473163
Attrib Lq6 -2.1371392560087528
Attrib Lq8 4.207192829827484
Attrib Lq10 1.4049443826404049
Attrib Lv1 -2.388002769060565
Attrib Lv2 -3.3526362420315468
Attrib Lv5 -5.591279489423096
Attrib A2 -4.375024470800115
Attrib P10 3.3173067204122964
Attrib P13 6.326763793648905
Sigmoid Node 6
Inputs Weights
Threshold -2.160592738712406
Attrib Lq5 0.028141977135804876
Attrib Lq6 0.3993623934184602
Attrib Lq8 1.7204855511379507
Attrib Lq10 0.3335685346251655
Attrib Lv1 -0.7362691423982776
Attrib Lv2 -0.4204618628498291
Attrib Lv5 -0.25966088606271165
Attrib A2 -0.3353675254779876
Attrib P10 0.75566234832932
Attrib P13 1.3771254150334875
Sigmoid Node 7
Inputs Weights
Threshold -2.9985879001693787
Attrib Lq5 0.5898002219771895
Attrib Lq6 1.5729069427337232
Attrib Lq8 3.708490806357934
Attrib Lq10 -0.71472785147079
Attrib Lv1 -1.39075177083523
Attrib Lv2 -0.9733354352980483

Attrib Lv5 0.9007928320275739
Attrib A2 -1.916511448989136
Attrib P10 3.9226463271975645
Attrib P13 5.5890708265997855
Class Non-dist.
Input
Node 0
Class Distressed
Input
Node 1

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	162	90%
Incorrectly Classified Instances	18	10%
Kappa statistic	0.6087	
Mean absolute error	0.1104	
Root mean squared error	0.2807	
Relative absolute error	39.3459 %	
Root relative squared error	75.3267 %	
Total Number of Instances	180	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.96	0.4	0.923	0.96	0.941	0.9	Non-dist.
	0.6	0.04	0.75	0.6	0.667	0.9	Distressed
Weighted Avg.	0.9	0.34	0.894	0.9	0.895	0.9	

=== Confusion Matrix ===

```
   a   b   <-- classified as
 144   6 |   a = Non-dist.
  12  18 |   b = Distressed
```

D.5 Support Vector Machines SMO Output Weka 3.6

=== Run information ===

Scheme: weka.classifiers.functions.SMO -C 100.0 -L 0.0010 -P 1.0E-12 -N 0 -M -V -1 -W 1 -K "weka.classifiers.functions.supportVector.RBFKernel -C 250007 -G 1.0E-5"
Relation: Financial_Distress-weka.filters.unsupervised.attribute.Remove-R1-4,7,9,11,14,16-17,19-30,32-33
Instances: 180
Attributes: 11
Lq5
Lq6
Lq8
Lq10
Lv1
Lv2
Lv5
A2
P10
P13
distress
Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

SMO

Kernel used:
RBF kernel: K(x,y) = e^-(1.0E-5* <x-y,x-y>^2)

Classifier for classes: Non-dist., Distressed

BinarySMO

100 * <0 0 0 0 1 1 1 0 0 0 > * X]
- 100 * <0.558212 0.302217 0.026975 0.681426 0.295648 0.295918 0.172987 0.072621 0.840381 0.784109 > * X]
+ 100 * <0.350312 0.220537 0.038536 0.633122 0.282876 0.277454 0.175584 0.090097 0.754975 0.684109 > * X]

