Predicting financial distress in IT and services companies in South Africa

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ABSTRACT

The study of bankruptcy is becoming more relevant and important as even large companies are failing that cause economic and social problems to the society. Using financial distress models to predict failure in advance is for most businesses absolutely essential in their decision making process. Hence, this study involves a critical investigation in the applicability of the Altman (1968) and Springate (1978) z-score models in predicting financial distress in IT and Services companies of South Africa.

The Altman and Springate models were however developed in a different economic environment, time horizon, industry and country. Testing these models in the South African context is important to determine the practical applicability and relevance of the models. The main objective of the study is to test the Altman and Springate models in determining practical predictive ability of failure in selected South African IT and services companies listed on the Johannesburg Security Exchange and to comment on the models applicability according to the empirical results. The study is designed into three sections. The first section will discuss the theoretical aspects of the study. The second part will be the discussion of the research results, and finally the conclusion and recommendations of the study will be presented.

The first sample companies was 24 failed and 46 nonfailed information technology and services companies listed on the Johannesburg Security Exchange from 1999 to 2003. The failed companies were matched to two nonfailed companies in the same sector according to their turnover size. Additional nonfailed real estate and information technology companies were added to evaluate the prediction ability of the models in these sectors using substantial samples, as the first sample results were inconsistent, especially on the nonfailed companies. Therefore, the final sample of the study is composed of 86 (24 failed and 62 nonfailed) services and information technology companies. The study employed an analysis of financial statements and derived the z-score of the sampled companies to test the predictive ability of the models in forecasting bankruptcy. The analysis utilized ratios, which are related to the models in the study.

The results reported in the empirical study for total failed and nonfailed sample companies show these models fail to predict failure and non-failure amongst South African service and information technology sample companies. The study is also extended to predict failure and non-failure to investigate if the models are more applicable to predict failure in some sub-sectors of the sampled services and information technology companies. The results are not consistent as the models predicted failure but not nonfailure, or vice versa. Therefore, the models are not successful to predict any sub-sector correctly.

It is generally assumed bankruptcy prediction models are useful regardless of industry, time horizon, and country. The findings reported in the study for each model indicated that the overall accuracy of the Altman and Springate z-scores models accuracy rate were reduced

when used on the South African service and information technology sample, which is different from those companies used to develop the original models. Therefore, the study concluded that the Altman and Springate bankruptcy prediction models are not justifiable to be applied to predict bankruptcy in the South African service and information technology.

Hence, it is not advisable to use these models in predicting failure in the non-manufacturing firms, especially in South African services and information technology companies.

Important recommendations were outlined based on the results of the study. Some of the recommendations are the development of practically applicable bankruptcy prediction models in the IT and services companies of South Africa to elevate inappropriate financial decisions, incorporation of other important indicators of financial well-being during bankruptcy prediction process, checking the practical applicability of prediction models after some period of time. The future research work based on this study is also suggested as developing models to the database in the study, developing new bankruptcy prediction model to the services and information technology companies of South Africa, testing the Altman and/or Springate models on the South African manufacturing and retailing companies, and testing bankruptcy prediction models to the non-listed relatively smaller turnover sized firms where the incidence of business failure is greater than larger corporations.

CHAPTER ONE

INTRODUCTION

1. Problem statement

The prediction and prevention of financial distress is one of the major factors that should be analyzed in advance as an early warning signal and to avoid the high cost of bankruptcy. Bankruptcy involves costs for both the shareholders and stakeholders. From the firm's standpoint, bankruptcy includes direct and indirect costs. Direct bankruptcy costs are the tangible, out-of-pocket expenses of either liquidating or attempting a reorganization of the failing enterprise. These include bankruptcy filing fees and legal, accountant, and other professional service costs (Altman, 1993:17).

In addition to the awareness of factors that can make a company successful, it is also useful for managers to have an understanding of business failures and bankruptcy, its causes and its possible remedies. It is also important for financial managers of successful firms to know their firm's rights and possible actions that should be taken when their customers or suppliers go into bankruptcy. According to Harlan and Marjorie (2002:184) an early warning system model that anticipates financial distress of supplier firms provide management of purchasing companies with a powerful tool to help identify and, it is hoped, rectify problems before they reach a crisis.

According to Bruno & Leidecker (2001: 51-52) no two experts agree on a definition of business failure. Some conclude that failure only occurs when a firm files for some form of bankruptcy. Others contend that there are numerous forms of organizational death, including bankruptcy, merger, or acquisition. Still others argue that failure occurs if the firm fails to meet its responsibilities to the stakeholders of the organization, including employees, suppliers, the community as a whole, and customers, as well as the owners. Other definitions of failure found in the literature include the following: firms that liquidate and go out of business without ever filing bankruptcy; firms that collapse and reduce to a fraction of their size; firms that seek a merger partner under conditions of financial distress; firms that cannot pay their bills when due; firms that are technically insolvent, that is the realizable value of all assets is insufficient to meet total liabilities.

According to Elloumi and Gueyie (2001:16), when a firm's business deteriorates to the point where it cannot meet its financial obligations, the firm is said to have entered the state of financial distress. The first signals of distress are usually violations of debt covenants coupled with the omission or reduction of dividends. Entry into financial distress can be defined as the first year in which cash flows are less than current maturities' long-term debt. As long as cash flow exceeds current debt obligations, the firm has enough funds to pay its creditors. The key factor in identifying firms in financial distress is their inability to meet contractual debt obligations.

However, financial distress symptoms are not limited to firms that default on their debt obligations. Substantial financial distress effects are incurred well prior to default. Firms enter financial distress as the result of economic distress, declines in their performance and poor management; a process of financial distress that begins with an incubation period characterized by a set of bad economic conditions and poor management who commit costly mistakes.

There are several indicators and information sources that can help in the prediction and prevention of financial distress. These are cash flow analysis of the current and future periods, corporate strategy analysis, which analyses the potential competitors of the firm or institution, its relative structure, plant expansions in the industry, the ability of firms to pass along cost increases, and the quality of management. Another information source comes from external variables such as security returns and bond ratings. Financial statement analysis is one of these methods that can be used in predicting financial distress, which focuses on financial variables. This analysis can be categorized and defined as profitability ratios; ratios relating to the efficiency of asset management; risk, short-term cash management and debt ratios; and stock market data (Samuels, Brayshaw, & Craner, 1995:8).

According to Williams & Ellis (1993:204) financial statement analysis provides analysts with the opportunity to examine how a company is performing when compared with previous years (horizontal analysis or time series comparisons) and with the performance of competitors in the industry (vertical analysis or cross-sectional comparisons). Horizontal analysis requires information to be collected for different points of time and then compared. This allows the analyst to assess whether the figures have changed, and whether performance has improved or deteriorated. By contrast, cross sectional analysis disaggregates a line of financial information or ratio into its constituent parts. This technique can be used to yield important insights into how a line of accounting information or ratio is formed, thereby assisting an understanding of what factors are important in determining a particular level of performance.

According to Chey et al. (1989:9), financial ratios can give a good overview of a company and highlights its strengths and weaknesses. They can also show a company's position and performance and indicate trends. Ratio analysis can be applied cross-sectionally (i.e., by comparing different companies at the same point in time) or longitudinally (i.e., by comparing the same over different points in time).

However, financial statements are not inclusive of the entire company's values and assets. As Fridson (1995:25) stated, first while it is in theory quite useful to have a summary of the values of all the assets owned by an enterprise, these values frequently prove elusive in practice. Second, many kinds of things have value and could be construed, at least by the layperson, as assets. Not all of them can be assigned a specific value and recorded on a balance sheet, however. For example, proprietors of service business are found of saying, "our assets go down the elevator every night". Everybody acknowledges the value of a company's "human capital"- the skills and creativity of its employees- but no one has devised a means of valuing it precisely enough to reflect it on the balance sheet. Accountants do not go to the opposite extreme of banishing all intangible assets from the balance sheet, but the dividing line between the permitted and the prohibited is inevitably an arbitrary one.

Bankruptcy predicting models, derived from these financial statement ratios, assist shareholders, stakeholders, company managers, and other directly and indirectly related entities such as suppliers, customers, and competitors in predicting financial problems of a company. This helps the companies to plan their strategies and to know the strengths and weakness of related companies and act accordingly. This is crucial for the company success. However, there are three main problems that old bankruptcy predication models may not be accurate predictors on services and information technology companies.

- First, the bankruptcy prediction models such as Altman and Springate were developed when manufacturing companies were dominant in the market, which is not true at present.
- Second, the service and information technology companies are characterized by a different set of financial norms than the manufacturing companies.
- The third problem is the effect of rapid changes in the services and information technology companies that makes bankruptcy prediction more difficult and complicated.

Therefore, there is a need to investigate whether these Altman and Springate models are still applicable in order to assist financial institutions, banks, and other organizations to predict failure accurately in the service and information technology companies.

1.2 Research aim and objectives

The use of financial distress models, derived from financial statement analysis, as a financial distress predicting technique is common in modern times. The Altman and Springate models are some of the most notable prediction models, which seem used routinely to analyze the financial wellbeing of companies. Therefore, the objectives of the study are:

- Primarily to test the practical applicability of Altman's (1968) and Springate (1978) bankruptcy prediction models to South African service and information technology companies listed in the Johannesburg Security Exchange, during 1999 to 2003.

- The secondary objective is to comment on the application correctness to predict failure of the models according to the results derived from the empirical study.

With the above objectives, the study attempts to answer the following research questions using the South African sample services and information technology companies:

- Whether Altman's and Springate's models z-score can be applied to predict bankruptcy using recent period financial information.
- Whether the models are useful for predicting bankruptcy of non-manufacturing firms as they are for predicting bankruptcy of manufacturing firms.
- Whether the practical applicability of the models is still justifiable in the current South African economic environment.

1.3 Scope of the study

In the light of its purpose, the scope of the study is restricted to the models in predicting financial distress in selected information technology and services companies. The principles involved are of general significance in all types of financial distress prediction techniques.

The scope does not include the technical aspects of financial distress prediction models. Within the scope as outlined, this study in no way pretends to be exhaustive on any aspect. Being objective-oriented in approach, it is essentially broad and empirical.

1.4 Research methodology

This study will use secondary data, such as those in published and unpublished reports, articles, academic journals, books, the Internet, and other publications. This information will be used to determine the application of the models in predicting financial distress. This study will also incorporate a review of existing literature.

The study will employ an analysis of financial statements to test the predictive ability of the models in predicting financial distress. The analysis will utilize ratios, which are related to the models in the study. The binomial test statistical technique is used to classify correctness of the models in predicting failure.

1.5 Research design and outline of chapters

The study is organized into seven chapters. The chapters consist of three sections: a literature review, empirical analysis, and the conclusion section of the study. The chapters are structured as follows:

- The first chapter introduces the importance of bankruptcy prediction; the chapter highlights the research problem and objectives of the study.

- The second chapter presents the theory of bankruptcy and reorganization. In this chapter the history, definition, reasons, and costs of bankruptcy are discussed. The importance of bankruptcy prediction, bankruptcy and reorganization, reasons for the increase in bankruptcy and the bankruptcy in service and information technology are also presented.

- The literature review in relation to past studies in corporate failure prediction models is presented in chapter three. The chapter consists different corporate prediction models developed since the Beaver (1967) univirate model. Failure prediction models in a South African perspective are also discussed in this chapter. It includes criticism of ratio based failure prediction models, and implications of bankruptcy prediction models.

- Chapter four is devoted to explore the Altman and Springate bankruptcy prediction models, as testing these models is the main objective of the study. The chapter discusses the multiple discriminant analysis statistical technique used in the development of both models, the Altman's and Springate models z-score variables and coefficients development, and the second generation of Altman model z-score, the zeta score.

- Chapter five will be the research approach utilised in conducting the study. In the chapter the sequence of the tasks performed in conducting the research work is introduced. The tasks are such as research design, research methodology, and the research sample are presented.

- Chapter six is the discussion of research results. The chapter includes the sample selection; methodology used in the selection of sample companies, model testing, and the prediction results of Altman and Springate models to the failed and nonfailed companies.

- Chapter seven is the conclusion of the entire study with results from literature review and the empirical study, and recommendations for application of Altman and Springate bankruptcy prediction models.

CHAPTER TWO

BANKRUPTCY AND REORGANIZATION

2.1 Introduction

Business opportunities have the tendency for financial distress and even failure. Timmons & Spinelli (2004:52) states that the chance of failure is different from industry to industry and from company to company. This depends on the general economy and the business environment. Business organizations, most of the time, recover as a result of cyclical changes in the business environment after short time. In some cases, however, companies terminate business through bankruptcy, merger, or other form of liquidation.

According to Rose et al. (2002:22-26) bankruptcy is the most drastic form of business failure. Bankruptcy involves huge amounts of costs to a business organization itself, negative effect to the industry, and the economy in general. These are substantial losses to the creditors and owners. Financially distressed companies may be reorganized if the economic value of the entity is worth more than the liquidation value.

The chapter will introduce the importance of business failure and bankruptcy with the emphasis on the recent history of bankruptcy. The remaining part of the chapter discusses the definition of financial distress and business failure, the importance of bankruptcy prediction, the reasons of bankruptcy, bankruptcy and reorganization, reasons for the increase in bankruptcy, and bankruptcy in the service and information technology.

2.2. History of bankruptcy

In the following section the history of bankruptcy is presented in to two sections: the importance of bankruptcy and the recent history of bankruptcy.

2.2.1 The importance of bankruptcy

Bankruptcy is not localized to a specified economy or industry and it is affecting firms all over the world and brings a significant impact on the economy of a country. Zopounidis & Dimitras (1998:2) discussed failure as a worldwide problem, and the number of failing firms is important for the economy of a country and can be considered as an index of the development and robustness of the economy.

The very long process of bankruptcy is economically disastrous for both stakeholders and owners of business entities, which needs a law that governs the whole process. Dealing with insolvent estates for legal procedures dates back to ancient Roman law. The principles of insolvency got extensive codification during the middle ages, and then the study of insolvency prediction evolved. Smith and Winakor did the first study in 1935, during the Great Depression era, then in 1942, Merwin showed that failing firms exhibit significantly different ratios than do successful firms (Sung et al., 1999:65).

The social and economic costs associated with insolvency need a law to govern the whole process. The South African Law Commission (2000:10) referring to the Legal Department of International Monetary Fund, stated that the overall objective of insolvency laws are (1) the allocation of risk among participants in a market economy in a predictable, equitable, and transparent manner; and (2) to protect and maximize value for the benefit of all interested parties and the economy in general (chapter 2 of the document which is available on-line at: www.imf.org/external/pubs/ft/orderly/index.html).

In the case of forced bankruptcy, which is initiated by creditors, the process require the involvement of the civil authorities in the settlement of the credits. Schwartz (1996:26) summarizes that bankruptcy law enables the right of the creditors to collect, guarantee ratable distribution of asset value among creditors according to contractual priorities, and provide debt restructuring possibilities.

In South Africa the term insolvency is used rather than bankruptcy. Insolvency is company failure with firms undergoing a formal liquidation procedure upon classification as failed (Truter, 1996:2). The Insolvency Act 24 of 1936 of South Africa is the replacement of the Insolvency Act 32 of 1916. During 1996 a draft insolvency Bill and Explanatory Memorandum was published as Discussion Paper 66, and in 1999 a further draft Insolvency Bill and Explanatory Memorandum was published as Discussion Paper 66 and 86 (South African Law Commission, 2000:9). These amendments were important in the modernization of the law of insolvency.

2.2.2 Recent history of bankruptcy

There is an increased attention in bankruptcy and other forms of business failure in recent years. It is continued to be a topic of interest to researchers from the field of accounting, economics, and finance. The substantial increase in business failures recently, and the resultant losses for creditors, has promoted a renewed interest in exploring all possible means by which business failures can be predicted in their early stages, thus permitting quick remedial action in an effort to minimize loan losses (Doukas, 1986:479).

The increase in the size of liabilities of failed firms and the proportion of large firms that file for bankruptcy has been even more marked. According to Chuvakhin & Gertmenian (available on-line at http://abr.pepperdine.edu/031/bankruptcy) the size of the companies going bankrupt has been a distinct trend of filing for bankruptcy over the past several years.

As failure is increasing and the liabilities involved become larger from time to time, the law to administer bankruptcy becomes important and more complicated. Altman (1993:6) as a leading authority on bankruptcy summarized the role of bankruptcy law as follows: “In any economic system, the continuous entrance and exit of productive entities are natural components. Since there are costs to society inherent in the failure of these entities, laws and procedure have been established (1) to protect the contractual rights of interested parties, (2) to provide for the orderly liquidation of unproductive assets, and (3) when deemed desirable, to provide for a moratorium on certain claims in order to give the debtor time to become rehabilitated and to emerge from the process as a continuing entity.”

Bankruptcy is also no longer the case of only small businesses and high-risk new firms. In the U.S., 257 public companies with total assets of $256 billion filed for bankruptcy in 2001, which was the highest number of bankruptcy filings since 1980, as well as 191 in 2002, which is above the average 113 for the period 1986-2000. This number is even large compared to the number of filings during the last recession, 125 filings in 1991 and 91 filings in 1992 (Chuvakhin & Gertmenian, http://gbr.pepperdine.edu/031/bankruptcy).

In many cases bankruptcy is the action forced by creditors. However, some governments protect firms from forced bankruptcy. According to White (1996:469), the US discourage involuntary bankruptcy filings by requiring that three or more creditors together initiate an involuntary bankruptcy petition, where as European bankruptcy laws encourage any involved party or creditors, managers, members of the boards of directors, workers' representatives, and the bankruptcy court itself to initiate involuntary bankruptcy filings. Therefore, the creditors only control the timing of the bankruptcy.

Bankruptcy is not a final outcome, but rather a temporary state. Barniv, Agarwal & Leach (2002:515) stated that following bankruptcy filing event, the court confirm one of three possible final resolutions, namely, acquisition, emergence or liquidation. If the firm is reorganized according to legal proceedings, there is often a partial liquidation of assets with the surviving firm being diminished in size. Bankruptcy also affects the final outcome by transferring primary control from the owners to the creditors and the bankruptcy court. This is due to the firm failure to be profitable, to turn around, and finally failure in finding an asset-preserving ability, which is seen as management failure.

2.3 What is bankruptcy?

At this stage the review of the common understanding of corporate failure and bankruptcy is useful. Altman (1993:4-5), the most influential researcher in the area of corporate failure and failure prediction, summarized bankruptcy into five generic terms:

- Economic failure means the realized rate of return on invested capital, with allowance for risk considerations, is significantly and continually lower than prevailing rates on similar investments;
- Business failure, which is characterized by cessation of operation following assignment or bankruptcy, execution, foreclosure, or attachment; and those voluntary withdraw leaving unpaid obligations, or have been involved in court actions, and those voluntarily compromise with creditors and result in losses to the creditors;
- Technical insolvency, which is when a firm cannot meet its current obligations as a result of inadequate cash flow;
- Insolvency in a bankruptcy sense is more critical and chronic, which is the condition in which the company's total liabilities exceeds a fair valuation of its total assets; and
- Bankruptcy itself, which is the formal declaration of bankruptcy through legal means to either liquidate its assets or attempt a recovery program.

The definition of financial failure or bankruptcy is diverse, and it is not uniform in the literature. The application of a general concept of insolvency that includes financial distress presented by Beaver (as cited in Laitinen & Laitinen, 2000:329) is the inability of a firm to pay its financial obligations as they mature. Beaver classified a company as failed when any of the following events occurred:

- Bankruptcy,
- Bond defaults,
- An overdrawn bank account, or
- Nonpayment of preferred stock dividend

According to Altman (1993:224), based upon the criteria of the International Shoe decision (International Shoe v. FTC, 280 U.S. 291 (1931)), Blum stated one of the following three events constitutes failure:

- Inability to pay debts as they come due,
- Entrance into a bankruptcy proceeding, or
- An explicit agreement with creditors to reduce debts.

The definition of financial distress based on previous research (Kida, 1980; Mutchler, 1985) classify a stressed company if it exhibited at least one of the following financial distress signals:

- Negative working capital in the current year,
- A loss from operations in any of the three years prior to bankruptcy,
- A retained earnings deficit in year 3 (where year 1 is the last financial statement date preceding bankruptcy), or
- A bottom line loss in any of the last three years before bankruptcy.

Hopwood et al. (1994:412) discussed three types of corporate failures, the first type includes companies whose failure occurs before they become established, the second type includes companies whose failure is precipitated by a slide into insolvency and portended by signs of financial stress in the financial ratios, and the third includes companies whose failure is sudden and with no apparent signs of financial distress.

Although, more frequently failure takes the form of slow decline and then disappearance, it can be in the form of a merger or sale of assets. But the most drastic financial failure is bankruptcy. At the end both personal and business bankruptcies have the tendency to carry bad reputation.

The definition of financial distress, including bankruptcy, of this study resembles the definition of Altman. Financial distress is the cessation of operation, not payment of current obligations due to cash flow problems, the firm's total liabilities are in excess of total assets, and the formal declaration of bankruptcy.

2.4 The importance of bankruptcy prediction

The importance of bankruptcy prediction has a long history in the literature. Zavgren (1985:20) stated that Beaver (1966) pioneered empirical research in business failure prediction using an univariate model. The approach used achieved a moderate level of predictive accuracy, although it had certain shortcomings especially a lack of integration of the various ratios. Later multivariate studies usually employed discriminant analysis.

According to Mckee & Lensberg (2002:437) bankruptcy prediction has been a major research topic in accounting and finance ever since Altman's study in 1968 employing multiple discriminant analysis, and it has been studied extensively by many researchers such as Altman (1982), Edmister (1972), Jones (1987). Dugan & Zavgren (1988:50) referring Beaver stated that "a prediction can be made without making a decision, but a decision cannot be made without, at least implicitly, making a prediction."

There are both theoretical and practical reasons for studying corporate failure and bankruptcy prediction. O'Leary (1998:187) discussed the importance of bankruptcy prediction as, "…prediction of bankruptcy probably is one of the most important business decision-making problems facing auditors, consultants, management and government policy makers".

The crisis of business failure may make patterns visible that would be difficult to detect under more normal circumstances. Also the stressful decision-making environment may have different responses than those observed under more normal circumstances. Therefore, if certain patterns can be detected which appear to have predictably negative effects on corporate survival, that would be useful information for managers and investors, whether or not they were likely to face with corporate failure.

Pacey & Pham (1990:316) referring to Altman (1983) stated that the international survey of business failure models, which covers ten countries, identified that corporate failure can be predicted with an exceptionally high degree of accuracy ranging from 70% to 95% of correct classification of failed firms for three years and one year prior to failure date, respectively.

Nowadays big, successful and promising companies are seen going bankrupt due to lack of prediction of future financial status. Charan & Useem (2002:36) stated "…each month seems to bring the sound of another giant crashing to earth, Enron, WorldCom, Global Crossing, K-mart, Polaroid, Arthur Anderson, Xerox, Qwest, they fall singly, they fall in groups, they fall with the heavy thud of employees laid off, families hurt, shareholders furious… and not just any companies, but big, important, FORTUNE 500 companies that aren't supposed to collapse."

Failure prediction also helps companies to know the financial status of other companies who do business with them. The consequences of a large company’s bankruptcy can be especially devastating as it affects so many other businesses and individuals and because many of its suppliers and other business associates depend disproportionately on this one customer (Chuvakhin & Gertmenian, http://gbr.pepperdine.edu/031/bankruptcy).

The lack of sound credit and evaluation policy may cause financial problems and even bankruptcy. Shin & Lee (2002:321-328) mentioned that many financial institutions are paying a heavy price for their indiscriminate practices, and corporate bankruptcy have put several institutions on the brink of insolvency.

According to Timmons & Spinelli (2004:581) the obvious benefit of being able to predict crisis is that owners, employees, and significant outsiders, such as investors, lenders, trade creditors – and even customers- could see trouble brewing in time to take corrective actions. The importance of bankruptcy prediction will be concluded by the statement that Sung et al. (1999:64) made, as corporate bankruptcy brings with it economic losses to management, stockholders, employees, customers, and others, together with great social and economic cost to the nation, thus accurate prediction of bankruptcy has become an important issue in finance. The costs of bankruptcy, which are most important in predicting bankruptcy in advance, will be discussed in detail later in the chapter.

2.5 Reasons for bankruptcy

There are reasons for bankruptcy, which can be identified and predicted in advance. According to Bruno & Leidecker (1988:51-52) research findings indicate that business failure results from definable causes and that an understanding of these causes can help prevent failure. When they discussed the general conclusions emerging from the literature regarding firm failure, causes of failure, and prevention, they mentioned:

- Failure is a process that occurs over time; it is not a sudden death,
- Within failing companies, specific identifiable factors are present that cause the failure,
- Once identified, these factors can be used to predict the propensity for failure,
- Knowledge of the presence of these factors can lead to steps intended to avoid or prevent failure,
- There are both external and internal factors that influence failure,
- The external factors are those attributable to general economic effects,
- The internal factors can be linked to the various functional areas,
- The single most pervasive factor is poor management, which may manifest itself in a variety of ways, and
- General failure factors may influence many businesses across a number of industries, while specific failure factors affect firms in specific industries.

Although bankruptcy may be caused by environmental or macroeconomic factors, most of the time bankruptcy to the established and historically profitable firms is due to faulty managerial decision-making. Charan & Useen (2002:36-42) contend that causes of failure are in addition to acts of God, managerial error, relaxation due to success, acts of competitors, bad news is not welcome by CEO's, and overdosing on risk.

The main factors that can be associated with bankruptcy are economic recession, change in technology, and bad management. Businesses can be under stress and the chance of failure may be increased due to a general recession or more localized declines in the economic environment. New technology is another environmental factor, which destroy the demand for old products or services; also the demographic, and cultural trends may reduce demand. Governmental regulation may affect competition. However, in the same circumstances, some businesses survive while others fail (Norton, 1989:10).

Financial factors such as inadequate cash flow, excessive debt, or loss of creditor confidence are attributed to bankruptcy in the finance literature. These are not the exact causes of bankruptcy, but they are the symptoms of decline and failure. Initial under capitalization and assuming debt too early are the two important exceptions from the factors cited as reasons for failure of firms in the 1960's to the 1980's such as product timing, product design, inappropriate distribution or selling strategy, unclear business definition, over reliance on one customer, problems with the venture capital relationship, ineffective team, personal problems, one-track thinking, and cultural/social factors (Bruno & Leidecker, 1988:54-56).

Table 2.1 shows the causes of business failure for companies that have failed. This shows most business failures seem to be due to economic factors, financial causes, and lack of experience on the part of the owners of the business. Business problems lead to inadequate sales and heavy operation expenses, hence cash flow problems and inability to meet obligations (Moyer, McGuigan & Kretlow, 2001:801).

Table 2.1

Reasons of Business Failures

Underlying Causes	Percentage*
Economic factors (e.g. industry weakness, insufficient profits	41.0%
Finance factors (e.g., heavy operating expenses, insufficient capital)	32.5
Experience factors (e.g., lack of business knowledge, lack of line experience, lack of management experience)	20.6
Neglect (e.g., poor work habits, business conflicts)	2.5
Fraud	1.2
Disaster	1.1
Strategy factors (e.g., receivables difficulties, over expansion)	1.1
	100%

****Results are based on primary reason for failure.***

Source: The Dun and Bradstreet Corporation, Economic Analysis Department, March 1991.

According to Brigham & Gapenski (1996:892) studies show that financial difficulties are usually the result of a series of errors, misjudgments, and interrelated weaknesses that can be attributed directly or indirectly to management, and signs of potential financial distress are generally evident before the firm actually fails.

Gaither, (as cited by Fedchenko, 2001:10) to explain failure, stated that business owners fail to understand the difference between mark-up and gross profit and suggested that a business should be able to keep at least 5 percent of its sales after taxes as profit, and pointed out ten signs of potential bankruptcy:

- Negative bank balance,
- An inability to borrow from a bank,
- An inability to pay current taxes,
- Not enough investment,
- Too much involvement from unproductive family members,
- Not getting financial statements on time,
- A payroll that's not in line with gross profit,
- The owner's salary is too high,
- The owner is never at work and loses track of workers, and
- Liabilities are exceeding assets. He also stated that the biggest cause of bankruptcy is too high payroll, and advised the benchmark should not be more than 45% of gross profit.

2.6 Costs of bankruptcy

In addition to the general economic loss, bankruptcy involves direct and indirect costs in the company's perspective. As an example of the bankruptcy costs associated with filing for Chapter 11 bankruptcy protection for American Geneva Steel Co. was $38.4 million, of the total loss of 63.5 million in three months. The cost was for bankruptcy filing, professional fees, the write-off of deferred loan fees on the senior notes and certain executing contracts (American Metal Market, 1999:3).

According to Moyer et al. (2001:464), financial distress costs include the costs incurred to avoid bankruptcy as well as the direct and indirect costs incurred if the firm files for bankruptcy protection. Moyer discussed the costs as follows:

- As the firm increased its level of debt, lenders may demand higher interest rates to compensate for the increased financial risk taken by the firm. The higher interest payments constitute a cost to the firm. Or they may choose not to lend at all, the firm may have to forgo acceptable projects, thus the firm incurs an opportunity cost.
- Some customers and potential customers may lose confidences in the firm's ability to continue in existence and instead buy from other companies more likely to remain in business. This loss of customer confidence is another financial distress cost.
- A distressed company which leads to bankruptcy must incur legal and accounting costs as it attempts to restructure itself financially.
- The opportunity costs of the funds that are unavailable to investors during the bankruptcy proceedings (for example, it took over eight years to settle the Penn Central bankruptcy).

- Finally if it is forced to be liquidated, assets may have to be sold at less than their market values. These costs are also bankruptcy costs.

Ross et al. (2002:426) referring to White, Altman, and Weiss, estimated the direct costs of financial distress to be about 3 percent of the market value of the firm, while Altman estimated both direct and indirect costs of financial distress are frequently greater than 20 percent of firm value.

Arnold (2002:823) discussed some examples of direct and indirect costs of financial distress:

Direct costs

- Lawyers' fees.
- Accountants' fees.
- Courts fees.
- Management time.

Indirect costs

- Uncertainties in customers' minds about dealing with this firm – lost sales, lost profits, lost goodwill.
- Uncertainties in suppliers' minds about dealing with this firm – lost inputs, more expensive trading terms.
- If assets have to be sold quickly the price may be very low.
- Delays, legal impositions, and the tangles of financial reorganization may place restrictions on management action, interfering with the efficient running of the business.
- Management may give excessive emphasis to short-term liquidity, e.g. cut R&D and training, reduce trade credit and stock levels.

- Temptation to sell healthy businesses as this will raise the most cash.
- Loss of staff moral, tendency to examine possible alternative employment.
- To conserve cash, lower credit terms are offered to customers, which impacts on the marketing effort.

Even though bankruptcy costs are not easy to calculate, Altman (1984:1067-1089) has measured the size of bankruptcy costs for industrial firms. He defines bankruptcy costs to consist of direct costs (costs paid by debtors in the bankruptcy and restructuring process) and indirect costs (costs associated with the loss of customers, suppliers, and key employees plus the managerial effort expended to manage the firm in its distressed condition). Altman found evidence that the direct costs of bankruptcy average about 6 percent of firm value at the time of filing for bankruptcy. Direct plus indirect costs as a percentage of firm value averaged 12.1 percent three years prior to filing and 16.7 percent at the time of filing. Thus it appears that bankruptcy costs are significant, and even if one adjusts for the expected time of occurrence and the probability of occurrence.

Arnold (2002:825) discussed some factors influencing the risk of financial distress costs. The susceptibility to these factors varies from company to company. Some of the influences are:

- The sensitivity of the company's revenues to the general level of economic activity. If a company is highly responsive to the ups and downs in the economy, shareholders and lenders may perceive a greater risk of liquidation and/or distress and demand a higher return in compensation for gearing compared with that demanded for a firm which is less sensitive to economic events.

- The proportion of fixed to variable costs. A firm which highly operationally geared, and which also takes on high borrowing, may find that equity and debt holders demand a high return for the increased risk.
- The liquidity and marketability of the firm's assets. Some firms invest in a type of asset which can be easily sold at a reasonably high and certain value should they go into liquidation. This is of benefit to the financial security holders and to they may not demand such a high-risk premium.
- The cash-generative ability of the business. Some firms produce a high regular flow of cash and so can reasonably accept a higher gearing level than a firm with lumpy and delayed cash inflows.

Brigham & Gapenski (1994:379) stated that bankruptcy costs may be incurred by a firm in financial distress even if it does not go into bankruptcy. Bankruptcy is just one point on the continuum of financial distress.

The economic impact on the owners, employees, customers, and suppliers, and the costs of bankruptcy or reorganization, makes research on bankruptcy prediction important. Mckee & Lensberg (2002:436) stated the importance as follows, the high individual, economic and social costs encountered in corporate failures or bankruptcies have spurred searches for better understanding and prediction capability.

2.7 Bankruptcies and Reorganization

In the process of bankruptcy-reorganization, the firm's creditors, owners, and in general the welfare of the public is concerned. When a firm is financially distressed, the bankruptcy filing depends on the financial soundness of the entity. The alternatives for failing business as discussed by Moyer et al. (2001:801) are:

- Voluntary or informal basis: attempt to resolve its difficulties with the creditors.
- It can petition the courts for assistance and formally declare bankruptcy (Formal).
- The creditors may also petition the courts, and this may result in the company being involuntarily declare bankrupt.

The decision to be made is whether to reorganize or liquidate. Here the business's liquidation value and its going-concern value have to be determined. Barniv et al. (2002:497), stated that as the court confirms a reorganization or rehabilitation plan following the bankruptcy filing, there are three alternatives:

- Acquired by other firms or
- Emerged as independent entities or
- Liquidated.

Bankruptcy occurs when the firm has more legitimate claims on its assets than it can manage. When the firm files for bankruptcy, creditors become active participants in the firm's decision-making process under the oversight of a bankruptcy proceeding. The creditors may have different expectations with regard to the value of alternative outcomes in addition to their different priorities in their claims on the firm's assets.

If the firm is completely liquidated, the distribution of the proceeds will be simple. The negotiations become more complex if the firm is partly or entirely to be organized. This is because the accounting for current assets and liabilities, and prospects for future profitability of the reorganized firm must be estimated. This also requires the estimation of health in the industry, the nature of the competition, the value of the nonfinancial assets of the firm, and quality of the management.

Both liquidation and reorganization are available courses of action in most countries of the world and are based on the following premise: If an entity's intrinsic or economic value is greater than its current liquidation value, then from both the public policy and entity ownership viewpoints, the firm should attempt to reorganize and continue. If, however, the firm's assets are worth more dead than alive, that is, if liquidation value exceeds economic value, liquidation is the preferable alternative (Altman, 1983:4).

A company may emerge almost totally transformed. If the firm had been essentially sound with only limited threats from which it needed specific or short-term relief, recovery may be quick and complete. Recovery may be difficult or impossible if the firm had been subject to major financial or strategic deterioration.

The main aim in the reorganization process is to restructure the capital of the financially distressed firm, hence to solve the burden of debtor's liabilities. Altman (1993:6) summarized reorganization as sound and with potential economic and social benefit, that enable the financially troubled firm to continue in existence and maintain whatever goodwill it still possesses, rather than to liquidate its assets for the benefit of its creditors. The justification of the application is the benefit that continued existence would result in a healthy going concern worth more than the value of its assets sold in the marketplace.

According to Brigham & Gapenski (1996:893) some firms are thought to be too big or “too important” to fail, and mergers, industry or governmental intervention are often used as an alternative to out-right failure and liquidation. These interventions are having many reasons. In the case of financial institutions, the main reason is to prevent an erosion of confidence and a consequent run on the banks. Also, because bankruptcy is a very expensive process gives private industry strong incentives to avoid outright bankruptcy.

Katz et al. (1985:70) discussed about the strategies for investing in bankrupt companies and other financially strained groups, and funds, such as Merrill Lynch’s Phoenix Fund, that invest in issues of companies undergoing reorganization or displaying poor operating and financial conditions, are becoming increasingly popular, and suggests that trading strategies for earning abnormal returns may be developed by following signals of corporate distress or recovery.

2.8 Reasons for the increase in bankruptcy

The rate of bankruptcy is increasing every year during recent years. The reason is not clear to what extent the continuing high failure rate is due to temporary effects and to what extent it reflects long-term changes in the national economic structure. The increase is not only in bankruptcy rate; there is also increase in the size of the corporations involved. Following is the discussion of the general and other causes of increase in bankruptcy.

2.8.1 General reasons of increase in business failure

Altman (1983:42-44) states that small and young firms are more vulnerable to ill economic conditions in combination to the deterioration in firm liquidity, increased leverage, and dramatically reduced coverage of financial payments of interest and principal. This is because of financing new loan at higher rate; access to long-term loan and equity markets is not easy to small firms.

Another cause of the increase in bankruptcy can be actions that companies deliberately elect for bankruptcy as a corporate strategy to limit the liability obligations or to get relief from life threatening obligations to employees (Altman, 1993:7). Therefore, early filing for bankruptcy is also an important decision for management. White (1996:470) stated, the earlier the firms enter bankruptcy the less financially distressed they are, as the firm liquidation minimizes losses to creditors and reorganization maximizes the likelihood of saving the firm.

Sometimes, bankruptcy codes brought about by the Bankruptcy Acts motivate companies to file early and protect themselves from forced bankruptcy caused by debtors. Under the Bankruptcy Code of US, the that went into effect in 1979, the number of business bankruptcy filings increased from 29,000 in 1970s to 44,000 in 1980, and average over 60,000 per year from 1983 to 1991 with a high of almost 90,000 in 1987 (Altman, 1993:7).

Some causes of the increase in bankruptcy are directly attributed to the decisions made by management in relation to the dynamic changing of the world business environment. As discussed in America's network (available on-line at http://www.americasnetwork.com), the causes of the company's under that discussion are change in technology, expensive investment in disparate locations, investment in not well-known highly ambitious projects, low margin business, and high write out costs.

Timmons & Spinelli (2004:580-581) stated that external forces not under the control of management could increase the occurrence of financial distress. Among the most frequently mentioned are recession, interest rate changes, changes in government policy, inflation, the entry of new competition, and industry or product obsolescence. Most causes of failure could be found within company management. Although there are many causes of trouble, the most frequently cited fall into three broad areas:

- Inattention to strategic issues such as misunderstood market niche, mismanaged relationships with suppliers and customers, diversification into an unrelated business area, mousetrap myopia, the big project, and lack of contingency planning,
- General management problems are lack of management skills, experience, and know-how, weak finance function, turnover in key management personnel, big-company influence in accounting, and
- Poor financial/accounting systems and practices are like poor pricing, overextension of credit, and excessive leverage, lack of cash budgets/projections, poor management reporting, lack of standard costing, and poorly understood cost behavior;

Another reason of failure for commercial banks and financial institutions are decision-making problems in credit evaluation and their risk measurements due to the high level of risk associated with wrong decisions. Among these, the important risks to deal with have been a worldwide structural increase in the number of bankruptcies, more competitive margins on loans, and an increasing cost associated with monitoring solvency in order to control the risks (Altman & Saunders, 1997; Wolf, 1995).

2.8.2 Age and size of business formation and failure rate

Firm's age and the tendency to failure especially in small business is an important factor that needs to be considered. The highest failure propensity is between 2-5 years of a firm's existence, with the peak in the third and forth years. During the 2–5 year age period, over 50% of all failures occur. Moyer et al. (2001:799) stated the age of failed business is an interesting finding. About 30 percent of all companies that fail had been in business 3 years or less and 50 percent had been in business 5 years or less. Only about one-quarter had been in business more than 10 years.

Hall & Young (1990:57) confirmed that firms fail certainly in the infancy, in the study they conducted, the mean number of years that small firms traded before becoming insolvent was 6.9 years, half less than 4 years. Out of the 300 firms in the sample, only 18 traded for 20 years or more and 5 for 40 years or more, and 32 per cent of firms that failed did so within the first two years of operation.

One research firm estimates the failure rate for startups is 46.4%. The Small Business Administration of the US determined that in 1999 there were 588,900 startups, while 528,600 firms closed their doors. The failure rates also vary widely across industries. In 1991, for instance, retail and services accounted for 61 percent of all failures and bankruptcies in that year. Government data, research, and business mortality statistics agree on that startups run a high risk of failure. Another study found that of 565,812 firms one year old or less in the first quarter of 1998 only 303,517 were still active by the first quarter of 2001. This is an average failure rate of 46.4% (Timmons & Spinelli, 2004:52).

Banks and other financial institutions, to control the loan structure and to make sure small firms stay in the business, have been using loan covenants. These are controls over management's investment decision, more frequent financial reports, extra collateral, and increasingly restrictive working capital and debt to equity ratio. Although, banks and other financial institutions recoup their loss through increased fees and continued receipt of principal payments, they have on occasions suspended or reduced interest payments, and lengthened short-term loans as competition become intense. Therefore, small and medium-sized firms may be forced to liquidate, as financial institutions are better off (Altman, 1983:45).