- 100 * <0.519751 0.203034 0.017341 0.754457 0.254021 0.271137 0.271688 0.263301 0.866501 0.798062 > * X]
- 100 * <0.112266 0.087515 0.007707 0.731455 0.118732 0.095238 0.146494 0.015146 0.883499 0.816667 > * X]
+ 100 * <0.81289 0.098016 0 0.748706 0.354305 0.182702 0.390649 1 0.830431 0.765116 > * X]
- 100 * <0.847193 0.673279 0.001927 0.882116 0.334437 0.376579 0.367273 0.04 0.885987 0.819767 > * X]
+ 100 * <0.72973 0.444574 0.036609 0.874641 0.360927 0.405248 0.171948 0.195728 0.786899 0.557752 > * X]
+ 100 * <0.284823 0.225204 0.003854 0.762507 0.355251 0.359086 0.211948 0.050097 0.826285 0.762016 > * X]
+ 100 * <0.504158 0.396733 0.406551 0.770558 0.184011 0.210398 0.202078 0.075728 0.860282 0.789922 > * X]
- 100 * <0.348233 0.228705 0.040462 0.726279 0.231315 0.182216 0.247273 0.078058 0.860282 0.793798 > * X]
+ 100 * <0.703742 0.343057 0.007707 0.653824 0.293283 0.281341 0.107532 0.15767 0.877695 0.808527 > * X]
- 100 * <0.747401 0.309218 0.242775 0.805635 0.228477 0.163751 0.238442 0.125049 0.893035 0.823643 > * X]
+ 100 * <0.579002 0.347725 0.007707 0.714204 0.281457 0.207483 0.242597 0.133592 0.793118 0.729845 > * X]
- 100 * <0.52183 0.336056 0.346821 0.684876 0.229896 0.246842 0.221818 0.115728 0.797678 0.783721 > * X]
- 100 * <0.54158 0.494749 0.00578 0.779758 0.283349 0.207483 0.306494 0.031845 0.841625 0.763953 > * X]
- 100 * <0.372141 0.371062 0.157996 0.776308 0.312677 0.151603 0.318442 0.011262 0.869818 0.763566 > * X]
- 100 * <0.759875 0.610268 0.061657 0.722829 0.302744 0.320214 0.25974 0.07068 0.847015 0.786047 > * X]
+ 100 * <0.644491 0.280047 0.038536 0.706153 0.272942 0.19242 0.162078 0.092816 0.825041 0.761628 > * X]
- 100 * <0.465696 0.210035 0.088632 0.686026 0.19158 0.159378 0.187532 0.132816 0.883499 0.813953 > * X]
+ 100 * <0.697505 0.651109 0.019268 0.779758 0.421003 0.391642 0.447273 0.066019 0.790216 0.751938 > * X]
+ 100 * <0.171518 0.064177 0.001927 0.444508 0.37228 0.329932 0.052987 0.108738 0.681177 0.693798 > * X]

- 100 * <0.565489 0.413069 0.206166 0.715354 0.273888 0.234694 0.224935
0.029126 0.855307 0.78876 > * X]
+ 100 * <0.93659 0.231039 0.017341 0.738355 0.397351 0.39553 0.343896
0.173981 0.854478 0.79186 > * X]
- 100 * <0.404366 0.34189 0.019268 0.593445 0.222327 0.13654 0.093506
0.029515 0.810531 0.744186 > * X]
- 100 * <0.597713 0.364061 0.003854 0.715354 0.35667 0.231778 0.282597
0.132816 0.822554 0.757752 > * X]
+ 100 * <0.54158 0.116686 0.001927 0.498562 0.512299 0.500972 0.331948
0.359612 0.605721 0.626357 > * X]
+ 100 * <0.536383 0.226371 0.104046 0.691777 0.360454 0.247813 0.426494
0.321942 0.798507 0.739535 > * X]
- 100 * <0.530146 0.417736 0.021195 0.79356 0.239357 0.206025 0.202078 0.08
0.875622 0.778682 > * X]
+ 100 * <0.697505 0.191365 0.015414 0.619321 0.464522 0.439747 0.310649
0.351845 0.697761 0.655039 > * X]
+ 100 * <0.651767 0.670945 0 0.791834 0.365184 0.365403 0.403636 0.04466
0.80141 0.760853 > * X]
+ 100 * <0.888773 0.887981 0.069364 0.718804 0.324976 0.358115 0.371948
0.060583 0.858624 0.781783 > * X]
+ 100 * <0.753638 0.471412 0.090559 0.562967 0.404447 0.353256 0.434805
0.092039 0.748342 0.688372 > * X]
- 100 * <0.884615 0.492415 0.007707 0.688327 0.311731 0.344509 0.258182
0.105243 0.845771 0.779845 > * X]
- 100 * <0.529106 0.248541 0.007707 0.60207 0.23983 0.149174 0.145455 0.12
0.825871 0.752326 > * X]
+ 100 * <0.356549 0.154026 0.003854 0.684301 0.113056 0.13897 0.005714
0.127379 0.825456 0.760465 > * X]
+ 100 * <0.356549 0.262544 0.150289 0.663025 0.333964 0.189018 0.287792
0.100583 0.851575 0.784884 > * X]
- 100 * <0.196466 0.140023 0.011561 0.795285 0.218543 0.173469 0.024416
0.026019 0.870647 0.805426 > * X]
- 100 * <0.850312 0.785298 0.017341 0.689477 0.322611 0.347911 0.147013
0.032233 0.847015 0.779845 > * X]
- 100 * <0.612266 0.247375 0.028902 0.603795 0.24456 0.167153 0.073247
0.120388 0.845771 0.791085 > * X]
- 100 * <0.407484 0.240373 0.011561 0.721104 0.23983 0.135569 0.273247
0.083883 0.86194 0.795349 > * X]