2.9 Bankruptcy in service and information technology

The causes and factors affecting service and information technology firms are similar to that of other industries. In addition, the rapid changes and modernization of technology with sophisticated service deliver systems; make firms in the service and information technology industry more susceptible to failure.

According to Timmons & Spinelli (2004:52-53) the impact of financial distress or failure may vary from one industry to the other. Some industries may have a higher incidence of distress and failure than others. Cyclical changes in the business environment or successful managerial action may recover the companies in a relatively short time. In some cases the companies experience a decline that terminates in business failure and corporate dissolution through bankruptcy, merger, or other forms of liquidation, usually at substantial loss to creditors and owners.

For example, the amount of credit and the complex types of creditors involved in financial institutions need attention in the banking industry. As Park & Han (2002:256) stated, because of the growth of credit evaluation and large loan portfolios, the banking industry is actively developing more accurate credit evaluation models.

The failure rate in the technology according to Timmons & Spinelli (2004:53) in the 1999 study by the US Small Business Administration shows the failure rate across industries vary. The technology sector had a high rate of failure at 53.9 percent. The software and services segment of the technology industry had an even higher failure rate; 55.2 percent of startups tracked closed their doors.

2.10 Chapter summary

The purpose of the chapter is to highlight the key issues in the history, definition, importance, reasons, and causes of bankruptcy. The definition of bankruptcy according to different researchers can be summarized as an economic failure, cessation of operation, insolvency, bond defaults, overdrawn bank accounts, non payment of preferred stock dividend, inability to pay debt, agreement with creditors to reduce debt, current year negative working capital, loss in any three years prior to bankruptcy, and retained earnings deficit.

The costs involved in the process of bankruptcy, which is as high as 20 percent of the value of the firm, is the most important issue in the study of corporate bankruptcy. Therefore, predicting and avoiding bankruptcy in advance is valuable as it saves costs, hence improve the well being of the parties involved.

The main reasons for failure are economic and financial factors. Knowledge of reasons of failure improves the ability to deal with and to be aware of difficulties in advance. The other option of financially distressed entity is reorganization. Reorganization has potential economic and social benefits that enable the financially distressed firm to continue in existence rather than to liquidate for the benefit of its creditors.

CHAPTER THREE

PAST STUDIES IN CORPORATE FAILURE PREDICTION MODELS

3.1 Introduction

The main concern of the chapter is the past studies in corporate failure prediction. The past studies will be discussed in different parts as the statistical models (primary, multiple discriminant analysis, logit regression), Gambler's ruin mathematical/ statistical models, and the artificial neural networks (ANNs) models. The South African perspective of failure prediction models and the criticism of ratio based failure prediction models are also part of the chapter. The discussion on other bankruptcy predicting models such as cash flow and returns and return variation models will also be presented. The chapter ends with a summary that highlights the main issues in the chapter.

3.2 Corporate failure prediction models

Bankruptcy prediction was a dominant theme in the study of business failure. In the formulation of bankruptcy predicting models, many variations of models have been proposed. Most of the cases discriminate between bankrupt and non-bankrupt firms over some period before the firm status become known, and the accounting and financial variables are then examined to determine whether they can classify the firms appropriately. There are four types of bankruptcy prediction models based on financial statement ratios, cash flows, stock returns, and return standard deviations (Mossman et al., 1998:35-38).

Using the financial statement ratios, different approaches where developed to predict business failure. Bankruptcy prediction (available on-line at http://www.solvency.com/bankrupred) stated that in the late 1960's, attempts to develop bankruptcy prediction models began. These are three distinct types of models to predict bankruptcy: (1) statistical (multiple discriminate analysis [MDA], logit analysis, and probit analysis) models, (2) gambler's ruin mathematical/statistical models, and (3) artificial neural network models.

In the following section detailed discussion will follow on the financial statement ratio models, as the aim of the study is to test models from financial statement ratios. A brief discussion on cash flow and stock return models are also included.

3.3 The statistical (multiple discriminant analysis, logit analysis, and probit analysis) models

Financial variables (ratios) are used to test multiple discriminant analysis (MDA) and logit models. However, as Mar-Molinero & Serrano-Cinca (2001:166) stated, both logit and discriminant analysis require, before implementation, a selection of the variables that enter the model, and the selection of the final set of variables is complex, delicate and important.

As summarized in bankruptcy prediction (available on-line at http://www.solvency.com/bankpred), the multivariate statistical models are developed and refined by Lev (1974), Deakin (1972), Ohlson (1980), Taffler (1982), Platt & Platt (1980), Gilbert, Menon, and Schwartz (1990), and Koh and Killogh (1990), and almost all the traditional models have been either matched-pair multi-discriminate models such as Altman's or logit models such as Ohlson's.

3.3.1 Beaver (1966)

As summarized by Altman (1993:222-224), Beaver defined failure as the inability of a firm to pay its financial obligations as they mature. The sample was composed of 79 failed firms representing 38 different industries during the years 1954 to 1964. The classification of failed firms was according to industry and asset size. As Beaver is the first researcher to propose a bankruptcy prediction model, the discussion on Beaver's model will be emphasized.

Beaver (1966:71-127) used 30 ratios, which are computed for each of five years prior to failure. The criteria in selecting these ratios are: (1) popularity in the literature, (2) performance in previous studies, and (3) definition of the ratio in terms of a cash flow concept. Beaver selected the following six variables as best, based on the lowest percentage error for each group in the five year period, (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, and (6) no-credit interval.

Beaver's empirical experiment was conducted in three major steps. First the comparison of mean value, which is referred as a profile analysis to indicate that it described the general relationships between failed and nonfailed firms. Here he found the anticipated differences in the mean values for each of the six ratios in all five years before failure. As the year of failure approached, the average failed firm showed substantial deterioration. On the other hand the performance of the average nonfailed firm was relatively constant.

In the second step he performed the classification test using dichotomous prediction. After arranging the 30 ratios in ascending order for both failed and nonfailed firms, Beaver found out the cutoff point that minimized the percentage of incorrect prediction.

Beaver concluded the cash flow to total debt ratio is the overall best predictor. Beaver's Type I error (error in predicting bankrupt firm) was increased substantially as the number of years before failure increased from 22% to 47%, but the Type II error (error in predicting nonbankrupt firm) was fairly low and stable between 3 to 8%. Type I errors are more costly than Type II errors; therefore a truly minimized misclassification rate should incorporate these differing costs. Beaver treated the costs of misclassification as being symmetrical and employed a priori probability of failure of .5.

The theoretical framework presented by Beaver was the cash flow or liquid asset-flow model. The term viewed firms as a reservoir of liquid assets, which is supplied by inflows and drained by outflows. The reservoir serves as a buffer against variations in the flows, then the solvency of the firm can be defined in terms of the probability that the reservoir will be exhausted, at which point the firm is unable to pay the obligations as they mature. The four important concepts presented in depicting the relationship between the liquid-asset-flow model and the ratios are: the size of the reservoir, the net liquid-asset flow from operations, debt held by the firm, and the fund expenditures for operations. Thus, Beaver presented a description of liquidity bankruptcy.

Beaver's most important contribution is that to suggest a framework for the evaluation of accounting data not merely for failure prediction. The major findings was financial data or accounting data subject to some important qualifications have the ability to predict failure for at least five years before failure. The important qualifications are needed because first not all ratios predict with the same degree of accuracy. The other reason is higher level of success achieved predicting nonfailure than failure, and finally financial ratios should be complemented by frequency distributions and likelihood ratios for decision making purposes.

3.3.2. Deakin (1972)

Deakin (1972:167-179) proposed an alternative business failure model to the ones developed by either Beaver (1966) or Altman (1968). Deakin considered Beaver's empirical results for the predictive accuracy and Altman's multivariate approach because of its intuitive appeal, and to capture the best of both of these studies by employing the 14 ratios Beaver used and to search for the linear combination of these ratios with greatest predictive accuracy. His analysis was based on 32 firms that failed between 1964 and 1970, and then each failed firm was matched with a nonfailed firm on the basis of industry classification, asset size, and year of financial data.

Deakin's 14 ratios that are used on the classification result, using the cash-flow-to-total-debt ratio is similar to that of Beaver (1966). The failed firms analyzed by Deakin show highly volatile movements in total debt compared to the monotonic upward trend observed by Beaver. The cash flow, net income, and total debt have relatively stable movements for the nonfailed firms in both samples. The classification error increased substantially when Deakin tried to reduce the number or variables.

He concluded that discriminant analysis could be used to predict business failures as far as three years in advance with a fairly high accuracy. Deakin suggested that further testing is required before a conclusive judgment about his model can be rendered due to the relatively small sample size.

3.3.3 Edmister (1972)

Edmister's (1972:1477-1493) purpose was to develop, test, and analyze financial ratios to predict the failure of small business; those with a loan from the Small Business Administration. Included in the sample were borrowers and guarantee recipients from the Small Business Administration for the period 1954 to 1969. He analyzed 19 financial ratios, which were important in previous failure prediction studies. Edmister focused upon testing four hypotheses:

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

Edmister developed a seven-variable, zero-one linear regression equation:

$$Z = 0.951 - 0.523 X_1 - 0.293 X_2 - 0.482 X_3 + 0.277 X_4 - 0.452 X_5 - 0.352 X_6 - 0.924 X_7$$

Where,

Z = Zero-one dependent variable

X_1 = Annual funds to Current liabilities

X_2 = Equity to Sales

X_3 = Net working capital to Sales, divided by RMA* average ratio

X_4 = Current liabilities to Equity, divided by RMA average ratio

X_5 = Inventory to Sales, divided by RMA average ratio

X_6 = Quick ratio divided by the trend in RMA quick ratio

X_7 = Quick ratio divided by RMA quick ratio

****RMA ratios are average ratios for firms in a similar industry and of similar size, as developed by Robert Morris Associates.***

The model's classification result achieved accuracy of at least 90%. Using $Z \geq 0.530$ to determine nonfailure and $Z < 0.530$ for failure, all of the failed firms and 86% of the nonfailed firms were classified correctly for an overall accuracy rate of 93%. Edmister found two useful points, dividing a ratio by its respective industry average, and classifying ratios by quartiles.

Edmister argued that three consecutive statements are required for effective analysis of small business, unlike Beaver (1966), Altman (1968), and Blum (1974), who found that one financial statement is sufficient of accurate classification. He also reported that the predictive power of ratio analysis depended on both the choice of analytical method and the selection of ratios (Sung et al., 1999:66).

Altman (1983:159) argued that, because of the increasing number of small business failures and the interest in assisting small business, the analysis of financial characteristics of distressed small business is needed. Nevertheless, as the financial ratios for small businesses are dispersed widely it is difficult to obtain a meaningful data set without some sort of adjustment.

3.3.4 Blum (1974)

The purpose of Blum's model was to quantify the probability of the point at which a company considered failing by analyzing the financial and marker data of failed firms. He developed the failing company model (FCM) to aid the antitrust division of the Justice Department in assessing the probability of business failure (Altman, 1993:224).

The sample of (Blum, 1974:1-25) consisted of 115 firms that failed from 1954 to 1968 with a minimum of $1 million in liabilities at the time of failure, paired with 115 nonfailed firms on the basis of industry, size, and year. He postulated a general framework for variable selection based upon the concept of a business firm as a reservoir of financial resources with the probability of failure expressed in terms of expected cash flows. By constructing FCM, Blum selected 12 variables to measure the cash flow parameters with three common factors underlying the cash flow framework; liquidity, profitability, and variability.

By employing the multiple distcriminant analysis, the overall accuracy rates on average was 94% when failure occurred within one year after the most recent statement date, 80% for the prediction two years prior to failure, and the accuracy declined to 70% for three years prior to failure. The Type I and

Type II errors have relatively stable and realistic values across the three ranges, except for the first year prior.

3.3.5 Libby (1975)

Libby's (1975:150-161) study was designed to determine whether accounting ratios provide useful information to loan officers trying to predict business failures. He used Deakin's 14-variable set, and asked commercial bank loan officers to analyze the ratios and to predict either failure or nonfailure. Libby's sample consisted 60 firms (30 failed and 30 nonfailed) drawn at random of the 64 Deakin's sample. Chosen at random, the 14 ratios are computed for one of the three years prior to failure, to result in an equal number of firms for each of the three years before failure, 10 failed and 10 nonfailed.

Using principal component analysis he identified five independent sources of variation within the fourteen-variable set. This correctly identified 51 of the 60 firms based upon the derivation sample and 43 of 60 using a double, cross-validation sample. Libby used the reduced set for his experiment because of these results and the greater manageability of the five variable set.

Libby found that the loan officers' predictive accuracy was superior to random assignment and concluded that the ratio information was utilized correctly. After Libby participated 43 commercial loan officers, giving them 70-ratio data set of five ratios each. He concluded that, on the other tests:

- There were no significant difference between the mean predictive accuracy of the small and the large bank representatives,
- There were no significant correlations between predictive accuracy and loan officer characteristics, such as age and experience,

- There were no differences in short-term, test-retest reliability between user subgroups, and
- There was a relatively uniform interpretation of the accounting data across bankers.

3.3.6 Zavgren (1985)

Zavgren (1985:24-29) used logistic regression (logit) techniques to generate a probability of failure as a financial risk measure, and to test the pattern of significance of the financial attributes in the models over a five year period prior to failure. He analyzed a sample of 45 failed and 45 non-failed manufacturing firms, which filed during the 1972 to 1978. The failed and healthy firms are matched according to the industry code and total asset size. The ratios used by Zavgren are as follows:

Table 3.1: Financial ratio data set, 2004

Ratio	Factor	Factor Loading
1. Total Income/Total Capital	Return on Investment	0.97
2. Sales/Net Plant	Capital Turnover	0.95
3. Inventory/Sales	Inventory Turnover	0.97
4. Debt/Total Capital	Financial Leverage	0.97
5. Receivables/Inventory	Receivables Turnover	-0.99
6. Quick Assets/Current	Short-term Liquidity	0.81
7. Cash/Total Assets	Cash Position	0.91

Source: Zavgren (1985:24)

The concluding points by Zavgren is that the models estimated were found to be highly significant at greater than the 99 percent confidence level in distinguishing between failing and healthy firms over the five year period. The significance of the coefficients for each of the variables in the models was traced for each of the five years. The efficiency ratios were found to have the most significance over the long run, which indicated that efficiency in the utilization of assets is difficult to modify over the short run. Profitability was not found to be a significant distinguishing characteristic. The negative coefficient and high significance of the acid test ratio in later years would indicate that ability to meet current obligations is a very important factor in avoiding bankruptcy. The coefficients of the liquidity measure in earlier years and its negative sign indicate that the failing firms were more interested in liquidity than productive opportunities. Debt proved to be a significant characteristic and was consistently higher for ailing than for healthy firms.

Financial ratios can provide highly significant measures for evaluating bankruptcy risk. In addition, the pattern of significance of the coefficients in these models indicates that these variables would be important for helping a manager or analyst to assess risk.

3.3.7 Nam Jinn (2000)

Nam & Jinn (2000:189) applied the logit maximum likelihood estimator as a statistical technique for a sample of 46 non-financial listed firms from a variety of industries. They studied the predictive model of business failure using the sample of listed companies that went bankrupt during the period from 1997 to 1998, when a deep recession driven by International Monetary Fund sanctions started in Korea. The measure of firm's ability of serving short-term debts, interest expenses to sales and account receivables turnover ratio are variables that comprise the prediction model.

The Type I accuracy was 80.4% and the Type II accuracy was 73%, and most of the firms that went bankrupt during the economic crisis from 1997 to 1998 had shown signs of financial distress long before the crisis, they concluded the crisis was not just a temporary foreign exchange crisis, but also a result from poor performance of Korean firms over a long period.

3.4 Gambler's ruin mathematical/statistical model

Gambler's ruin model assumes that the firm has a given amount of capital, K, and that a change in K is Z, which are random. Positive changes in K result from positive cash flows from operations. Under these assumptions the firm will go bankrupt if $K+Z < 0$. The capital K can be measured by either market or accounting values leading to different specifications (Laitinen, 1995:439).

3.4.1 Wilcox (1976)

As discussed by Altman (1993:232), Wilcox (1971) conducted research upon the applications of the Gambler's ruin model to business risk. The studies of 1971, 1973, and 1976 were focused on the development of a theoretical model to explain Beaver's (1966) results better and to generate hypotheses leading to potentially better predictors of failure. He focused on the net liquidation value and the factors that cause it to fluctuate.

Katz et al. (1985:71) stated that Wilcox views the exhaustion of liquidity reserves that precedes bankruptcy as the behavioral basis for firm failure, and for whatever combination of reasons, a firm may drain its liquidity for a number of consecutive years, if it stops drawing on its liquidity before depleting all its liquid reserves, the firm may remain solvent, otherwise, failure ensues.

Wilcox sample of 1973 was composed of 52 firms that failed during 1955 to 1971. The firms matched on the basis of industry group, size, and availability of data for the same years as the failed firms up to nine years prior to failure. He collected data about net income, cash dividends, stock issued, cash plus marketable securities, current assets, total assets and total liabilities. Wilcox, in his updated results of 1976 claimed that the approach used was compared favorably with Beaver and Altman's models.

Wilcox argued that most bankruptcy studies lacked a conceptual framework and scarce bankruptcy information was statistically used up by searching procedure, and he concluded that most bankruptcies could be avoided. However, such prevention requires more than the superficial attempts to reduce risk that have characterized most bankruptcies over the past three decades (Altman, 1983:161-164).

Wilcox model as cited in Katz et al. (1985:71) is expressed as follows:

Pr (failure) = 1 if $X < 0$

$$\left(\frac{1-X}{1-X}\right)^{N} \quad \text{if } X > 0,$$

Where

N = adjusted cash position/a,

X = mean adjusted cash flow/a, and

a = [(mean adjusted cash flow)^2 + variance of adjusted cash flow]$^{1/2}$.

Wilcox defines adjusted cash position as cash plus 0.7 times current assets other than cash plus 0.5 times long-term assets minus liabilities. He defines adjusted cash flow as net income minus dividends minus 0.3 times the period-to-period increase in noncash current assets minus 0.5 times the period-to-period increase in long-term assets plus stock issued in a merger or acquisition. Although Wilcox model lacks a cutoff point, the authors found that $X>0$ indicates health and $X<0$ indicates distress.

3.4.2 Deakin (1977)

Altman (1983:151) stated that Deakin extended his 1972 analysis to a 1977 study building upon Libby's factor analysis contribution to assess the impact, frequency, and nature of bankruptcy misclassification. His purpose was to provide an indication of the frequency and nature of misclassification of nonfailing companies, and to compare auditors' opinions with the model's predictive ability.

Deakin's sample consisted of 80 firms randomly selected from Moody's Industrial Manual and matched only by year of data, and 63 failed firms, 32 companies from his 1972 study and 31 firms from a 1974 study by Altman and McGough that failed in 1970 and 1971. The five-ratio set derived by Libby is computed for the 143 firms, using data two years prior to failure.

The linear and quadratic classification results using the Lachenbruch holdout technique were 94.4% and 83.9% respectively. Between the linear and quadratic equations for Type I and Type II errors were very different, therefore Deakin adopted the following fail-nonfail decision rule for his validation tests (1) classify as failing if both the linear and quadratic functions classify as failing, (2) classify as nonfailing if both the linear and quadratic functions classify as nonfailing, and (3) investigate further if the functions produce conflicting results.

The follow-up analysis was for the three-and-one-half-year period from 1972 until June 30, 1975. Deakin defined failure as bankruptcy, liquidation, or reorganization. If this definition were the appropriate criterion for judging the predictive accuracy of the model, only 18 (6.2%) of the 290 predicted failures were accurately classified. By including dividend cuts or omissions in the definition, Deakin's model correctly identified 224 firms, which is 77.2% as failure. However, based upon the sample of 100 predicted nonfailures, 35 firms that eventually had stress were not identified as failure, which is a 35% error rate.

Deakin analyzed 47 companies that went bankrupt form 1972 to 1974, as an alternative test of his model. This is done to assess the model's accuracy with respect to a holdout sample of "hard-core" failures. The five variable-model correctly identified 39 of the failure, two years prior to failure. There was a misclassification of one firm, and seven companies were identified as in need of further investigation.