\+ 100 * <0.068607 0.005834 0.009634 0.575618 0.315989 0.357629 0.111169 0.827961 0.614842 0.626357 > * X]

\- 100 * <0.805613 0.693116 0.175337 0.812536 0.379376 0.350826 0.33974 0.080777 0.863184 0.794574 > * X]

\+ 100 * <0.805613 0.467911 0.256262 0.652674 0.264428 0.195335 0.278961 0.23767 0.805556 0.743798 > * X]

\- 100 * <0.606029 0.172695 0.092486 0.730305 0.279565 0.246842 0.298701 0.210485 0.871061 0.805426 > * X]

\+ 100 * <0.288981 0.108518 0.001927 0.373778 0.933775 0.374636 0.697662 0.058252 0.212272 0.277132 > * X]

\+ 100 * <0.126819 0.023337 0.013487 0.531915 0.505203 0.368805 0.376623 0.070291 0.551824 0.534884 > * X]

\- 100 * <0.400208 0.322054 0.111753 0.558367 0.231315 0.239553 0.096623 0.031845 0.773217 0.724806 > * X]

\+ 100 * <0.482328 0.311552 0.030829 0.689477 0.272469 0.120991 0.24 0.093592 0.80141 0.74186 > * X]

\+ 100 * <0.20894 0.143524 0.001927 0.687752 0.343898 0.295918 0.376623 0.055534 0.815506 0.72093 > * X]

\+ 100 * <0.756757 0.112019 0.013487 0.698677 0.22895 0.229349 0.274286 0.56233 0.869403 0.80155 > * X]

\- 100 * <0.288981 0.256709 0.061657 0.785509 0.326868 0.123421 0.344416 0.041942 0.806799 0.743798 > * X]

\- 100 * <0.379418 0.207701 0.171484 0.778033 0.181173 0.057337 0.194805 0.128155 0.851575 0.787209 > * X]

\+ 100 * <0.662162 0.411902 0.057803 0.550316 0.547777 0.560739 0.326234 0.055922 0.648839 0.589922 > * X]

\- 100 * <0.452183 0.234539 0.111753 0.573318 0.086093 0.097182 0.055065 0.076117 0.751244 0.683721 > * X]

\+ 100 * <0.706861 0.451575 0.023121 0.968373 0.395932 0.2862 0.263377 0.109903 0.849502 0.682558 > * X]

\- 100 * <0.644491 0.410735 0.044316 0.72973 0.305109 0.269679 0.265974 0.136699 0.837065 0.773643 > * X]

\+ 100 * <0.073805 0.031505 0.007707 0.457734 0.597446 0.165209 0.556883 0.042718 0.477612 0.512016 > * X]

\- 100 * <0.725572 0.185531 0.013487 0.759057 0.263009 0.208455 0.127273 0.306408 0.889718 0.83062 > * X]

\- 100 * <0.849272 0.399067 0.156069 0.758482 0.260643 0.262391 0.262857 0.20699 0.87272 0.817054 > * X]

\- 0.9883

Number of support vectors: 60

Number of kernel evaluations: 20877 (64.358% cached)

Logistic Regression with ridge parameter of 1.0E-8
Coefficients...

```
               Class
Variable       Non-dist.
=======================
pred        -1132.4247
Intercept    -1129.6096
```

Odds Ratios...

```
               Class
Variable       Non-dist.
=======================
pred                0
```

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	167	92.7778 %
Incorrectly Classified Instances	13	7.2222 %
Kappa statistic	0.7214	
Mean absolute error	0.1023	
Root mean squared error	0.2326	
Relative absolute error	36.4742 %	
Root relative squared error	62.4206 %	
Total Number of Instances	180	