Deakin (1977:79) model is as follows:

$$I = -1.369 + 13.855X_1 + 0.060X_2 - 0.601X_3 + 0.396X_4 + 0.194X_5$$

Where,

I = Overall index

X_1 = Net income/ total assets

X_2 = Current assets/ total assets

X_3 = Cash/ total assets

X_4 = Current assets/ current liabilities

X_5 = Sales/ current assets

Similar methodologies have attempted to improve upon the robust but restrictive discriminant structure. Based on the regression analysis, Ohlson's (1980) logit regression framework, and Zmijewski's (1984) probit analysis model attempted to quantify the likelihood of bankruptcy and to assess more directly the impact of specific variables on the distress probabilities. Other statistical methodologies in the literature include logit analysis (Martin 1977), the arctangent regression approach (Korobow 1985), and factor logistic analysis (West 1985) (Sung et al., 1999:66).

3.5 Artificial neural networks models (ANNs)

Beginning in the late 1980s, neural networks became the dominant research methodology in artificial intelligence; researchers actively applied neural networks to classification problems including bankruptcy prediction. Most neural network studies in bankruptcy prediction centered on the comparison of performance (prediction accuracy) of neural networks and other methodologies such as discriminant analysis, logit analysis, genetic algorithms, decision tree, and others. A number of studies report that the performance of neural networks is slightly better that of other techniques, but generally the results are contradictory or inconclusive.

The first attempt to use ANNs to predict bankruptcy is made by Odom & Sharda (1990). A number of studies further investigated the use of ANNs in bankruptcy or business failure prediction. Rahimian et al. (1993) test the same data set used by Odom & Sharda (1990), using three neural network paradigms: backproagation network, Athena and Perception. Recent studies in artificial neural networks (ANNs) show that ANNs are powerful tools for pattern recognition and pattern classification due to their nonlinear nonparametric adaptive-learning properties.

Shah & Murtaza (2001:80) stated that as the system require less storage, more robust to noise or missing data, and have generalization ability, the neural systems are much faster than conventional statistical approaches. They also argued that the statistical approach like discriminant analysis required assumptions, which are fairly restrictive because the Gaussian distribution has to be assumed, and such assumptions might not be traceable to real world problems. On the other hand, using a neural network approach such assumption can be avoided since the application does not require Gaussian distribution assumptions.

Another discussion by Mar-Molinero & Serrano-Cinca (2001:166) of neural networks models, such as the multilayer perceptron (MLP), has been used in studies on company failure. This was the same as the one carried out by Altman et al. (1994). Bell et al. (as cited in Shah & Murtaza, 2001:81) compared the use of logistic regression and a neural network model to forecast commercial bank failures. They found similar performance between two methods, with minor improvements on the margin.

Many researchers in bankruptcy forecasting, including Sharda & Wilson (1996), Tam & King (1992), and Wilson & Sharda (1994), report that neural networks produce significant better prediction accuracy than classical statistical techniques. However, the relationship between neural networks and traditional classification theory is not fully recognized (Richard & Lippmann, 1991:461-483).

Shah & Murtaza (2001:81) mentioned that, Raghupathi et al (1991), Salchenberger (1992), Tam et al. (1992), and Raghupathi (1995) used various architectures of neural networks to solve bankruptcy prediction problems in the past. Lee et al. (1996), Serrano-Cinca (1996), Brockett et al. (1997), Jain & Nag (1997), and Luther (1998), are some of the recent studies in this area.

Lee et al. (1996:63-72) compared the performance of three hybrid neural network models against those Korean bankruptcy data, with the results that hybrid neural network models have superior performance compared to multiple discriminant analysis and interactive dichotomizer (ID3) models for bankruptcy prediction in terms of predictive accuracy and adaptability. Serrano-Cinca (1996:227-238) developed a neural network based decision support system for financial diagnosis of companies; this was a self-organizing neural network model, which was used in decision support systems.

Jain & Nag (1997:201-216) also developed neural network models to predict the success or failure of new ventures. They compared the performance of neural network models with that of similar logit models, and they concluded that neural network models provide a promising and more generalizable approach compared with statistical models to solve two-group classification problems like bankruptcy prediction.

A neural network model consisting of one input layer, one hidden layer, and one output layer that were trained using genetic algorism was used by Luther (1998:57-73). This performance was compared with that of a logit model for predicting bankruptcy, which results in the neural network model having significantly higher prediction accuracy than the logit model.

The argument by Zhang et al. (1999:16) is that the validity and effectiveness of these conventional statistical methods depend largely on some restrictive assumptions such as the linearity, normality, independence among predictor variables and a pre-existing functional form relating the criterion variable and predictor variable.

Salchenberger et al. (1992:899-916) presents an ANN approach to predicting bankruptcy of savings and loan institutions. Tam and Kiang's paper (1992) has had a greater impact on the use of ANNs in general business classification problems as well as in the application of bankruptcy predictions. Using bank bankruptcy data, they compared neural network models to statistical methods such as linear discriminant analysis, logistic regression, k nearest neighbor and machine learning method of decision tree. Their results show that neural networks are generally more accurate and robust for evaluating bank status.

The conclusion by Zhang et al. (1999:28-29) is that neural networks with their flexible nonlinear modeling capability do provide more accurate estimates, leading to higher classification rates than other traditional statistical methods, and they used a cross-validation technique to evaluate the robustness of neural classifiers with respect to sampling variations, the variation across samples in training and test classification rates were reasonably small. They also stated that neural networks provide significantly better estimate of the classification rate for the unknown population as well as for the unseen part of the population in comparing neural networks and logistic regression methods.

Shah & Murtaza (2001:83-84) used a sample of 60 firms with six bankrupt and 54 non-bankrupt firms, which is successful in the prediction of 73% of all firms correctly. Eighty three percent of the sample of bankrupt firms and 72% of non-bankrupt firms were predicted accurately into respective categories in the fourth year of operations, and they concluded that the model was successfully applied and improved current methodologies. They suggested that the model will have an immediate and practical application in the fields of accounting information systems, the state and national regulatory agencies, the banking industry and the securities market. But they acknowledged that the noted results are limited to the computer and software industry and a particular set of financial ratios. They also proposed the model may be improved by including some cash flow variables and nonfinancial factors.

Based on the review of results of the past studies, Shah & Murtaza (2001:82) concluded that neural network based models outperform conventional statistical models like logistic regression, discriminant analysis, k nearest neighbor, and ID3 in predicting bankruptcy.

Another approach to construct qualitative models on bankruptcy prediction is called subjective models based on experts' problem-solving knowledge. Here the experts work with the subjective knowledge framework to induce appropriate conclusions from the integration of quantitative and qualitative information that can be used in estimating the default risk of the borrower.

One such study is conducted by Kim & Han (2003:638) that proposed a genetic algorithm-based (GA) data mining method, which is the first work, capable of extracting decision rules from experts' qualitative bankruptcy decisions, and used the neural networks and inductive learning methods. The results of the experiment show that the GA method has significantly better performance in terms of predictive accuracy and coverage, and there is an indication of reasonable level of agreement achieved between the GA and experts' knowledge.

Kim and Han concluded that the study provides effective supports in incorporating experts' subjective knowledge that facilitate efficient development of bankruptcy prediction models and the qualitative study can be helpful for developing hybrid models. Shin & Lee (2002:322) argued that an advantage of this approach is that it is capable of extracting rules that are easy to understand for users like expert systems.

3.6 Studies focusing on comparing methods

In comparison of the traditional statistical methodologies and an artificial algorithm for distress classification, Altman et al. (1994:505-529) stated that a balanced degree of accuracy and other beneficial characteristics between the two methods, both techniques displayed results of over 90% initial and hold-out sample accuracy. An artificial intelligence algorithm neural networks was used. Neural networks is crucial in the fact that the model is not fixed, but can be modified on the basis of a learning procedure derived from the comparison of the network responses with those required by actual results. They concluded neural networks are not a clearly dominant mathematical technique compared to traditional statistical techniques such as discriminant analysis.

Scott (1981:317-344) compared several of the leading empirical models Beaver (1966), Altman (1968), Deakin (1977), Wilcox (1971), and Altman, Haldeman & Narayanan (1977) in terms of observed accuracies and their coherence to Scott's own conceptual bankruptcy framework. The framework assumed that the firm would go bankrupt if the sum of the liquidation value of assets and the change in these assets were negative.

Because all researchers used different data and different procedures, Scott found it hard to determine which model discriminate the best. By including the accounting and stock market data as well as earnings and debt variables, he concluded that the best multivariate models outperformed the best single variable and the ZETA model is as most convincing (Altman, 1993:235).

Studies that tried industry-relative variables to add information content of the accounting-based financial variables included Altman and Izan in 1982 and Platt & Platt in 1990 (Altman, 1993:236). An industry related approach has attractive stability characteristics, but the problem with such measures is the consistency and timeliness of the data as one attempt to apply the model on a regular basis over time. Financial ratio analysis, particularly when used to predict business failure, will be more accurate if the prediction model is industry specific (Platt & Platt, 1990:31-51).

Most methodologies used to predict failure share the common characteristics of requiring a strong knowledge of statistics in order to understand and use bankruptcy models. An alternative model for the analysis of company failure, is multidimensional scaling (MDS). MDS encompasses a set of techniques based on graphical representations and the end result is a statistical map. MDS bypasses many of the above shortcomings as suggested by Mar-Molinero & Ezzamel (1991). The study were however, concerned with explaining the process that a company follows on its path to failure rather than with prediction (Mar-Molinero & Serrano-Cinca, 2002:166).

Altman (1993:236) stated that other studies also aiming at improving the robust but restrictive discriminant structure, includes Ohlson's logit regression framework and Zmijewski's probit analysis model, which attempted to quantify the likelihood of bankruptcy and the impact of specific variables on distress probability.

There is also a difference amongst researchers preference between the prediction models. Ohlson (1980), Aziz, Emanuel, & Lawson (1988,1989) favor logistic regression (logit) over MDA for both theoretical and empirical reasons. Logit requires less restrictive statistical assumptions, and offers better empirical discrimination. Mcgurr & Devaney (1998:259-276) applied multiple discriminant analysis to analyze a sample of 66 failed and 66 non-failed US retail firms, in their analysis they achieved 78% accuracy as failed or non-failed firm.

3.7 A South African perspective

A number of failure prediction models have been developed in South Africa. Garbers and Uliana (1994:36-43) discussed models of Amiris, Ashton and Cohen (1978), Vietri (1979), Le Roux (1980), De la Rey (1981), and Clarke, Hamman and Smit (1991).

De la Rey (1981) performed the multivariate model at the Bureau of Financial Analysis in Pretoria. The model is as follows:

$$K = -0.01662a + 0.0111b + 0.0529c + 0.086d + 0.0174e + 0.01071f - 0.068811$$

Where,

K = Overall index (discriminant value)

a = Total outside funding / total assets * 100%

b = Profit before interest and tax / Average total assets * 100%

c = Current assets plus listed investments / Current liabilities * 100%

d = Profit after tax / Average total assets * 100%

e = Cash flow profit after tax / Inflation adjusted total assets * 100%

f = Total stocks / Inflation adjusted total assets * 100%

For practical reasons, the model is developed with the cut-off at Zero. A zone of uncertainty exists from –0.2 to +0.2, indicating a range where the result is inconclusive. A 96% success rate in classifying the companies in his sample as either failed or non-failed was achieved.

Vietri (1979) developed a multivariate model. The sample of Vietri included 40 failed and 40 non-failed non-listed companies from various industries, paired on size and period of failure. He used a multiple discriminant analysis, and tested for a comprehensive set of 64 variables. A secondary 10 companies were used to test the model. The variables tested firstly under the condition of shareholders' loans as long-term debt and then as equity, which resulted in the large sample of ratios. The model is as follows:

$$Z = -0.03340R_1 - 2.72262R_2 - 0.03287R_3 + 0.02221R_4 + 0.00123R_5 + 1.82167R_6 - 1.81828$$

Where,

R_1 = Shareholders' Interest to Fixed Assets

R_2 = Cash Flow to Total Borrowings excluding Shareholders' Loan

R_3 = Stock to Net Working Capital

R_4 = Stock to Current Liabilities

R_5 = Sales to Working Capital

R_6 = Audit Report Qualified

In this study the cut-off score is –0.332. Firms achieving below the cut-off number classified as non-failed and a score above as failed. This model achieved 90% accuracy, and irrespective of industry it is useful in predicting failure for non-listed companies.

Clark, Hamman and Smit (1991:31-47) developed a model to be used by a South African financial institution, particularly for privately owned industrial operations. The definition of distress in this model is the inability to make scheduled loan repayments. Z-score above zero is classified as non-failed and those scores below zero are classified as failed. The multivariate model, that achieved a prediction accuracy of 85%, is as follows:

$$Z = -11.907 + 1.524\ ASS + 0.506\ ASSTO + 1.606\ SF/ASS + 2.226\ WC/ASS + 5.136\ CF/INT$$

Where,

ASS = Log (Total Assets/ Production Price Index)

ASSTO = Turnover/ Total Assets

SF/ASS = Shareholders' Funds/ Total Assets

WC/ASS = Net Working Capital/ Total Assets

CF/INT = EXP [(NPAT + Dep.)/ Total Assets] / EXP [Interest / Total Assets]

The model developed in the study conducted by Garbers and Uliana (1994), was the model developed by De la Rey (1981). It was compared to one other univariate and one of their own multivariate failure prediction models in terms of its success in timing distress signals, compared to lending bank's own distress signals. The De la Rey model and univariate Beaver (1966) model based on a cash flow to total debt ratio outperformed the banking model, but the third model, that of Clarke et al., did not outperform the banking distress signals, emphasizing the danger of indiscriminate application of these failure prediction models.

Oliver (as cited in Truter 1992:16) developed two different failure prediction models based on financial ratios one year before failure (Model A) and four years before failure (Model B). He tested the accuracy of the models at different points before failure, and showed that the one year Model A gives an accuracy of 90.7% when applied to companies four years prior to failure. Oliver concluded that it is impossible to determine a company's stadium of failure and suggested that different models be developed for different time dimensions, and argued this time dimension adjustment of existing models would increase a model's total classification accuracy.

By determining the macroeconomic variables and at the same time microeconomic variables, a two-stage model for prediction of corporate failure was developed in South Africa. Using the Bayes-Fisher discriminant analysis, the chosen microeconomic variables such as firm specific financial and non-financial variables, were modeled. Then R-score is obtained for different levels of the business failure rate for the two years prior to failure. The model incorporated prior reference to economic variables, as the adverse economic variables increase failure. Depending the state of the economy, they proposed a range of failure prediction scores (Court and Radloff, 1993:9-19).

3.8 Criticism of ratio based failure prediction models

Robertson & Mills (1991: 20-22) criticized the ratio-based failure prediction models. They commented on the problems encountered in meeting the strict mathematical standards of these failure prediction models and other such as the application of industry based models to evaluate companies in other industries, the validity of models in observing trends, the validity of arbitrarily changing cut-off points, the validity of changing the specification of any of the ratios contained in the model, and the validity of using parts of a corporate failure model for decision making during a company turnaround. The models also do not cope with financial theories, as they are concerned with inadequate data in the form of financial ratios, and the models are offered without detailed operating instructions. They suggested an alternative neural prediction model, which is based on a new approach to fundamental ratio analysis, allowing the researcher to examine ratios across calculating different means, the calculation of a misclassification and the calculation of a year-to-year change factor.

Johnson (1970:1166-1172) in his critical comment questioned the ability of failure prediction models to forecast solely based on financial ratios. The three important issues he argued are; published ratios reflect only cash flows and their effect upon the financial statements ex-post, neither the absolute levels of ratios nor the relative magnitudes can be evaluated in isolation, and finally the inability of ratios to describe a dynamic system. He stressed that these studies do not prove ratios have predictive power, and failed and non-failed companies have dissimilar ratios. He claimed that no logical links had been established between given values of ratios and groupings of failed and nonfailed firms.

The most influential researcher in the area of corporate failure and bankruptcy, Altman (1970:1166-1172), refuted the comments made by Johnson by saying, “lacking in proper direction and substance”. He argued that the fundamental problem of Johnson’s reasoning is related to the failure to distinguish between aggregate-type, stochastic statistical results and the use of normative individual analysis.

Pacey & Pham (1990:316) briefly summarized the problems as the use of non-random, equal share, samples in model estimation and validation, and second, the use of arbitrary cut-off probabilities in prediction tests. On the other hand, Mossman et al. (1998:37) also stated that, although ratio models have been successfully implemented, little agreement exists regarding the best accounting ratios to determine likelihood of financial distress. Some researchers choose ratios according to popularity in the literature and others according to the most functioning ratios in their model.

3.9 Other bankruptcy prediction models

3.9.1 Cash Flow

Cash flow models are based on the fundamental finance principle that the value of a firm equals the net present value of its expected future cash flows. Bankruptcy will result if a firm has insufficient cash available to service debt outflows as they become due, and firm value is insufficient to obtain additional financing. If current cash flows accurately predict future financial status, then past and present cash flows should be good indicators of both firm value and probability of bankruptcy (Mossman et al., 1998:37).

A cash flow model of bankruptcy was developed by Aziz et al. (1988:419-437) following earlier studies by Gentry, Newbold, & Whitford (1985). The value of the firm is written as the sum of the streams of discounted cash flows to and from operations, government, lenders and shareholders. Comparing matched bankrupt and non-bankrupt firms, they find the group means for operating cash flows and cash taxed differ significantly in all five years prior to bankruptcy.

The findings of Aziz et al. (1988) seem intuitively reasonable. Operating cash flows should differ between bankrupt and non-bankrupt firms, because of investment quality and operational efficiency. Tax cash flows should also differ, because of the motivation underlying tax accounting. Although all corporations seek to minimize tax payments, distressed companies with little or no earnings will have no tax liabilities. Healthy firms will not be able to shelter all their income from taxation. Therefore, they will pay promptly to avoid incurring tax penalties.

Aziz & Lawson (1989:55-63) stated that cash flows has three justifications; it is useful in an array of financial purposes, cash flow ratios contain certain information not revealed by other financial ratios, and it is important in studying bankruptcy causes. They tested the accuracy of their cash flow model predictions against Altman's Z (1968) and Zeta (1977) models, and concluded that the cash flow model is superior to the Z model, and gives better early warning signals of bankruptcy than the Zeta model.

There are also some criticisms of cash flow based models. As summarized by Casey & Bartczak (1984:61-67) cash-flow based bankruptcy prediction is a poor predictor and also fails to even marginally improve a ratio-based model's prediction value, it also misses to classifying nonbankrupt firms at a higher rate than do ratio-based models.

3.9.2 Return and return variation models

Beaver (1966) is one of the first researchers to consider the impact of firm bankruptcy on stock returns. He finds that equity returns generally anticipate bankruptcy sooner than financial ratios, consistent with market efficiency. Altman & Brenner (1981:35-51) concluded that bankrupt firms experience deteriorating capital market returns for at least a year prior to bankruptcy. Clark & Weinstein (1983:489-504) observed negative market returns at least three years prior to bankruptcy. However, they found that the announcement of bankruptcy still releases new information to the market. They also compared market returns before bankruptcy for stocks, which became worthless and those which retained some value. Shares, which became worthless, appear to suffer greater losses.

However, bankrupt firms often do not lose their full share value upon bankruptcy due to a reallocation of rights during the bankruptcy process. Franks & Torous (1989), Romaswami (1987) and Dugan & Forsyth (1995) investigated when market returns demonstrate investor awareness of the financial condition of a failing firm.

Aharony et al. (1980:1001-1016) suggested a bankruptcy prediction model based on the variance of market returns. They found differences in the behavior of total and firm-specific variance in returns four years before formal bankruptcy is announced. The firm’s specific component of bankrupt firm return volatility increases as bankruptcy nears.

Dambolena & Khoury (1980:1017-1027) examined the variability of financial ratios of bankrupt and non-bankrupt firms. The ratios of firms approaching bankruptcy are less stable, and this instability may be related to the increasing variability of stock returns.

Researchers also tried to study the impact of non-financial factors that can be used to predict financial distress or bankruptcy. One of the studies conducted by Court (1991:3-15) was to determine the significance of certain non-financial variables in predicting corporate failure. Court, using logistic regression analysis, developed a model for predicting failure based on three variables: the delay in publishing the annual financial statements, directors' resignations and appointments, and director shareholdings. He showed that the delays in publishing the financial statements as well as changes to the board of directors are the more significant predictors of failure. This model, based solely on non-financial variables, was shown to produce better results than traditional ratio-based failure prediction models. Court concluded that traditional ratio-based models could be improved by including these non-financial variables.

As a sample of the stock return model, the Katz et al. (1985:71) model, used to analyze stock returns' using the "market model" is as follows:

$$R_{jt} = a_{jt} + b_j R_{mt} + U_{jt}$$

Where,

R_{jt} = the rate of return for firm j during period t,

a_j = the intercept term,

b_j = the beta coefficient,

R_{mt} = the market rate of return during period t, and

U_{jt} = a residual reflecting that portion of security j's return independent of the market.