=== Detailed Accuracy By Class ===

TP Rate FP Rate Precision Recall F-Measure ROC Area Class

	0.973	0.3	0.942	0.973	0.957	0.954	Non-dist.
	0.7	0.027	0.84	0.7	0.764	0.954	Distressed
Weighted Avg.	0.928	0.254	0.925	0.928	0.925	0.954	

=== Confusion Matrix ===

```
  a   b   <-- classified as
146   4 |   a = Non-dist.
  9  21 |   b = Distressed
```

D.6 Decision Trees Outputs

D.6.1 J48 – C4.5 Output Weka 3.6

```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     Financial_Distress-weka.filters.unsupervised.attribute.Remove-R1-4,7,9,11,14,16-17,19-30,32-33
Instances:    180
Attributes:   11
              Lq5
              Lq6
              Lq8
              Lq10
              Lv1
              Lv2
              Lv5
              A2
              P10
              P13
              distress
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree
------------------

Lv2 <= 0.792
|   P13 <= -0.092
|   |   A2 <= 0.109: Non-dist. (8.0)
|   |   A2 > 0.109
|   |   |   Lv1 <= 0.686: Non-dist. (5.0/1.0)
|   |   |   Lv1 > 0.686: Distressed (12.0/1.0)
|   P13 > -0.092: Non-dist. (139.0/4.0)
Lv2 > 0.792
|   P13 <= -0.014: Distressed (14.0)
|   P13 > -0.014: Non-dist. (2.0)
```

Number of Leaves : 6

Size of the tree : 11

Time taken to build model: 0.33 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	157	87.2222 %
Incorrectly Classified Instances	23	12.7778 %
Kappa statistic	0.5071	
Mean absolute error	0.1557	
Root mean squared error	0.343	
Relative absolute error	55.5221 %	
Root relative squared error	92.0443 %	
Total Number of Instances	180	

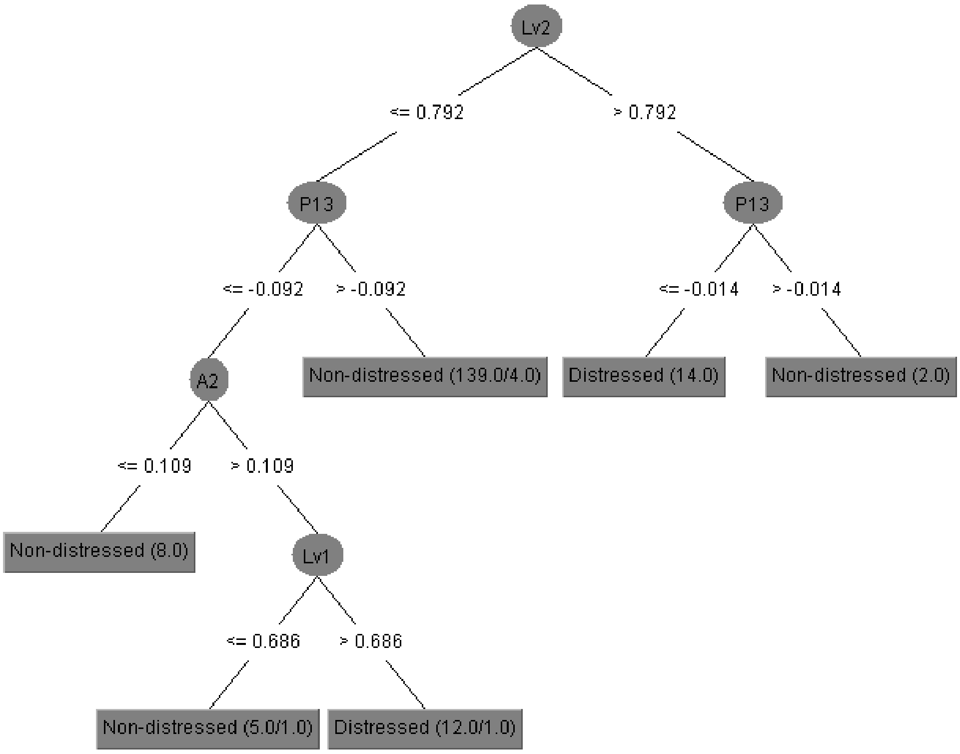
=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.94	0.467	0.91	0.94	0.925	0.732	Non-dist.
	0.533	0.06	0.64	0.533	0.582	0.732	Distressed
Weighted Avg.	0.872	0.399	0.865	0.872	0.867	0.732	