If the event does not change investor's expectations, then the residual term will, on average, equal zero. If the residuals around the release of the annual report differ from zero, the implication is that the firm's unsystematic, or company-specific, risk has changed.

Recent studies as summarized by Barniv et al. (2002:500) such as Richardson (1988) examined of the impact of recession on the prediction of corporate failure. Ward & Foster (1997) used loan default/ accommodation as a response measure for financial distress. Akhigbe & Madura (1996) examined the intra-industry effect on voluntary corporate liquidations. Platt et al. (1994) examined bankruptcy discrimination with real variables. Hsieh (1993) discussed optimal cutoff points in bankruptcy prediction models, and other aspects of bankruptcy prediction and related issues are also discussed (Ro et al., 1992; Tennyson et al., 1990; and Platt & Platt, 1990).

3.10 Implications of bankruptcy prediction models

There is an indication that many users of financial information find bankruptcy prediction models useful. According to Dugan & Zavgren (1988:50) two Big Eight firms are currently using some type of bankruptcy prediction models for analytical review purposes, one Big Eight firm retained professor Altman to develop a variant of the model presented in his 1968 article. The auditors in that firm use the model mostly in situations where other sources of audit evidence already indicate the existence of going concern problem then used to corroborate the other evidence accumulated by the auditor.

The other application of bankruptcy prediction is the evaluation of a loan, the assessment of loan performance, and the evaluation of loan extension. It also helps practitioners to improve decisions by providing insights about a company’s credit risk that are not directly attainable from its financial statements or other sources. Altman (1983:192) discussed that many commercial banks now see the value of these models and “are using some form of failure-default classification model in their leading function”.

Other professionals are also using bankruptcy prediction models to solve and support the subjective decision making problems. As, Hopwood et al. (1994:410-411) suggest auditors can use bankruptcy prediction models to improve their decision, and it can also serve as substantial argument against auditors in lawsuits for negligence.

3.11 Chapter summary

The main points discussed in the chapter are the literature reviews on the past studies in corporate failure prediction. Beaver started in discriminating financially distressed and nondistressed companies using accounting and financial variables. The models developed to predict bankruptcy are of three types: that use financial statement ratio, cash flows, and the stock return model.

The most important criticisms of the models are their strict mathematical standards, lack of adequate data, arbitrarily changes in cut-off points, and they are offered without adequate operating instructions. Despite the criticism, the usefulness of bankruptcy predicting models is practically helping firms for analytical review purposes, evaluation of loan, and to support subjective decision problems.

Many modern and most sophisticated models are developed in the prediction of financial bankruptcy. The main reason this study will test Altman's model is because the model is popularly used and publicly available. The next chapter will discuss Altman's Z-score and Springate models in detail.

CHAPTER FOUR

THE ALTMAN AND SPRINGATE BANKRUPTCY PREDICTION MODELS

4.1 Introduction

To describe the practical applicability and popularity of the Z-score model Altman (1993:179) stated that "Although ancient by econometric standards, the original model is still cited and more importantly is still being studied in the classroom and applied in a variety of situations by practitioners." As the main objective of this study is to test the Altman's Z-score, the following chapter will discuss the development, sample selection, important variables, and practical applicability of the Z-score.

The chapter also discuses the mathematical bankruptcy prediction models, especially the multiple discriminant analysis. Discussion on the second generation of Z-score, that is, the ZETA score is another part of the chapter. The second bankruptcy prediction model to be tested in this study is the Canadian Springate Z-score, which is an extension of the Altman's Z-score applied in Canada. As the model's statistical technique and sample development is the same as Altman's Z-score, the chapter discusses only the sample, and statistical results of the model.

4.2. The mathematical bankruptcy prediction models

Almost all bankruptcy prediction models are based on the comparison of the characteristics of a sample of bankrupt firms prior to bankruptcy with the characteristics of a sample of nonbankrupt firms. Then the information from the comparison is used to classify the firms in the combined sample or for building a model which can be used to predict whether a firm not in the sample will go bankrupt. The bankruptcy models attempts to predict when a firm will enter a state in which bankruptcy is possible and the probability of its occurring once that state is reached.

Bankruptcy prediction models can not be used to determine with certainty whether a particular firm will go bankrupt or when a firm either makes a successful turnaround and does not reach the state where bankruptcy can occur, or the firm reaches that state and does not go bankrupt. If the firm is in the bankrupt region, it can turn around until the bankruptcy occurs.

4.3 Multiple discriminant analysis

Multiple discriminant analysis is a statistical technique that has been utilized in a variety of disciplines since its first application in the 1930's. In those years, multiple discriminant analysis was used mainly in the biological and behavioral sciences. In recent years, this technique has become increasingly popular in the practical business world as well as in academia (Altman, 1993:128). The application of discriminant analysis to two-category (dichotomous) classification problems in empirical financial research has substantially increased. However, discriminant analysis has given relatively little attention to design and interpretation difficulties, which lead to the conclusions and generalizations that can be drawn tenuous and questionable (Joy & Tollefson, 1975:723).

Altman (1968:590-591) stated that although previous studies established certain important generalizations regarding the performance and trends of particular measurements, the adaptation of their results for assessing bankruptcy potential firms, both theoretically and practically, is questionable. The methodology used was essentially univariate in nature and emphasis was placed on individual signals of impeding problems. Ratio analysis presented in this fashion is susceptible to faulty interpretations and is potentially confusing. Therefore, the shortcomings inherent in any univariate needs an appropriate extension of the previous studies to build upon their findings and to combine several measures into a meaningful predictive model.

According to Statsoft (available on-line at http://www.statsoftinc.com/textbook/stdiscan.html) discriminant function analysis is used to determine which variables discriminate between two or more naturally occurring groups. Discriminant analysis is a very useful tool for detecting the variables that allow the researcher to discriminate between different groups and for classifying cases into different groups with a better chance of accuracy.

Eisenbeis (1977:875) stated that the standard discriminant analysis procedures assume that the variables used to describe or characterize the members of the groups being investigated are multivariate normally distributed. In practice, deviations from the normality assumption, especially in economics and finance, appear to be more likely. Violations of the normality assumptions may bias the tests of significance and estimated error rates. Hence, it is of interest to determine whether the assumption holds and what effects its relaxation may have on the tests and on the classification.

In the practical application of multiple discriminant analysis, Brigham & Gapenski (1996:919) stated “multiple discriminant analysis has been used with success by credit analysts to establish default probabilities for both consumer and corporate loan applicants, and by portfolio managers considering both stock and bond investments. It can also be used to evaluate a set of pro forma ratios to gain insights into the feasibility of a reorganization plan filed under the Bankruptcy Act.”

Discriminant function is a latent variable which is created as a linear combination of discriminating (independent) variables, such that $L = b_1x_1 + b_2x_2 + \ldots + b_nx_n + c$, where the b’s are discriminant coefficients, the x’s are discriminating variables, and c is a constant (PA 765 Research Methodology Links, http://www2.chass.ncsu.edu/garson/pa765/discrim.htm).

Another advantage of multiple discriminant analysis discussed by Altman (1993:182-183) is the reduction of the analyst’s space dimensionality, that is, from the number of different independent variables to G-1 dimension(s), where G equal the number of original a priori groups. The analysis is concerned with two groups, consisting of bankrupt and nonbankrupt firms. Therefore, the analysis is transformed into its simplest form, that is, one dimension. The discriminant function of the form $Z = V_1X_1 + V_2X_2 + \ldots + V_nX_n$ transforms the individual variable values to a single discriminant score, or Z value, which is then used to classify the object where

$V_1V_2, \ldots, V_n$ = discriminant coefficients, and

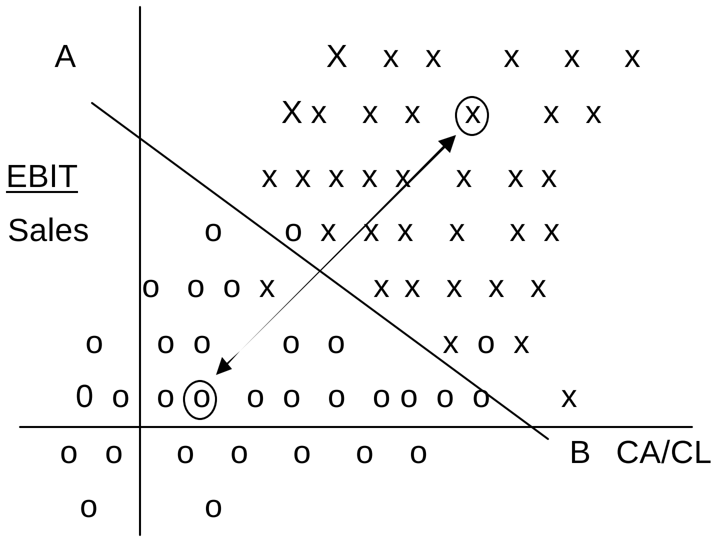
$X_1X_2, \ldots, x_n$ = independent variables.

The multiple discriminant analysis computes the discriminant coefficients, V_1, while the independent variable X_1 are the actual values, and j = 1,2, … , n.

In the utilization of a comprehensive list of financial ratios in assessing a firm's bankruptcy potential, some of the measurements will have a high degree of correlation or collinearity with each other. While this aspect is not serious in discriminant analysis, it usually motivates careful selection of the predictive variables or 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.

Altman (1968:592) discussed the primary advantage of MDA in dealing with classification problems as the potential of analyzing the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics. And he stated that as linear and integer programming has improved upon traditional techniques in capital budgeting, the multiple discriminant analysis approach to traditional ratio analysis has the potential to reformulate the problem correctly. Specifically, combinations of ratios can be analyzed together in order to remove possible ambiguities and misclassifications observed in earlier traditional ratio studies.

Figure 4.1: Linear discriminant analysis, 2004



o = bankrupt firms; x = nonbankrupt firms

Source: Altman, 1993:183

The Z-score model is a linear analysis in that five measures are objectively weighted and summed up to arrive at an overall score that then become the basis for classification of firms into one of the a priori groupings. Figure 4.1 shows a two variable analysis where measures of profitability and liquidity are plotted for a sample of healthy (x) and sick (o) firms. The discriminant model selects the appropriate weights which will separate as far as possible the average values of each group while at the same time minimizing the statistical distance of each observation (the individual x's and o's) and its own group mean. Each observation is then " projected" on the line (AB) which best discriminates between the two groups.

4.4 Altman's Z-score

Chuvakhin & Gertmenian (available on-line at http://gbr.pepperdine.edu/031/bankruptcy) discussed the critical breakthrough in bankruptcy prediction came in 1968 when Edward Altman decided to abandon the search for a single ratio and built a comprehensive, statistical model using a technique called multiple discriminant analysis. Bankruptcy Action.com (available on-line at http://www.bankruptcyaction.com/insolart1.htm) also stated "Edward I. Altman (1968) is the dean of insolvency predictors, he was the first person to successfully use step-wise multiple discriminate analysis to develop a prediction model with a high degree of accuracy."

Altman conducted three subsequent tests, 86 companies that had gone bankrupt in 1969-1975, 110 in 1976-1995, and 120 in 1997-1999. Then he recommended a lower cutoff of 1.81 and treating Z-scores between 1.81 and 2.675 as a "gray area" or "ignorance zone." A company in the ignorance zone means the company in question has a chance to go bankrupt. Interestingly, Altman found that in 1999, 20 percent of U.S. industrial firms referenced in Compustat data tapes had Z-score below 1.81. In other words, the unusually high incidence of bankruptcy in 2001-2002 was to be expected. Altman's another equally innovative idea was the use of a combination of accounting and market-based indicators to forecast bankruptcy. At the time, finance scholars often questioned the validity of accounting measures, while accounting researchers thought that observing the equity market had little to do with debt-related issues such as bankruptcy (Chuvakhin & Gertmenian, available on-line at http://gbr.pepperdine.edu/031/bankruptcy).

4.4.1 Development of the model

In the following section of the chapter, the Altman's Z-score bankruptcy prediction model's development, which is the sample selection, variable selection and test, and the practical applicability, will be discussed.

4.4.1.1 Sample selection

According to Altman (1993:184-185) the initial sample was composed of 66 corporations with 33 firms failed and 33 firms nonfailed groups. The bankrupt group was manufacturers that filed a bankruptcy petition under chapter X of the national bankruptcy act of the U.S. from 1946 through 1965. The aim was to examine a list of ratios in period t in order to make predictions about other firms in the following period (t + 1), but this was not possible due to data limitations. The sample's mean asset size was $6.4 million, with a range of between $0.7 million and $ 25.9 million. Due to the industry and size differences, there was a careful selection of nonbankrupt firms. Group 2 consists of a paired sample of manufacturing firms' chosen on a stratified random basis. The firms were stratified by industry and by size, with the asset size range restricted to between $1 and $25 million. The mean asset size of the firms in Group 2 ($9.6 million) was slightly greater than that of Group 1, but matching exact asset size of the two groups seemed unnecessary. Firms in Group 2 were still in existence in 1966. The data collected were from the same years as those compiled for the bankrupt firms. For the initial sample test, the data were derived from financial statements dated one annual reporting period prior to bankruptcy. The data were derived from Moody's Industrial Manual and selected annual reports. The average lead-time of the financial statements was approximately seven and one-half months.

In the development of the model, the asset size group to be sampled was an important issue. The decision to eliminate both the small firms, which were under $1 million in total assets, and the very large companies from the initial sample essentially, was due to the asset range of the firms in Group 1. Additionally, the incidence of bankruptcy in the large-asset-size firm was quite rare prior to 1966. However, the large firm is no longer invulnerable to financial distress. The absence of comprehensive data negated the representation of small firms. A frequent argument is that financial ratios by their nature have the effect of deflating statistics by size, and that therefore a good deal of the size effect is eliminated.

4.4.1.2 Variable selection

Balance sheet and income statement data were collected for the firms selected. As large number of variables found to be significant indicators of corporate problems in past studies, a list of 22 potentially helpful variables (ratios) are compiled for evaluation. Grice & Ingram (2001:54) stated that Altman compiled a list of 22 financial ratios and classified each into one of five categories – liquidity, profitability, leverage, solvency, and activity. The ratios were not selected on a theoretical basis, but rather, on the basis of their popularity in the literature and Altman's belief about their potential relevancy to bankruptcy. There were also few new ratios included in the analysis. The cash flow to debt ratio, which was the best single predictor in the study of Beaver study (1967), was not considered because of the lack of consistent and precise depreciation data.

As discussed by Altman (1993:185-188) the five variables were selected from the original list of 22 variables, which were doing the best overall job together in the prediction of corporate bankruptcy. The profile did not contain all of the most significant variables measured independently as this would not necessarily improve upon the univariate, traditional analysis described earlier.

Altman utilized the following procedures in order to arrive at a final profile of variables:

- Observation of the statistical significance of various alternative functions including determination of the relative contributions of each independent variable,
- Evaluation of intercorrelations among the relevant variables,
- Observation of the predictive accuracy of the various profiles, and
- Judgment of the analyst.

The final discriminant function is as follows:

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

Where

X_1 = working capital/total assets,

X_2 = retained earnings/total assets,

X_3 = earnings before interest and taxes/total assets,

X_4 = market value equity/book value of total liabilities,

X_5 = sales/total assets, and

Z = overall index.

X_1, working capital/Total Assets (WC/TA)

The working capital/total assets ratio is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is the difference between current assts and current liabilities. Here, the liquidity and size characteristics are explicitly considered. Altman (1993:186) explained the logic behind this ratio as a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets. This ratio was the most valuable from the three liquidity ratios evaluated. Other two liquidity ratios tested were the current ratio and the quick ratio.

As discussed by Chuvakhin & Gertmenian (available on-line at http://gbr.pepperdine.edu/031/bankruptcy) a firm with a negative working capital is very likely to experience problems meeting its short-term obligations. Conversely, a firm with a significantly positive working capital rarely has problems paying its bills.

X_2, Retained Earnings/Total Assets (RE/TA)

Retained earnings is the account which reports the sum of past year's profit or losses of a firm over its entire life. Altman (1993:186) noted that the retained earnings account is subject to change via corporate quasi-reorganizations and stock dividend declarations. While these occurrences are not evident in the study, it is conceivable that a bias would be created by a substantial reorganization or stock dividend and appropriate readjustments that could be made to the accounts. A relatively young firm will show a low retained earnings to total asset ratio because it has not had time to build up its cumulative profits. Therefore, the age of a firm is implicitly considered in this ratio. Hence, it may be argued that the young firm is somewhat discriminated against in the analysis, and its chance of being classified as bankrupt is relatively higher than that of another, older firm. But, Altman stated this as the situation in the real world and he discussed "…The incidence of failure is much higher in a firm's earlier years. In 1990, approximately 47% of all firms that failed did so in the first five years of their existence."

Accumulated earnings may indicate the firm's financial strength or weakness. "Significant retained earnings mean a history of profitable operation and ability to withstand periods of losses. Low retained earnings, on the other hand, may signal that a single bad year or even quarter, can put the company out of business" (Chuvakhin & Gertmenian, available on-line at http://gbr.pepperdine.edu/031/bankruptcy).

X_3, Earnings before Interest and Taxes/Total Assets (EBIT/TA)

This ratio is the firm's earnings power from the investment on assets without the influence of taxes and interest. This is useful to compare firms in different tax situations and different degrees of financial leverage. Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure. Insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm's assets, in which the value is determined by the earning power of the assets.

Chuvakhin & Gertmenian (available on-line at http://gbr.pepperdine.edu/031/bankruptcy) discussed this as a particularly concern because failing to meet interest payments would technically put the company into default on its debt obligations. Earnings before interest and taxes is often used as an approximate measure of cash flow generated by the firm's operation, which is an estimate of the size of the cash pool available for distribution between three major groups of claimants: creditors (interest and principal), government (taxes), and shareholders (dividends).

X_4, Market Value of Equity/Book value of Total Liabilities (MVE/TL)

The market value of equity is the market price of common stock share multiplied by the number of common shares outstanding. The liabilities include current and long-term liabilities. The measure shows how much the firm's assets can decline in value, measured by market value of equity plus debt, before the liabilities exceed the assets and the firm becomes insolvent. Altman (1993:187) stated that this ratio adds a market value dimension, which other failure studies did not consider. And he noted that the reciprocal of X_4 is the familiar debt/equity ratio often used as a measure of financial leverage, it is also a slightly modified version of one of the variables used effectively by Fisher (1959) in a study of corporate bond interest rate differentials. This ratio is appeared to be more effective predictor than commonly used similar ratios.

There are two ways to resolve the puzzle for what does market value of the firm's equity has to do with its ability to service its debt. First, if the firm goes bankrupt, the value of its stock falls almost to zero very quickly. Thus if a firm has significant market capitalization, it should be perceived as an indication of the market's belief in its solid financial position. Second, if a firm has significant market capitalization and begins to experience temporary financial difficulties, it could resort to issuing more common stock at relatively high prices. Although the resulting cash infusion dilutes the existing shareholder's interest, it would be beneficial to creditors because it would improve the company's chances to repay its outstanding obligations (Chuvakhin & Gertmenian, available on-line at http://gbr.pepperdine.edu/031/bankruptcy).

X_5, Sales/Total Assets (S/TA)

This ratio is a measure of a firm's use of its total resources to generate sales and it is a summary measure influenced by the asset management ratios. Altman stated that this final ratio is important because, as indicated below, it is the least significant ratio on an individual basis. In fact, based on the statistical significance measure, it would not have appeared at all. However, because of its unique relationship to other variables in the model, the sales/total assets ratio ranks second in its contribution to the overall discriminating ability of the model.

Altman discussed that the practical analyst may have been concerned by the extremely high relative discriminant coefficient of X_5. This seeming irregularity is due to the format of the different variables. Table 4.1 illustrates the proper specification and form for each of the five independent variables.

Table 4.1: Variable means and test of significance, 2004

Variable	Bankrupt Group Mean[a]	Nonbankrupt Group Mean[a]	F Ratio[b]
X_1	-6.1%	41.4%	32.60[c]
X_2	-62.6%	35.5%	58.86[c]
X_3	-31.8%	15.4%	26.56[c]
X_4	40.1%	247.7%	33.26[c]
X_5	1.5X	1.9X	2.84

[a] ***n = 33***

[b] ***$F_{1.60}$ (0.001) = 12.00; $F_{1.60}$ (0.05) = 4.00***

[c] ***Significant at the 0.001 level.***

Source: Altman 1993:188

Many individuals found that a more convenient specification of the model is of the form:

$$Z = 1.2X_1 = 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

Using this formula needs inserting the more commonly written percentage, for example, 0.10 for 10%, for the first four variables (X_1 – X_4) and round the last coefficient off to equal 1.0 from 0.99. The last variable continues to be written in terms of number of times. The score for individual firms and related group classification and cutoff scores remain identical.