=== Confusion Matrix ===

```
   a    b   <-- classified as
 141    9 |   a = Non-dist.
  14   16 |   b = Distressed
```

Figure D 1: C4.5 Decision Tree



D.6.2 CHAID Output SPSS 15

Table D 1: CHAID Model Summary

Specifications	Growing Method	CHAID
	Dependent Variable	Distressed
	Independent Variables	Lq8, Lq6, Lv5, A2, Lq5, Lv1, Lv2, P10, P13, Lq10
	Validation	Cross Validation
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	2
	Minimum Cases in Child Node	1
Results	Independent Variables Included	Lq10, Lv1, Lv5
	Number of Nodes	11
	Number of Terminal Nodes	7
	Depth	2

Figure D 2: CHAID Decision Tree

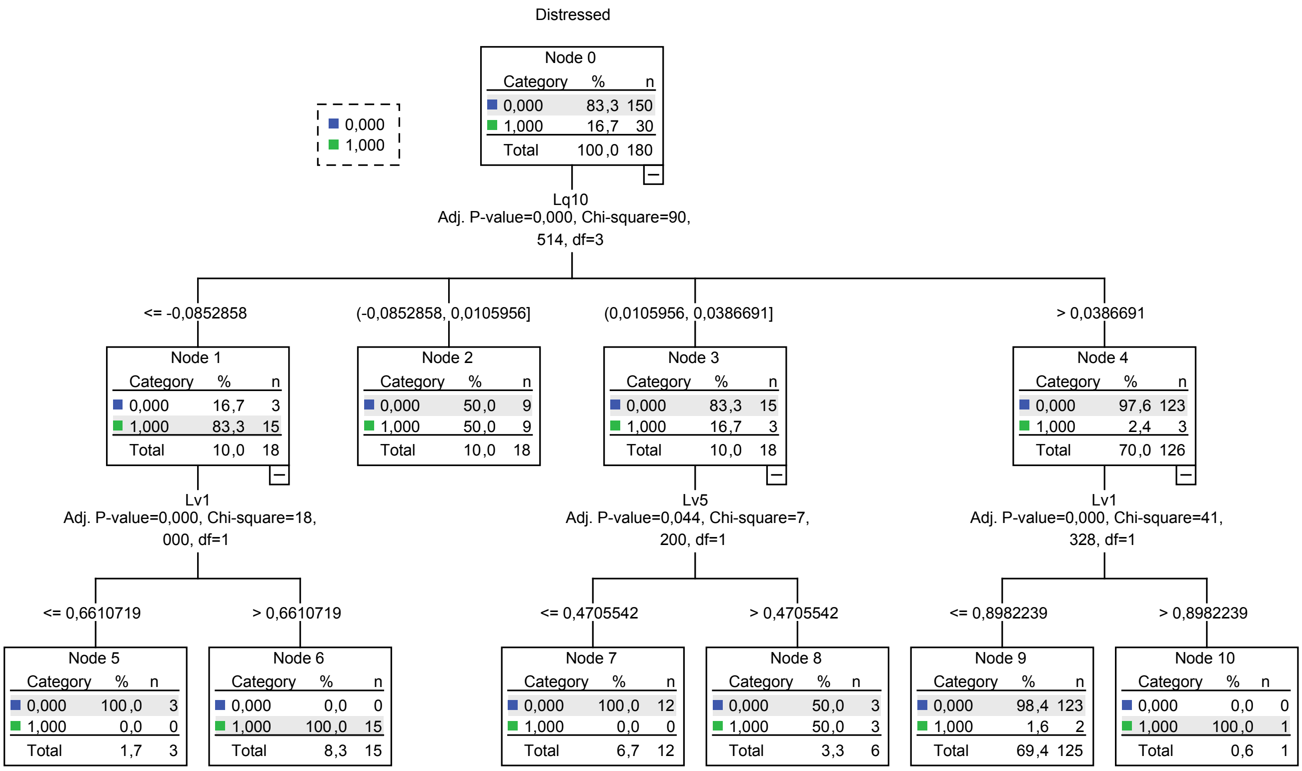


Table D 2: CHAID Classification

Observed	Predicted 0	1	Percent Correct
0	150	0	100.0%
1	14	16	53.3%
Overall Percentage	91.1%	8.9%	92.2%

Growing Method: CHAID

Dependent Variable: Distressed

D.6.3 CRT Output SPSS 15

Table D 3: Model Summary

Specifications	Growing Method	CRT
	Dependent Variable	Distress
	Independent Variables	Lq5, Lq6, Lq8, Lq10, Lv1, Lv2, Lv5, A2, P10, P13
	Validation	Cross Validation
	Maximum Tree Depth	5
	Minimum Cases in Parent Node	2
	Minimum Cases in Child Node	1
Results	Independent Variables Included	P13, P10, Lq10, Lv1, Lq6, Lv2, Lv5, Lq5, A2, Lq8
	Number of Nodes	15
	Number of Terminal Nodes	8
	Depth	5

Figure D 3: CRT Decision Tree

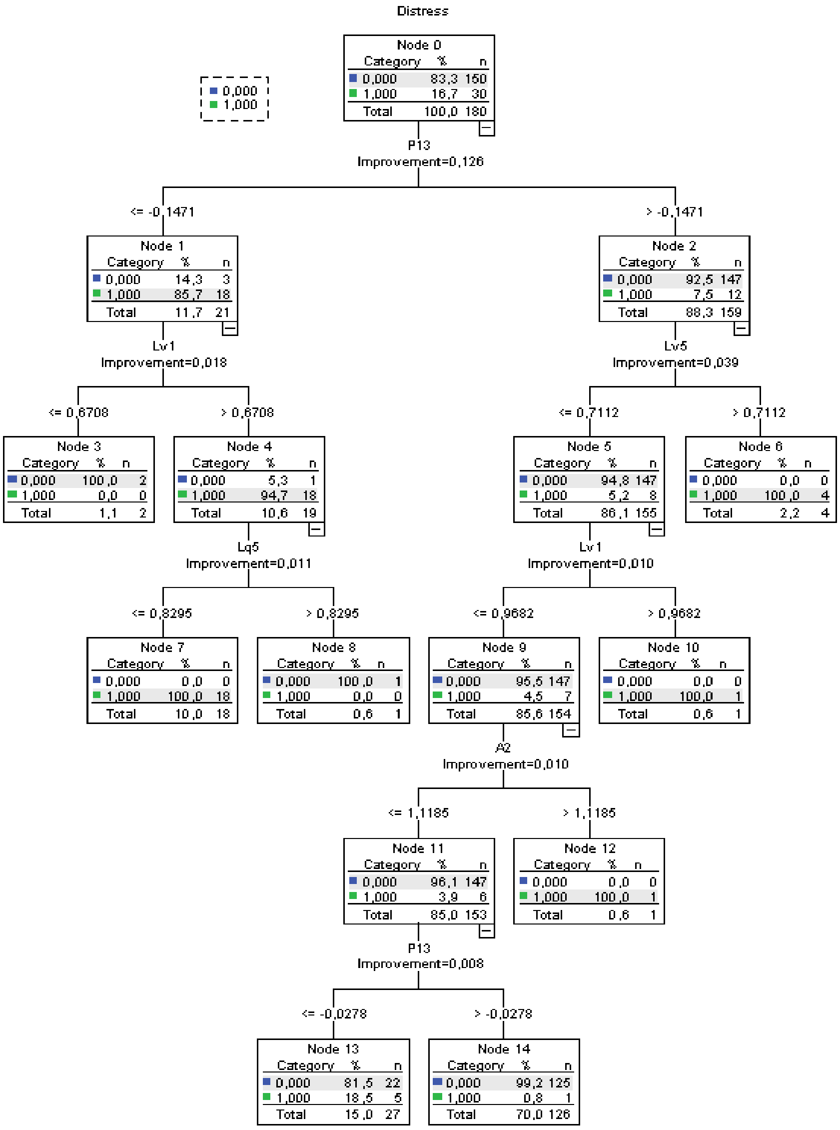


Table D 4: CRT Classification

Observed	Predicted		
	0	1	Percent Correct
0	150	0	100.0%
1	6	24	80.0%
Overall Percentage	86.7%	13.3%	96.7%