4.4.1.3 Variable tests

Altman (1993:188) performed an F-test to test the individual discriminating ability of the variables. This test relates the difference between the average values of the ratios in each group to the variability (or spread) of values of the ratios within each group. Variable means measured at one financial statement prior to bankruptcy and the resulting F-statistics are presented in Table 4.1.

Indicating extremely significant difference in these variables among groups, the variables X_1 through X_4 are all significant at the 0.001 level,. Variable X_5 does not show a significant difference among groups and the reason for its inclusion in the variable is not apparent as yet. On a strictly univariate level, all of the ratios indicate higher values for the nonbankrupt firms. Also all of the discriminant coefficients display positive signs. Therefore, the greater a firm's bankruptcy potential, the lower its discriminant score (Altman, 1993:188).

Altman (1993:189) stated that one useful technique in arriving at the final variable profile is to determine the relative contribution of each variable to the total discriminating power of the function. The relevant statistic observed is a scaled vector. Since the actual variable measurement units are not all comparable to each other, simple observation of the discriminant coefficients is misleading. The adjusted coefficients shown in Table 4.2 enable us to evaluate each variable's contribution on a relative basis.

Table 4.2: Relative contribution of the variables, 2004

Variable	Scaled Vector	Ranking
X_1	3.29	5
X_2	6.04	4
X_3	9.89	1
X_4	7.42	3
X_5	8.41	2

Source: Altman 1993:189

Table 4.2 indicates that the large contributors to group separation of the discriminant function are X_3, X_5, and X_4 respectively. The profitability ratio contributes the most, which is not surprising if one considers that the incidence of bankruptcy in a firm that is earning a profit is almost nil. What is surprising, however, is the second highest contribution of X_5 (sales/total assets). Recall that this ratio was insignificant on a univariate basis: the multivariate context is responsible for illuminating the importance of X_5. A probable reason for this unexpected result is the high negative correlation (-0.78) that observed between X_3 and X_5 in the bankrupt group. The negative correlation is also evident in subsequent bankrupt group samples.

The logic behind the high negative correlation in the bankrupt group discussed by Altman is that as firms suffer losses and deteriorate toward failure, their assets are not replaced as much as they were in healthier times. Also, the cumulative losses have further reduced the asset size through debits to retained earnings. The asset size reduction apparently dominates any sales movements.

In the variable selection process, Altman (1993:190) stated, four of the five variables display significant differences between groups. Here the importance of multiple discriminant analysis is its ability to separate groups using multivariate measures. A test to determine the overall discriminating power of the model is F-value, which is the ratio of the sums-of-squares between-groups to the within-groups sums-of-squares. When this ratio is maximized, it has the effect of spreading the means of the groups apart and, simultaneously, reducing the dispersion of the individual points (firm Z-values) about their respective group means. This F-test is appropriate because the objective of the multiple discriminant analysis is to identify and utilize those variables, which best discriminate between groups and which are most similar within groups.

The group means of the original two-group sample are:

Group 1 = -0.29 $\quad$ F = 20.7

Group 1 = +5.02 $\quad$ $F_{5.60}$ (0.01) = 3.84

The significance test therefore rejects the null hypothesis that the observations come from the same population. After the values of the discriminant coefficients are estimated, it is possible to calculate discriminant scores for each observation in the sample, or any firm, and to assign the observations to one of the groups based on this score. This is done to compare the profile of an individual firm with that of the alternative groupings. The comparisons are measured by a chi-square value and assignments are made based upon the relative proximity of the firms' score to the various group means.

4.4.2 Review of empirical results

In the discussion of the model's empirical results Altman (1993:190-199) started by illustrating the format for presenting the results. In the multigroup case, results are shown in a classification chart or accuracy matrix. Table 4.3 shows how the chart is set up.

Table 4.3: Classification results format, 2004

	Predicted Group Membership	
Actual Group Membership	Bankrupt	Nonbankrupt
Bankrupt	H	M_1
Nonbankrupt	M_2	H

Source: Altman 1993:191

The actual group membership was equivalent to the a priori groupings, and the model attempts to classify these firms correctly. At this stage, the model is basically explanatory. When new companies are classified, the nature of the model is still basically one of classification unless the firms are assessed in periods after the model was built. In this case, we begin the prediction phase.

The H's stand for correct classifications and the M's stand for misclassification. M_1 represents a Type I error and M_2 a Type II error. The sum of the diagonal elements equals the total correct "hits" and when it is divided into the total number of firms classified (66 in the case of the initial sample), it yields the measure of success of the multiple discriminant analysis in classifying firms, that is, the percent of firms correctly classified.

4.4.2.1 Initial Sample of the model

The initial sample of 33 firms in each of the two groups was examined using data compiled one financial statement prior to bankruptcy. Since the discriminant coefficients and the group distributions are derived from this sample, a high degree of successful classification was expected. This should occur because the firms were classified using a discriminant function, which in fact, was based upon the individual measurements of these same firms. Table 4.4 shows the classification matrix for the original sample.

Table 4.4: Classification results, original sample, 2004

	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 1993:191

The model was extremely accurate in classifying 95% of the total sample correctly. The Type I error proved to be only 6% while the Type II error was even better at 3%. Altman stated, although there is obvious upward bias, the results are encouraging.

4.4.2.2 The model's results two statements prior to bankruptcy

In the second test, it is observed the discriminating ability of the model for firms using data compiled two statements prior to bankruptcy. The two-year period was an exaggeration since the average lead-time for the correctly classified firms was approximately 20 months; with two firms having a 13-month lead. Altman (1993:191) noted that the reduction in accuracy was understandable as impending bankruptcy is more remote and the indications are less clear. The results are shown in Table 4.5.

Table 4.5: Classification results, two statements prior to bankruptcy, 2004

	Number Correct	Percent Correct	Percent Error	n	Actual	Predicted Group 1 (Bankrupt)	Predicted Group 2 (Nonbankrupt)
					Group 1	23	9
					Group 2	2	31
Type I	23	72	28	32			
Type II	31	94	6	33			
Total	54	83	17	65			

Source: Altman 1993:192

Here, the Type II error is slightly larger (6% vs. 3%) in this test, but still it is extremely accurate. Nevertheless, 72% correct assignment is evidence that bankruptcy can be predicted two years prior to the event. Further tests will be applied below to determine the accuracy of predicting bankruptcy as much as five years prior to the event.

4.4.2.3 The samples' potential bias and validation techniques

The resulting accuracy is biased upward because of two factors as the firms used to determine the discriminant coefficients are reclassified. These factors are sampling errors in the original sample and the search bias. The search bias is inherent in the process of reducing the original set of variables (22) to the best variable profile (5). The possibility of bias due to intensive searching is inherent in any empirical study. While a subset of variables is effective in the initial sample, there is no guarantee that it will be effective for the population in general.

Altman (1993:192) performed a search bias test to estimate parameters for the model using only a subset of the original sample, and then classified the remainder of the sample based on the parameters established. A simple t-test was then applied to test the significance of the results. Five different replications of the suggested method of choosing subsets (16 firms) of the original sample are tested, with results listed in Table 4.6. The five replications include:

- Random sampling,
- Choosing every other firm starting with firm number one,
- Starting with firm number two,
- Choosing firms 1 through 16, and
- Choosing firms 17 through 32.

Table 4.6; Accuracy of classifying secondary sample, 2004

Replication[c]	Percent of Correct Classifications	Value of t[a,b]
1	91.2	4.8”
2	91.2	4.8”
3	97.0	5.5”
4	97.0	4.5”
5	91.2	4.8”
Average	93.5	5.1”

[a]***Significant at the 0.001 level.***

[b]***t = (proportion correct – 0.5)*** ÷ $\sqrt{0.5(1.0-0.5)/n}$.

[c]***Total number of observations per replication (n) = 34.***

Source: Altman 1993:193.

The hypothesis that there is no difference between the group and substantiate that the model does, is rejected by the test. This, in fact, possesses discriminating power on observations other than those used to establish the parameters of the model. Therefore, any search bias does not appear significant.

4.4.2.4 Secondary sample of bankrupt firms

In testing the model for both bankrupt and nonbankrupt firms, two new samples were introduced. The first contains a new sample of 25 bankrupt firms whose asset size rang is similar to that of the initial bankrupt group. On the basis of the parameters established in the distriminant model to classify firms in this secondary sample, the predictive accuracy for this sample as of one statement prior to bankruptcy is described in Table 4.7.

Table 4.7: Sample of nonbankrupt firms, 2004

	Bankrupt Group (Actual)			Predicted	
	Number Correct	Percent Correct	Percent Error	Bankrupt	Nonbankrupt
				24 n	1
Type I (Total)	24	96	4		

Source: Altman 1993:193

The results were superior to the initial discriminant sample, that is, 96% vs. 94%. Altman suggested that the possible reasons are the upward bias normally present in the initial sample tests is not manifested in this investigation and/or that the model, as stated before, is not optimal.

4.4.2.5 Secondary sample of nonbankrupt firms

Altman (1993:193-194) stated that, the sample companies were chosen either by the bankruptcy status, which is Group 1 or by their similarity to Group 1 in the aspect of their economic well-being. The firms suffer temporary profitability difficulties but not actually become bankrupt are examples of Type II error. To test the effectiveness of the discriminant model is to search out a large sample of firms that have encountered earnings problems and then to observe the Z-score's classification results.

In performing the above test, a sample of 66 firms was selected on the basis of net income or deficit reports in the years 1958 and 1961. Over 65% of these firms had suffered two or three years of negative profits in the previous three years. The firms were selected being that they were manufacturing firms and which suffered losses in the year 1958 or 1961, regardless of their asset size. They were taken at random from all firms listed in Standard & Poor's Stock Guide, January 1962 that reported negative earnings. The two base years were chosen due to their relatively poor economic performance in terms of GNP growth. The companies' bankruptcy potential were evaluated by the discriminant model.

The result show that 14 of the 66 firms were classified as bankrupt, with the remaining 52 correctly classified as shown in Table 4.8. Hence, the discriminant model correctly classified 79% of the sample firms. This percentage is all the more impressive when one considers that these firms constitute a secondary sample of admittedly below-average performance.

Altman (1993:194) discussed another interesting issue, that is the relationship of these “temporarily” sick firms’ Z-score and the “zone of ignorance.” Ten of the 14 misclassified firms in his secondary sample, had Z-scores between 1.81 and 2.67. This indicates that although they were classified as bankrupt, the prediction of their bankruptcy was not as definite as it is for the vast majorities in the initial last sample have Z-scores within the entire overlap area. This emphasizes that the selection process was successful in choosing firms, which showed signs of deterioration.

Table 4.8: Classification results, secondary sample of nonbankrupt firms, 2004

	Bankrupt Group (Actual)			Predicted	
	Number Correct	Percent Correct	Percent Error	Bankrupt	Nonbankrupt
				14	52
				n	
Type II (Total)	52	79	21	66	

Source: Altman 1993:194

4.4.3 The model’s practical applicability

Discussing the long range accuracy of the model, Altman (1993:195) stated that the previous results give important evidence of the reliability of the conclusions derived from the initial sample of firms. Then he suggested an extension to examine the firms to determine the overall effectiveness of the discriminant model for a longer period of time prior to bankruptcy. He mentioned that several studies, like Beaver (1967), showed firms exhibiting failure tendencies as much as five years prior to the actual failure. However, little is mentioned of the true significance of these earlier results. The question is if it is enough to show that a firm's position is deteriorating or is it more important to examine when in the life of a firm its eventual failure becomes an acute possibility? He also questioned the more remote years.

The accuracy of the model falls off consistently with the one exception between the fourth and fifth years, when the results are the opposite of what one would expect. Altman (1993:195) stated the most logical reason was that after the second year, the Z-score model becomes unreliable in its predictive ability, and also that the change from year to year has little or no meaning. However, the more recent models, e.g., ZETA have demonstrated high accuracy over a longer period of time.

Brigham & Gapenski (1996:919-920) discussing the practical applicability of Altman's model stated; the model has been used by Salmon Brothers, Morgan Stanley, and other investment banking houses to appraise the quality of junk bonds used to finance takeovers and leveraged buyouts. Another discussion is by Katz, et al. (1985:70), who stated that, "…for the 15-month period prior to the issuance of the annual report that triggered a shift in state, firms classified by the Altman model as recovering from distress displayed significant abnormal positive returns; those classified as deteriorating showed significant abnormal negative returns, both groups continued to exhibit abnormal returns in the expected direction over the nine months following the announcement date."

4.4.3.1 The predictive accuracy of the model

Altman (1993:195) examined the Z-score model on several samples of bankrupt manufacturers, including ones in the 1970s and 1980s and the Type I of accuracy has remained above 80%. The Type II accuracy has diminished, as an increasing number of firms appear to have financial profiles more similar to bankrupt companies but which do not fail. He estimated that the number of large firms who's Z-score below 1.81 was now at least 10% and that the probable Type II error for all firms, large and small, was at least 15%.

The assessment of Z-score by Altman for the Standard & Poor's 400 Industrial Index firms over the period 1973-1989, verify that the proportion of these large entities with scores below 1.8 fluctuated from a low of about 3% in 1980 to a high of 11% in 1986. The distribution of Standard & Poor's firm Z-scores in 1989, with the largest proportion falling in the 3 to 5 score range (safe zone) but still almost ten percent below 1.8. The years 1986 – 1989, and also for 1990 and 1991, have all had Z-scores below 1.8 for the largest and best companies in the 9 to 11% range. Clearly 10% of the S&P will not and have not failed over a two-year period. On the other hand, an increasing number of large firms failing with over 30 that had liabilities greater than one billion dollars failing in the 1989-1992 (third quarter) period. Many of these Chapter 11's bankrupt businesses were not industrial firms, however, and cannot be counted as part of the Standard & Poor's 400 (Altman, 1993:196).

4.4.3.2 The model's early warning and trend implications

When discussed the early warning and trend implication of the Z-score, Altman (1993:199) stated, "…one of the key ingredients to the effective application of distress classification models is the potential that they provide an early warning of impending crisis. Based on the above discussion, he suggested that the Z-score model is an accurate forecaster of failure for up to two years prior but the accuracy diminishes as the lead time increases. Unfortunately, models of this type do not indicate the timing of failure. This is understandable since the exact timing of bankruptcy is often determined based on noneconomic considerations, or legal bankruptcy may never occur despite the distressed situation."

Altman (1993:201) provided two most important conclusions of the trend, namely (1) the observed ratios show a deteriorating trend as bankruptcy approaches, and (2) the most serious change in the majority of these ratios occurred between the third and the second years prior to bankruptcy. The degree of seriousness is measured by the yearly change in the ratio values. The latter observation is extremely significant because it provides evidence consistent with conclusions derived from the discriminant model. Therefore, the important information inherent in the individual ratio measurement trends takes on deserved significance only when integrated with the more analytical discriminant analysis findings.

4. 4.4 What about if the books are misstated?

Moyer et al. (2001:70) stated that generally accepted accounting principles (GAAP) provide companies with a great deal of latitude in the preparation of key financial statements used to measure performance. They discussed some of the tricks like timing store openings and assets sales in a way that keeps earnings growing at a smooth rate, acceleration (delay) of shipments at the end of a quarter reporting period to either increase (decrease) sales in a weak (strong) quarter, capitalizing normal operating expenses, taking "big bath" write offs, and increasing reserves in good times and drawing down on them in bad times.

An interesting feature of the Z-score model is its ability to withstand certain types of accounting irregularities. In the recent high-profile bankruptcy of WorldCom, management improperly recorded billions of dollars as capital expenditures instead of as operating expenses. But such treatment would have a twofold impact on financial statements: (1) overstating earnings, and (2) overstating assets. Overstating earnings would increase the X_3 ratio in the Z-score model, while overstating assets would actually decrease three ratios, X_1, X_2, and X_5 (all three are calculated with total assets in the denominator). Therefore, the overall impact of these accounting improprieties on the company's Z-score is likely to be downward (Chuvakhin & Gertmenian, available on-line at http://gbr.pepperdine.edu/031/bankruptcy).

Table 4.9 shows an examination, which is done to validate the above reasoning. The Z-score for WorldCom for fiscal years ending December 31, 1999, 2000, and 2001 based on its annual reports were computed. The results showed that the company experienced a rapid deterioration in its Z-score. Even though WorldCom is not a manufacturing company, this shows how the above accounting impropriety can affect the Z-score.

Table 4.9: Z-score analysis for WorldCom, 2004

(accounting data prior to restatements)

Ratio	Definition	1999	2000	2001
X_1	Working capital/total assets	(0.08)	(0.08)	0.00
X_2	Retained earnings/total assets	(0.01)	0.03	0.04
X_3	Earnings before interest and taxes/total assets	0.08	0.08	0.02
X_4	Market value of equity/book value of total liabilities	3.58	1.13	0.54
X_5	Sales/total assets	0.39	0.40	0.31
Z	**Z-score**	**2.697**	**1.274**	**0.798**

Source: Chuvakhin & Gertmenian (available on-line at http://gbr.pepperdine.edu/031/bankruptcy)

4.4.5 Some criticisms of Z-score

Scott (1981:317-344) noted potential search bias in the variable selection technique used by Altman. Lack of the theory of bankruptcy invites the researcher to consider a multitude of variables and then to reduce the original set to the most accurate subset. The resulting subset of variables often proves ineffective when applied to a sample of firms or periods other than those used in developing the model.

Another critical suggestion is that of Grice & Ingram (2001:54), which state the hold-out sample accuracy rates in Altman's and other studies are potentially upwardly biased, that is, the hold-out sample accuracy rates are higher than the rates users should expect when they apply the models for three reasons:

- The estimation and hold-out sample periods are not substantially different,
- The hold-out sample consists of firms from the same restricted set of industries as those in the estimation sample, and
- The holdout samples are small and are not proportional to actual bankruptcy rates.

4.5 The Zeta score

Zeta score, developed by Altman, Haldeman and Narayanan (1977), is a second-generation model with several improvements to the original Z-score of Altman (1968). This ZETA score was developed based on a sample of 53 bankrupt and 58 non-bankrupt firms, including both retailers and manufacturers, matched by industry and year of data.

According to Altman (1993:207-208) the main reasons for the improvement of the Z-score model are the change in the size and financial profile of business failures in recent years, the need to have a model based on more current data spanning a shorter collection period, a model that would not be industry specific especially to include the retailing industry, to include a more careful analysis of data and footnotes to financial statements and the need to test and assess several recent advances and controversial aspects of discriminant analysis.

In the development of the model Altman et al. (1977:29-50), made certain financial reporting adjustments. The adjustments are related to capitalization of leases, reserves, minority interests and other liabilities on the balance sheet; captive finance companies and other non-consolidated subsidiaries; goodwill and intangibles, and capitalized research and development costs; capitalized interest and certain other deferred charges. To analyze the results using linear and quadratic structures, discriminant analysis was used. The authors used six different techniques for reducing the variable set to an acceptable number, introducing the application of a variety or new methods, including forward stepwise, backward stepwise, scaled vector, separation of means test, and the conditional deletion test. These different techniques bore very similar results.

A seven variable model was selected after an iterative process of reducing the number of variables. Here the discriminant coefficients were not disclosed. Therefore, the seven variables contained in the model will only be discussed:

X_1 = Return on assets as measured by earnings before interest and taxes to total assets

X_2 = Stability of earnings as measured by a normalized measure of standard error of estimated around a 10-year trend in X_1

X_3 = Debt service as measured by interest coverage ratio, being earnings before interest and taxes to total interest payments

X_4 = Cumulative profitability as measured by retained earnings to total assets

X_5 = Liquidity as measured by the current ratio

X_6 = Capitalization as measured by common equity to total capital

X_7 = Size as measured by firm's total tangible assets

With a success classification of over 90% for one-year prior, and 70% accuracy up to five years, the ZETA method appeared to be accurate for up to five years prior to failure. The authors discussed that the inclusion of retailing firms in the same model as manufacturing firms did not affect the results negatively. They found that the ZETA model outperformed alternative bankruptcy classification strategies in terms of expected cost criteria, utilizing prior probabilities and explicit cost of error estimates. The ZETA model is regarded as a more accurate and relevant failure prediction model, specifically targeted for credit worthiness analysis of firms for financial and non-financial institutions, identification of undesirable investment risk for portfolio managers and individual investors. The model also aid in more effective internal and external audits of firms with respect to going concern considerations (Altman et al., 1977:51).