Growing Method: CRT
Dependent Variable: Distress

E. AUROC Based on Predicted Group Membership SPSS 15

Figure E 1: ROC Curve

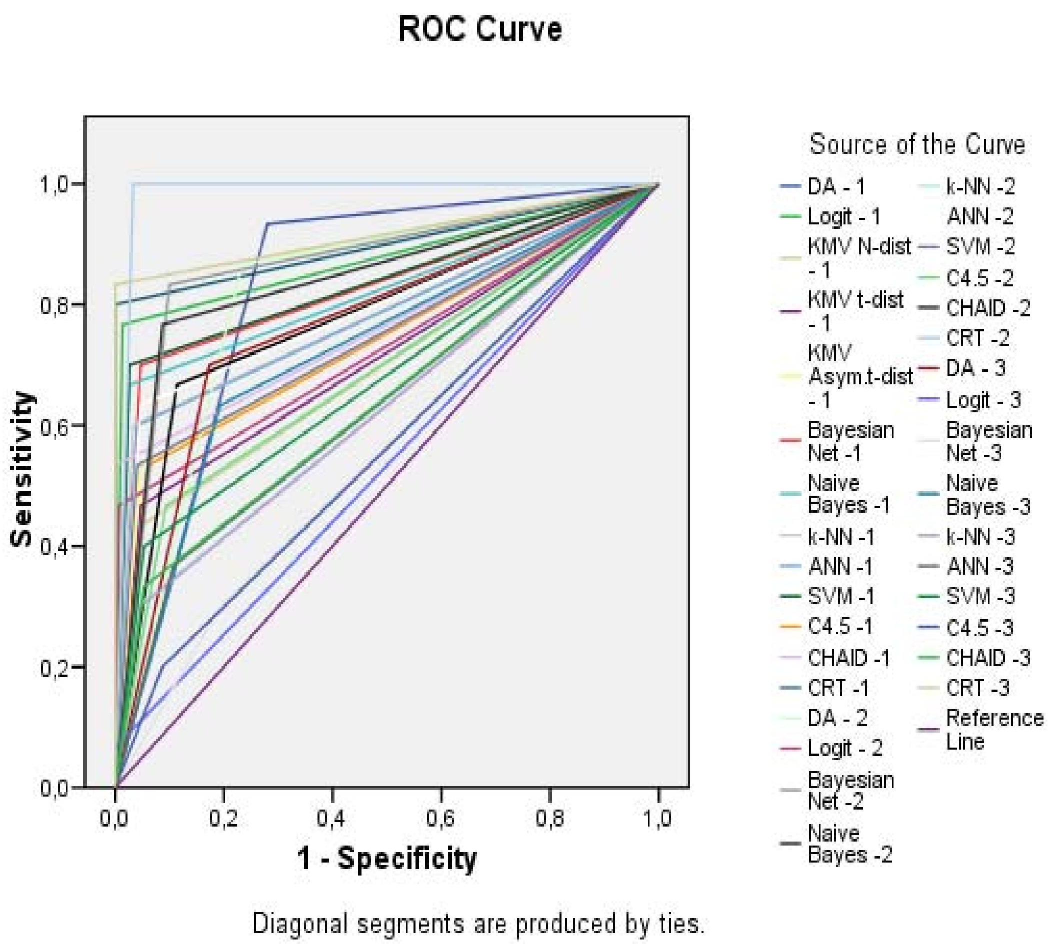


Table E 1: AUROC

Test Result Variable(s)	Area
DA - 1	0.826667
Logit - 1	0.876667
KMV N-dist - 1	0.693333
KMV t-dist - 1	0.71
KMV Asym.t-dist - 1	0.743333
Bayesian Net -1	0.826667
Naive Bayes -1	0.82
k-NN -1	0.783333
ANN -1	0.78
SVM -1	0.836667
C4.5 -1	0.736667
CHAID -1	0.766667
CRT -1	0.9
DA - 2	0.816667
Logit - 2	0.73
Bayesian Net -2	0.866667
Naive Bayes -2	0.776667
k-NN -2	0.63
ANN -2	0.793333
SVM -2	0.746667
C4.5 -2	0.686667
CHAID -2	0.84
CRT -2	0.983333
DA - 3	0.763333
Logit - 3	0.533333
Bayesian Net -3	0.553333
Naive Bayes -3	0.72
k-NN -3	0.626667
ANN -3	0.63
SVM -3	0.673333
C4.5 -3	0.556667
CHAID -3	0.64
CRT -3	0.916667

-1: One annual period prior to failure

-2: Two annual periods prior to failure

-3: Three annual periods prior to failure