4.6 Springate's Z-score

According to Doukas (1986:479) Springate modified Altman's MDA formula for Canadian use. Subsequently testing showed that this formula was accurate 88% of the time. As stated in Bankruptcy Action.Com (available on-line at http://www.bankrupltcyaction.com/insolart1.htm), the model was developed in 1978 at Simon Fraser University by Gordon L.V. Springate, following procedures developed by Altman in the US, using a step-wise multiple discriminate analysis to select four out of 19 popular financial ratios that best distinguished between sound business and those that actually failed. The Springate model takes the following form:

$$Z = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4$$

Where,

X_1 = Working Capital/Total Assets

X_2 = Net Profit before Interest and Taxes/Total Assets

X_3 = Net Profit before Taxes/Current Liabilities

X_4 = Sales/Total Assets

The cutoff is when:

$Z < 0.862$; then the firm is classified as "failed"

This model achieved an accuracy rate of 92.5% using the 40 companies tested by Springate. Botheras (1979) tested the Springate Model on 50 companies with an average asset size of $2.5 million and found an 88.0% accuracy rate. Sands (1980) tested the Springate Model on 24 companies with an average asset size of $63.4 million and found an accuracy rate of 83%.

Boritz et al. (available on-line at http://papers.ssm.com/so13/papers.cfm?abstract_id=470803-20k) discussed that there may be some problems working with Canadian data as the Altman model was developed using US data. The Canadian business and legal environment differs from the US environment. Also, the business environments have changed in the more than twenty-five years since the Altman model was estimated. From the three bankruptcy predicting models available in Canada, they tested two of them in comparison to two US models, and they concluded the Springate model has the lowest Type I error rate.

4.7 The research importance of Altman's Z-score model in the study

The Altman Z-score model as a major tool for this bankruptcy prediction models study is established because of many reasons. Even though the prediction accuracy of other bankruptcy prediction models such as neural networks is more statistically convincing, the Altman's Z-score is still popular. Most of the methodologies used to predict failure share the common characteristics of requiring a strong knowledge of statistics in order to understand and use the model.

Altman's Z-score model is still popular regardless being dated and the industry difference. The application of the model needs a study in different time horizon, industry, and different economic environment. Therefore, this study aims to imply the applicability of the model in these different conditions.

As discussed in chapter three, other statistical models are not a clearly dominant techniques compared to traditional statistical techniques such as discriminant analysis. Some of the reasons that make Altman's Z-score as dominant and important in the study are the following:

- Users find that the combination of accounting and financial market data can be the relatively unexciting financial statement analysis field to greater interest and application. The prediction of financial distress holds upper hand as the fact that corporate financial distress is now more relevant than at any time.
- Altman's Z-score is especially easy to understand and apply.
- The Z-score model has proven to be quite accurate over these last 35 years and remains an objective, established tool to be combined with other means to assess the health of companies.
- The model's publicly availability is also an important issue.

4.7 Chapter summary

The purpose of this chapter has been to elaborate the mathematical methods used in classifying bankrupt and nonbankrupt firms by applying multiple discriminant analysis, the Altman's Z-score, and the Springate Z-score.

The multiple discriminant analysis is stated to be a superior statistical method than the univarate analysis used by Beaver 1967. The chapter discusses the Altman's Z-score sample selection and test, and practical applicability. Altman's Z-score is the first model to utilize the multiple discriminant analysis technique. Although it was developed in 1968, the model is still popularly used by many practitioners.

The model's easy application and its popularity make it more attractive than other models used to predict bankruptcy. Z-score is an accurate forecaster of failure for up to two years prior to bankruptcy, but the accuracy diminishes as the lead time increases. The degree of failure seriousness is measured by the yearly change in the ratio values. The model also has an interesting feature to withstand certain types of accounting irregularities.

A second-generation to the Altman's Z-score (1968), developed by Altman, Haldeman, and Narayanan in 1977 is the Zeta score. The Zeta model was accurate up to five years prior with a success classification of over 90% for one year and 70% accuracy up to five years. The inclusion of retailing firms did not affect the results of the model negatively.

CHAPTER FIVE

RESEARCH METHODOLOGY

5.1 Introduction

Chapter one discusses briefly the research methodology that will be used in this study to test the applicability of Altman's and Springate's Z-scores in the South African context. In this chapter a more detailed discussion of the research methodology is required since the central part of research activity is to develop an effective research strategy or design. As discussed by Mouton (2001:56), research methodology focuses on the research process and the kind of tools and procedures to be used. This chapter will outline first research design that is suitable to the investigation, research methodology, the target population, the research sample, data collection, and statistical test applied in the study.

5.2 Research Design

Research design is defined by Welman & Kruger (2000:46) as a plan according to which research participants (subjects) are selected in order to collect information. Here, the description is what is going to be done with the participants with a view to reaching conclusions about the research problem. One of the most important issues in a research design is the aspects of empirical work that concerns the decisions such as what to be done on the population, which is the sample of that population, and which other populations are involved in the research to be establish (Jankowicz, 2000:199).

The critical significance of the research design is to hold all the parts and phases of the enquiry together. The research design tries to answer questions like what kind of study to be done, and what study type will best answer the research question. A poor design will fail to provide accurate answers to the question under investigation; a good research design will be precise, logic-tight and efficient.

There are different forms of in a research. Basically, one can distinguish between empirical and non-empirical studies. One can furthermore distinguish between primary (new) data versus the analysis of existing or secondary data; the nature of the data (numerical versus textual data), and the degree of control (highly structured conditions versus natural field settings). Within each basic form of research, more specific approaches are applicable. For instance, the sampling or selection of cases could be probabilistic or non-probabilistic, depending on the number of cases selected. The mode of observation or source of data also could be a survey or existing statistical data could be used (Mouton, 2001:154).

The research design choice of this study is comparative, which focuses on the similarities and especially differences between groups of units of analysis (Mouton, 2001:154). The study compares the individual company characteristics used to develop the models to the sample listed service and information companies in South Africa. The study will utilize ratios from the financial statements of the sample companies as a secondary data.

5.3 The research methodology

According to Jankowicz (2000:210), a research method is a systematic and orderly approach to the collection and analysis of data. What is collected is data, which is raw, specific, undigested and therefore largely meaningless. The analysis arranges the data in a meaningful manner and resolves research questions. There are several different analytical methods, which are commonly used in business and management research works. These methods vary according to the nature and scope of the topic and thesis, the sources of data to be used, the purposes of gathering data, the amount of control in obtaining the data, and assumptions to be made in analyzing the data.

The research methodology of this study first of all entails obtaining information of listed service and information technology companies in South Africa. From this list suspended companies were identified. Then actually failed companies were distinguished from the list of suspended companies. The failed companies were then compared to companies that matched in turnover and sector during the period 1999 to 2003.

5.4 The target population

The main objective of the study, as indicated in chapter one, is to test the practical applicability of Altman's and Springate's bankruptcy prediction models on service and information technology companies in the South African context.

The empirical study is based on the financial statements of the South African listed service and information technology companies. The target population for the information technology and service companies is established according to the Johannesburg Stock Exchange (JSE) sector classification. Table 5.1 shows the details of the listed service and information technology companies in the year 1999 to 2003.

Table 5.1: Listed Service and Information Technology companies according to JSE sector classification, 2004

JSE classification	
Banks	7
Real Estate	40
Support Service	21
Leisure and Hotels	16
Specialty and Other Finance	26
Insurance	16
Media and Entertainment	11
Health	3
Venture Capital	24
Development Capital	15
Investment Companies	12
Information Technology	29
Transport	10
Telecommunications	3
Total	233

Source: Bureau of Financial Analysis, 2004

According to Jankowicz (2002:192), sampling can be defined as the deliberate choice of a number of people, the sample, who are to provide you with data from which you will draw conclusions about some larger group, and the population, whom these people represent.

This study utilizes the listed service and information technology companies in South Africa as its population according to the Bureau of Financial Analysis classification. There are two ways in which you can draw a sample. Nonprobability sampling involves identifying and questioning informants because you are interested in their individual positions, role or background experience; it's likely that you'll want to pose different questions to them accordingly. In contrast, probability sampling involves in identifying and questioning people because they are members of some population (a section, department, organisation and so forth) and you want to ensure that your assertions are valid for your respondents and directly generalisable, without further inference, to that population (Jankowicz, 2002:193).

As the sampling methods differ in the type of study to be conducted, the research technique applied to get the sample of this study was the nonrandom sampling. The sampling used in the study is also limited to the number of service and information technology companies failed during the specified time period.

The research sample of this study is based on the number of failed service and information technology companies during 1999 to 2003. As a first step to identify the sample failed companies, list of South African listed service and information technology companies was examined thoroughly. After the identification of the sample failed companies, a matched sample of nonfailed companies were selected in relation to the size, turnover, and sector. The detailed procedure that was followed to select the sample companies will be discussed in the following section.

5.5 The research sample

A population frame is a listing of all elements such as people, product, firms etc. in the population from which the sample is to be drawn. The usefulness of the population frame in providing a listing of each element of the population is diminished if it is not be a current, updated document (Sekaran, 1992:225). Hence, the population frame must be current and consistent with the objectives of a study. Care must be given in to the question of inclusion and exclusion of sample elements from the population. This study utilizes the listed service and information technology companies in South Africa as its population according to the Bureau of Financial Analysis classification.

The value of the research information is largely dependent on the sample that represents the population under study. Welman & Kruger (2000:47-49) defined population as the study object, which may be individuals, groups, or the conditions, human products and events. The sample is a subset of the population that comprises some members selected from the population. The sample should be representative. Representativeness implies that the sample has the exact properties in the exact same proportions as the population from which it was drawn but in smaller numbers. Consequently, a representative sample is a miniature image, or likeness, of the population.

5.6 Sample Selection

The first sample was composed of 94 service and information technology companies of which 32 suspended and 62 nonsuspended. The next step dropped 8 suspended companies, which were suspended but did not actually fail, or due to irregular financial statement reports and the 16 nonsuspended companies that were matched by the similarity of turnover to those dropped companies. Therefore, the sample companies were reduced to 24 failed and 46 nonfailed companies. The mean turnover of the companies is R987 million with a range of between R0.150 million and R16,803 million.

The final sample test is conducted by adding six additional nonfailed real estate and ten information technology companies, to test the inconclusive results achieved by the first real estate and information technology sampled companies. These additional real estate and information technology companies are selected in relation to similarity of their turnover size to the sampled companies, and two other criteria being that they were a service or information technology company and availability of financial statements for at least one year. The main reason was to evaluate the prediction ability of the models in the real estate and information technology companies using substantial samples, as the first sample achieved inconclusive results specifically on the nonfailed companies.

Therefore, the final sample of the study is composed of 67 service and 19 information technology companies listed on the Johannesburg Security Exchange, with 24 failed and 62 nonfailed firms in each of the two groups. The failed group is companies that are stated as suspended and actually failed according to the Bureau of Financial Analysis of South Africa from 1999 through 2003. In the analysis, annual financial statements up to five years prior to bankruptcy (failed) or prior to 2003 (nonfailed) were used. The main reason for using more than one year's financial data is to evaluate the predictive ability of the above mentioned bankruptcy prediction models not only one year prior to bankruptcy but also to evaluate whether the models have more than one year predictive ability. The failed companies are matched to the nonfailed companies on the size of turnover and sector. For each failed company two nonfailed companies, which are in the same sector and with similar turnover, are selected. The mean turnover of the final sample companies is R1,051 million with a range of between R0.150 million and R20,677 million. Table 6.1 shows the sample companies' turnover distribution.

Table 5.2: Sample company turnover distribution, 2004

Turnover (Rand in millions)	Failed	Nonfailed	Added
< 1	1	1	
1 –10	3	2	1
11 – 100	10	24	5
101 – 500	6	10	7
501 – 1000	2	2	2
>1001	2	7	1
Total	24	46	16

The financial ratios for both models were calculated for each firm in both sampled groups. In the next step, the Altman and Springate z-scores were derived for each of these samples using the coefficients of original models. Companies were predicted to be failed or nonfailed based on these scores. The accuracies of the models z-score were calculated by dividing the number of firms correctly predicted by the total number of firms in the sample. Altman's and Springate's z-score cutoff point applied to classify failed and nonfailed companies are 2.675 and 0.862, respectively.

5.7 Methodology used in the selection of sample companies

The service and information technology companies are selected using three steps. The first step was to identify group one, which are companies categorized as suspended; the next step was to identify companies actually failed in the past five years from 1999 to 2003. In the third step, two companies, which are in the same industry and whose turnover size range is similar to that of the failed companies are selected.

5.8 Data collection

Mouton (2001:108) states that the aim of data analysis is to understand the various constitutive elements of one’s data through an analysis of the relationships between concepts, constructs or variables, and to see whether there are any patterns or trends that can be identified or isolated, or to establish themes in the data. According to Sekaran (1992:275), after data have been collected from a representative sample of the population, the next step is to analyze the data so that the research question or hypotheses can be tested. The steps needed to obtain data are:

- Identifying data,
- Getting a feel for the data,
- Testing the applicability of data, and
- Appling data to the research question.

These considerations were adhered to in the data collection process of this study. After the identification of the population, the data were collected in three steps. The first step was the identification of service and information technology companies from the list of listed companies from the Bureau of Financial Analysis. As the second step, the companies that failed in the year 1999 to 2003 and have financial statements for at least four years are identified. Then the nonfailed companies, which are similar to the failed companies in turnover and sector, were identified.

5.9 Statistical test applied

In this research study, different methods of statistical processing have been applied. SPSS, version 11.5 (Chicago: SPSS Inc.) software program exclusively applicable to statistical processing, is used for processing the data. Binomial statistical analysis, in addition to the usual descriptive statistical methods such as means, medians, standard deviation and frequency distribution, is used to analyse the percentages correctly and incorrectly classified by Altman's and Springate's bankruptcy prediction models.

5.10 Chapter Summary

In the chapter, the research methodology followed to achieve an acceptable result is discussed. The identification and definition of the target population in terms of the objectives of the study is presented. In the study, the sample companies are selected in relation to the sector and number of failed information technology and service companies. The characteristics of the failed companies are to be compared with matching samples of nonfailed companies. Data analysis is done using the binomial statistical technique and it is anaylsed satisfactorily. The next chapter will be the research data presentation, analysis and discussion.

CHAPTER SIX

DISCUSSION OF RESEARCH RESULTS

6.1 Introduction

Testing the practical prediction ability of bankruptcy prediction models is important as the inability to predict failure cause serious damage to the economic environment. Popular bankruptcy prediction models such as Altman and Springate are commonly used to evaluate the financial well being of companies. Hence, the study extensively uses the Altman (1968) and Springate (1978) bankruptcy prediction models and variables as a mechanism for exploring the characteristics of the failing and nonfailing sample companies to predict bankruptcy.

This chapter is devoted to the testing of Altman's (1968) and Springate's (1978) models to their practical prediction ability. The research question is whether these models are also applicable to information technology and services companies in South Africa, given that these models were originally developed for manufacturing and retail companies. The test of the applicability of these models using a sample of 86 service and information technology companies in South Africa listed on the Johannesburg Security Exchange is described. The results derived from the original Altman and

Springate models using the sampled companies' ratios to predict bankruptcy up to five years before the event of failure will be reported.

The multiple discriminant statistical methodology, used by both Altman and Springate models, investigates a set of financial and economic ratios in the context of bankruptcy prediction. In addition to the aggregate economic and other conditions related to an individual firm, the economic and financial ratios are most important predictive factors of a specific business entity as the fundamental business failure problem lie within the firm itself.

In this part of the study, the most important ratios developed by Altman and Springate are calculated, the individual firms' z-scores are derived and the results are presented.

6.2 Model Testing

Using the final year coefficients to predict bankruptcy based on data before the final year has the advantage of requiring data gathered for only one year for the matching firms. This is based on the assumption that the relationship between the variables is stable over time, which may not be logical. Following the pattern of changes in the variables over time may be useful in understanding the decline process. Therefore, in this study, the binomial statistical technique is applied to test the predictive ability of the models on data available up to five years before bankruptcy for both failed and nonfailed companies, and the analysis is repeated for each year. The raw data used to calculate the coefficients and the calculation of the Altman and Springate models are shown in Appendix A.

6.3 The Empirical Results, Analysis and Discussion

The objective of the empirical research is to present the relationship between the model's results calculated using the financial characteristics (ratios) of sample companies and the ability to classify as failed or nonfailed companies using the Altman's and Springate's bankruptcy prediction models. Therefore, the empirical results will test the models' accuracy in predicting the sample companies in total and per sector. Table 6.1 shows the description of failed and nonfailed sample service and information technology companies. In the study, the service and information technology companies are considered as industry and the companies in the industry are considered as sectors of the industry.

Table 6.1: Description of sample companies, 2004

Sector	Failed	Nonfailed	Added*	Total
Venture Capital	5	10		15
Real estate	4	8	6	18
Leisure & hotels	3	6		9
Development capital	2	4		6
Support services	3	6		9
Information technology	3	6	10	19
Specialty & other finance	1	2		3
Insurance	1	2		3
Investment companies	2	2		4
Total	24	46	16	86

****Additional real estate and information technology were selected for further analysis in these sectors because of the uncertain results derived from the first sampled companies.***

In the next section, the classification accuracy of the models to the sample companies is discussed. Evidence related to the models' predictive ability is reported. The empirical results are evaluated and presented using: (1) sample containing only failed companies, (2) sample containing only nonfailed companies, (3) sample containing both failed and nonfailed companies, and (4) a subset of different industries containing failed and nonfailed companies. In the following discussions, N is used to indicate the number of sample companies. As in real world the failed proportion is smaller than the nonfailed companies, the failed to nonfailed test proportion used is 0.28 to 0.72. Z1 refers to the z-score one year prior to bankruptcy (to failed) or the results for the financial year 2003 (to nonfailed), while Z5 refers to the z-score five years prior to failure or the z-score for the financial year 1999. The summary of z-score calculations is shown in Appendix B.

6.3.1 Altman's z-score prediction result

The prediction results of Altman's bankruptcy prediction model to the sample of failed and nonfailed companies are discussed below.

6.3.1.1 Failed companies

Table 6.2 discusses the classification result of failed companies using the Altman's model z-score. The model seems to be working in predicting the failed companies accurately. The accurate classification results for:

- One year financial statement prior to failure is 79 percent,
- Two years is 78 percent,
- Three years is 72 percent,
- Four years is 65 percent,
- Five year is 75 percent, and
- The average accuracy result for the five years is 74%.

These results show, even though the accuracy rate is not as high as the original results achieved by Altman that the 79 percent prediction rate is convincing to say the model is fairly accurate to predict bankruptcy. The declining rate shows the model's predictive ability reduces as failure becomes more remote. The overall average (74 percent) is good enough to conclude the Altman model is classifying reasonability accurate the sample failed companies.

Table 6.2: Failed companies prediction result of Altman's z-score, 2004

		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	19	.79	.25	.000
	Group 2	> 2.675	5	.21		
	Total		24	1.00		
Z2	Group 1	<= 2.675	18	.78	.25	.000
	Group 2	> 2.675	5	.22		
	Total		23	1.00		
Z3	Group 1	<= 2.675	13	.72	.25	.000
	Group 2	> 2.675	5	.28		
	Total		18	1.00		
Z4	Group 1	<= 2.675	11	.65	.25	.001
	Group 2	> 2.675	6	.35		
	Total		17	1.00		
Z5	Group 1	<= 2.675	12	.75	.25	.000
	Group 2	> 2.675	4	.25		
	Total		16	1.00		

6.3.1.2 Nonfailed companies

Altman's z-score classification results to nonfailed companies are depicted in table 6.3. The correct classification result for one year financial statement is too low (32 percent); two year financial statement accuracy rate is 33 percent. The correct classification in years three and four is 40 percent, and year five has accuracy rate of 47 percent. The average accuracy rate for the five years is 38 percent. The increasing percentage shows the abnormality of the model in predicting nonfailed sample companies.

Table 6.3: Nonfailed companies prediction result of Altman's z-score, 2004

		Category	N	Observed Prop.	Test Prop.	Asymp. Sig. (2-tailed)
Z1	Group 1	<= 2.675	42	.68	.25	.007
	Group 2	> 2.675	20	.32		
	Total		62	1.00		
Z2	Group 1	<= 2.675	41	.67	.25	.010
	Group 2	> 2.675	20	.33		
	Total		61	1.00		
Z3	Group 1	<= 2.675	36	.60	.25	.155
	Group 2	> 2.675	24	.40		
	Total		60	1.00		
Z4	Group 1	<= 2.675	37	.60	.25	.162
	Group 2	> 2.675	25	.40		
	Total		62	1.00		
Z5	Group 1	<= 2.675	30	.53	.25	.791
	Group 2	> 2.675	27	.47		
	Total		57	1.00		

6.3.1.3 Comparing failed versus nonfailed companies using Altman's model

Altman's model binomial test classification results of failed and nonfailed companies indicates the accuracy rates were significantly lower than the Altman's 95 percent classification accuracy rate, using the original sample reported by Altman (1968), refer to section 4.4.2.1. Although the predictive ability of the failed companies was almost acceptable, the real problem seems to be that the model incorrectly predicted failure amongst the nonfailing companies. Failure to predict nonfailed companies invalidates the general applicability of the model in the service and information technology companies.

6.3.2 Springate's z-score prediction results

The next section discusses the Springate's bankruptcy prediction model predicting results for the failed and nonfailed sample service and information technology companies.

6.3.2.1 Failed companies

The prediction results of Springate's z-score indicated in table 6.4 shows that the correct classification one financial statement prior to failure is 58 percent and year two classification result is 48 percent. Year three and four prediction results are 44 percent and 35 percent, respectively. The prediction result for year five is 50 percent, and the overall average accuracy of the model was 47 percent.

Table 6.4: Failed companies prediction result of Springate's z-score, 2004

		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	14	.58	.25	.001
	Group 2	> .8620	10	.42		
	Total		24	1.00		
Z2	Group 1	<= .86200	11	.48	.25	.015
	Group 2	> .86200	12	.52		
	Total		23	1.00		
Z3	Group 1	<= .86200	8	.44	.25	.057
	Group 2	> .86200	10	.56		
	Total		18	1.00		
Z4	Group 1	<= .86200	6	.35	.25	.235
	Group 2	> .86200	11	.65		
	Total		17	1.00		
Z5	Group 1	<= .86200	8	.50	.25	.027
	Group 2	> .86200	8	.50		
	Total		16	1.00		

6.3.2.2 Nonfailed companies

Table 6.5 depicts the classification results of Springate's z-score of nonfailed companies. The result for one year prior financial statement is 60 percent accuracy. Year two has 48 percent accuracy. In year three the accurate classification is 43 percent. Years four and five have correct classification of 55 percent and 54 percent, respectively. The average correct classification is 52 percent. The classification results using the Springate model are too low to predict nonfailed companies correctly.

Table 6.5: Nonfailed companies prediction results of Springate z-score, 2004

		Category	N	Observed Prop.	Test Prop.	Asymp. Sig. (1-tailed)
Z1	Group 1	<= .86200	25	.40	.25	.006
	Group 2	> .86200	37	.60		
	Total		62	1.00		
Z2	Group 1	<= .86200	32	.52	.25	.000
	Group 2	> .86200	29	.48		
	Total		61	1.00		
Z3	Group 1	<= .86200	34	.57	.25	.000
	Group 2	> .86200	26	.43		
	Total		60	1.00		
Z4	Group 1	<= .86200	28	.45	.25	.000
	Group 2	> .86200	34	.55		
	Total		62	1.00		
Z5	Group 1	<= .86200	26	.46	.25	.001
	Group 2	> .86200	31	.54		
	Total		57	1.00		

6.3.2.3 Comparing failed versus nonfailed companies using Springate's model

In all years, the binomial percentage shown is significantly lower compared to the original Springates' 92.5 percent accuracy rate, using the original sample reported by Springate (1978), refer to section 4.6. The prediction result is significantly too low to classify failed and nonfailed service and information technology companies correctly.

6.4 Comparing classification results of Altman versus Springate models

Summary classification results of both Altman and Springate models to the failed and nonfailed service and information technology sampled companies are shown in table 6.6 below. The Altman model seems to be more accurate in classifying the failed companies than Springate model. The prediction result of nonfailed companies using the Altman model is significantly weak. These results invalidate the prediction ability of the model to the service and information technology sampled companies. Although the Springate model predicted nonfailed marginally more accurate than the Altman model, the model still failed to predict both failed and nonfailed, which shows the model is not working to the sampled companies.

Table 6.6: Altman and Springate classification summary

	Altman		Springate	
Year	Failed	Nonfailed	Failed	Nonfailed
1	79	32	58	60
2	78	33	48	48
3	72	40	44	43
4	65	40	35	55
5	75	47	50	54
Average	74	38	47	52

6.5 Comparing failed versus nonfailed companies predictive accuracy

This section of the chapter will discuss the predictive accuracy of Altman's and Springate's models' z-scores in comparison to failed versus nonfailed companies. The model test results are presented one year, two years, and up to five years prior to bankruptcy, as it is preferred to analyze results individually. Lachenbruch (1967) as cited by Altman (1993:215) validation tests suggest an almost unbiased validation test of original sample results by means of jackknife approach: - that is one isolated observation at a time. The individual observation's classification accuracy is then cumulated over the entire sample.

6.5.1 Altman's z-score predictive result one year prior to failure

Table 6.7 shows the results using data compiled one financial statement prior to bankruptcy for the failed companies and one year financial statements of nonfailed companies. The model's classification accuracy is 45 percent of the total sample. The measure of success of the model in classifying the firms is calculated by adding the correctly classified sample companies (19+20) divided by total number of sample companies (86). The type I error, which is the prediction of failed companies as nonfailed is 6 percent, while the type II error, when companies which are actually nonfailed are predicted as failed, is much higher (49 percent). This implies the companies are wrongly predicted with financial problems while it is actually the opposite. Businesses, such as credit organizations, may not be willing to supply credit to these wrongly predicted companies in fear of potential bankruptcy. Therefore, the results show that the model is not classifying sample failed and nonfailed companies correctly.

Table 6.7: Altman's z-score classification result, one year prior to failure, 2004

Actual	Predicted		Total
	Failed	Nonfailed	
Failed	19	5	24
Nonfailed	42	20	62

6.5.2 Altman's z-score predictive result two years prior to failure

The figures displayed in table 6.8 shows the classification result of the model for companies using data complied two statements prior to bankruptcy. The classification accuracy is 45 percent. This result is expected to be weaker than the one year prior result, as impending failure is more remote and the indications are less clear. The type II error is also the same as the one year prior at 49 percent, which is too large. The test result to determine the accuracy of predicting failure for as much as five years prior to failure will be discussed next.

Table 6.8: Altman's z-score classification result, two years prior to failure, 2004

Actual	Predicted		Total
	Failed	Nonfailed	
Failed	18	5	23
Nonfailed	41	20	61

6.5.3 Altman's z-score long-range predictive results

The long-range predictive accuracy of the model shown in table 6.9 depicts the Altman model z-score predictive results. The table includes the results for years one and two, which was already discussed, to support the comparison of the results for the years three to five.

This analysis is important to examine the overall predictive effectiveness of the model for a longer period of time prior to failure, as many studies showed firms exhibiting failure tendencies as much as five years prior to actual failure. In determining these results, financial statements are gathered up to five years prior to failure. As some of the firms are in existence for less than three years, the number of sampled companies is reduced. It is expected to see the deteriorating results of predictive accuracy as the number of years to failure becomes more remote. However, the results achieved in this study for three to five years (50, 57, and 59 percent, respectively) are better than the Altman's original result for three, four and five years (48, 29, and 36 percent, respectively), (Altman, 1993:195).

It is also interesting to note that the results improve over the five year period. There seems to be no logical reason for this phenomenon. It is therefore concluded that, although the predictive ability of the Altman model is quite good three to five years prior to bankruptcy, these results are incidental. In addition, the weak performance of the Altman model one and two years prior to failure still invalidates the model.

Table 6.9: Altman's z-score classification results, five years prior to failure, 2004

		Hits			Misses			Percent
Year	N	Failed	Nonfailed	Total	Failed	Nonfailed	Total	correct*
1	86	19	20	39	5	42	47	45
2	84	18	20	38	5	41	46	45
3	78	13	26	39	5	34	39	50
4	79	11	34	45	6	28	34	57
5	73	12	31	43	4	26	30	59

****Total hits divided by total sample***

6.5.4 Springate's z-score predictive results one year prior to failure

Table 6.10 depicts the Springate's z-score classification accuracy of the sample for one year prior to failure financial statements or one year financial information of nonfailed companies. The model's classification accuracy is 59 percent of the total sample. The type I error is 12 percent while the type II error is much higher (29 percent). The results are therefore not encouraging.

Table 6.10: Springate's z-score classification results, one year prior to failure, 2004

Actual	Predicted		Total
	Failed	Nonfailed	
Failed	14	10	24
Nonfailed	25	37	62

6.5.5 Springate's z-score predictive result two years prior to failure

Table 6.11 shows the classification ability of the Springate's model for companies using data complied two financial statements prior to bankruptcy. The results of the model to classify sample companies correctly are significantly low (48 percent), that shows the model is not predicting accurately. Type I error is 12 percent and the type II error is 38 percent, which is too large. Springate's model test results to determine the accuracy of predicting failure up to five years prior to failure will be discussed next.

Table 6.11: Springate's z-score classification results, two years prior to failure, 2004

Actual	Predicted		Total
	Failed	Nonfailed	
Failed	11	12	23
Nonfailed	32	29	61

6.5.6 Springate's z-score long-range predictive result

The Springate model z-score prediction results for a longer period of time prior to failure are displayed in table 6.12. Financial statements are gathered and z-scores are calculated up to five years to analyse data, but due to lack of companies with financial statements more than two years, the number of sample companies was declining in the three to five years analysis. The prediction results of three, four and five prior financial statements are 44, 51, and 54 percent, respectively.

Table 6.12: Springate's z-score classification results, five years prior to failure, 2004

		Hits			Misses			Percent
Year	N	Failed	Nonfailed	Total	Failed	Nonfailed	Total	correct*
1	86	14	37	51	10	25	35	59
2	84	11	29	40	12	32	44	48
3	78	8	26	34	10	34	44	44
4	79	6	34	40	11	28	39	51
5	73	8	31	39	8	25	33	54

6.5.7 Long-term predictability: Altman versus Springate

Table 6.13 shows the Altman model z-score is better in classifying the failed companies than the Springate models'. On the other hand, the Springate model is better in classifying the nonfailed companies. Springate's correct total classification ability is relatively better in the first and second years, but it is weaker in the other years, than the Altman's model. However, the weak performance of the Altman model in the first two years prior to failure invalidates the Altman model even more than the Springate model.

Table 6.13: Altman and Springate failed and nonfailed correct classification

	Failed			Nonfailed			Percentage Correct	
Year	N	Altman	Springate	N	Altman	Springate	Altman	Springate
1	24	19	14	62	20	37	45	59
2	23	18	11	61	20	29	45	48
3	18	13	8	60	26	26	50	43
4	17	11	6	62	34	34	57	51
5	16	12	8	57	31	31	59	54

Although this discussion is addressing the relative value of the two models, the one and two years results for both models are validating the conclusion that both these models are not appropriate for predicting failure amongst service and information technology companies in South Africa.

Even though it seems as if the predictive ability of both improved from three to five years prior to bankruptcy, it must be coincidental, as this inconsistency is unexplainable and unacceptable. Both models have weak results in the long-range classification. Given the weak results of both models for one and two years prior to bankruptcy, as well as the coincidental improved results from 3 to 5 years prior to bankruptcy, it was decided to focus only on the one and two years prior to bankruptcy results in the following section.

6.6 Altman's and Springate's models sector predictive results

This study also evaluated whether the models are more useful for identifying failed companies in the different sectors of service and information technology companies. In the next section, the results of Altman's and Springate's z-scores to sector classification were presented to see whether the models provide more accurate classifications for companies in different sectors in contrast to the total sample. Subsets of the sample containing different sectors were used for this analysis. The author realises that the sample size in some of the sectors are too small to really make reliable conclusions, but it is still relevant to observe the results.

6.6.1 Altman's z-score sector classification for failed companies

Failed service and information technology sampled companies prediction results of Altman's bankruptcy prediction model are discussed in the following section.

a. Venture capital

Table 6.14 shows Altman's model z-score prediction results for the venture capital companies. The model is 100 percent accurate to predict failure one and two years prior to actual bankruptcy.

Table 6.14: Predicting failure amongst venture capital companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	5	1.00	.25	.001
	Total		5	1.00		
Z2	Group 1	<= 2.675	5	1.00	.25	.001
	Total		5	1.00		

b. Real Estate

Failure amongst real estate companies is predicted 100 percent accurately using the Altman's z-score for years one and two prior to failure, as shown in table 6.15 below.

Table 6.15: Predicting failure amongst real estate companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	4	1.00	.25	.004
	Total		4	1.00		
Z2	Group 1	<= 2.675	4	1.00	.25	.004
	Total		4	1.00		

c. Leisure & Hotels

Table 6.16 depicts the prediction results of leisure and hotels. The companies are predicted as failed 100 percent accurate using the Altman's z-score for one and two years prior to failure.

Table 6.16: Predicting failure amongst leisure and hotels companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	3	1.00	.25	.016
	Total		3	1.00		
Z2	Group 1	<= 2.675	3	1.00	.25	.016
	Total		3	1.00		

d. Development Capital

Predicting failure amongst development capital companies was 100 percent accurate using the Altman's z-score for year one and 50 percent for year two prior to failure, as shown in table 6.17 below.

Table 6.17: Predicting failure amongst development capital companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	2	1.00	.25	.063
	Total		2	1.00		
Z2	Group 1	<= 2.675	1	.50	.25	.438
	Group 2	> 2.675	1	.50		
	Total		2	1.00		

e. Support Service

Table 6.18 shows the prediction results of the support services. The companies are predicted as failed 67 percent accurate using the Altman's z-score for years one and two prior to failure.

Table 6.18: Predicting failure amongst support service companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	2	.67	.25	.156
	Group 2	> 2.675	1	.33		
	Total		3	1.00		
Z2	Group 1	<= 2.675	2	.67	.25	.156
	Group 2	> 2.675	1	.33		
	Total		3	1.00		

f. Information Technology

As shown in table 6.19, using the Altman model z-score the information technology prediction accuracy rate as failed for one and two years prior to failure is 33 percent and 50 percent, respectively, which is unacceptably low.

Table 6.19: Predicting failure amongst information technology companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	1	.33	.25	.578
	Group 2	> 2.675	2	.67		
	Total		3	1.00		
Z2	Group 1	<= 2.675	1	.50	.25	.438
	Group 2	> 2.675	1	.50		
	Total		2	1.00		

i. Investment Companies

Table 6.20 shows the prediction result of the model in the investment companies. In years one and two prior to failure, the investment companies are predicted 50 percent accurate using the Altman's Z-score model.

Table 6.20: Predicting failure amongst investment companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	1	.50	.25	.438
	Group 2	> 2.675	1	.50		
	Total		2	1.00		
Z2	Group 1	<= 2.675	1	.50	.25	.438
	Group 2	> 2.675	1	.50		
	Total		2	1.00		

There was one specialty and other finance, as well as one insurance company in the failed service and information technology sample. The Altman model z-score derived to the companies failed to predict the specialty and other finance, and classified correctly the insurance company. These results, given only one company per sector, are inconclusive, and will therefore be ignored for further decisions regarding the different sectors.

6.6.2 Altman's z-score sector classification for nonfailed companies

Detailed analysis of the various sector results using Altman's model z-score will be discussed next. Based on the inconsistent results of both models up to five years prior to bankruptcy, the detailed analysis per sector was only done for one and two years prior to bankruptcy.

a. Venture capital

Table 6.21 reports the classification accuracy of Altman's z-score when applied to the subset of nonfailed venture capital companies. The prediction accuracy as nonfailed is 30 percent in the first year and 33 percent in the second year.

Table 6.21: Predicting nonfailure amongst venture capital companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	7	.70	.25	.004
	Group 2	> 2.675	3	.30		
	Total		10	1.00		
Z2	Group 1	<= 2.675	6	.67	.25	.010
	Group 2	> 2.675	3	.33		
	Total		9	1.00		

b. Real estate

Accuracy rate as nonfailed for the real estate firms using the Altman's z-score, as shown in table 6.22, is 7 percent for one and two years prior to failure.

Table 6.22: Predicting nonfailure amongst real estate companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	13	.93	.25	.000
	Group 2	> 2.675	1	.07		
	Total		14	1.00		
Z2	Group 1	<= 2.675	13	.93	.25	.000
	Group 2	> 2.675	1	.07		
	Total		14	1.00		

c. Leisure and hotels

In the leisure and hotels sector of the service and information companies, the Altman's *z*-score model predicted nonfailure 17 percent accurate for one and two years, as shown in table 6.23.

Table 6.23: Predicting nonfailure amongst leisure and hotels companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	5	.83	.25	.005
	Group 2	> 2.675	1	.17		
	Total		6	1.00		
Z2	Group 1	<= 2.675	5	.83	.25	.005
	Group 2	> 2.675	1	.17		
	Total		6	1.00		

d. Development capital

As shown in table 6.24, the prediction accuracy of Altman's model *z*-score as nonfailed for the development capital is 25 percent for the one and two years.

Table 6.24: Predicting nonfailure amongst development capital companies using Altman *z*-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	3	.75	.25	.051
	Group 2	> 2.675	1	.25		
	Total		4	1.00		
Z2	Group 1	<= 2.675	3	.75	.25	.051
	Group 2	> 2.675	1	.25		
	Total		4	1.00		

e. Support services

Support services are predicted as nonfailed accurately 50 percent in one year and 67 percent in the second year, as shown in table 6.25.

Table 6.25: Predicting nonfailure amongst support service companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.765	3	.50	.25	.169
	Group 2	> 2.765	3	.50		
	Total		6	1.00		
Z2	Group 1	<= 2.765	2	.33	.25	.466
	Group 2	> 2.765	4	.67		
	Total		6	1.00		

f. Information technology

Table 6.26 is the prediction results achieved in the information technology companies. The companies are predicted as nonfailed, 50 percent in the first year and 56 percent in the second year.

Table 6.26: Predicting nonfailed amongst information technology companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.765	8	.50	.25	.027
	Group 2	> 2.765	8	.50		
	Total		16	1.00		
Z2	Group 1	<= 2.765	7	.44	.25	.080
	Group 2	> 2.765	9	.56		
	Total		16	1.00		

g. Specialty and other finance

The prediction results achieved for the specialty and other finance companies are shown in table 6.27. The companies are predicted accurately as nonfailed zero percent for the years one and two prior to failure.

Table 6.27 Predicting nonfailed amongst specialty and other finance using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.765	2	1.00	.25	.063
	Total		2	1.00		
Z2	Group 1	<= 2.765	2	1.00	.25	.063
	Total		2	1.00		

h. Insurance companies

Table 6.28 is the prediction results in the insurance companies. The companies are predicted accurately as nonfailed 50 percent for both years.

Table 6.28 Predicting nonfailure amongst insurance companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.765	1	.50	.25	.438
	Group 2	> 2.765	1	.50		
	Total		2	1.00		
Z2	Group 1	<= 2.765	1	.50	.25	.438
	Group 2	> 2.765	1	.50		
	Total		2	1.00		

i. Investment companies

Investment companies are predicted accurately as nonfailed 50 percent for years one and two, as shown in table 6.29.

Table 6.29: Predicting nonfailure amongst investment companies using Altman z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= 2.675	1	.50	.25	.438
	Group 2	> 2.675	1	.50		
	Total		2	1.00		
Z2	Group 1	<= 2.675	1	.50	.25	.438
	Group 2	> 2.675	1	.50		
	Total		2	1.00		

6.6.3 Altman’s model failed and nonfailed sector results summary

The summary of failed and nonfailed results is depicted in table 6.30. The Altman model classified 100 percent correct failed venture capital, real estate, leisure and hotels, and insurance companies. Development capital and support service classified as failed 75 percent and 67 percent, respectively. The model is significantly weak to classify information technology (42 percent), and investment companies (50 percent) as failed. The Altman’s model failed to predict the actual status of nonfailed companies in the venture capital, real estate, leisure and hotels, and development capital companies. The accuracy percentage achieved predicting failure is significantly weak. Average results derived to the sample nonfailed companies to predict as nonfailed are below 50 percent. The inability to predict non-failure amongst non-failing companies in the various sub-sectors, are illustrated by the following statistics. The percentages correctly predicting non-failure are:

- Venture capital companies - 32 percent,
- Real estate companies - 7 percent,
- Leisure and hotels companies - 17 percent,
- Development capital companies - 25 percent,
- Specialty and other finance companies - 0 percent,
- Insurance companies - 50 percent, and
- Investment companies - 50 percent.

The model looks better in classifying support service and information technology companies correctly as non-failed, with 59 percent and 53 percent, respectively. However, the results of venture capital, real estate, leisure and hotels, development capital, specialty and other finance, and insurance companies are still significantly weak classifying the companies correctly as non-failure.

Table 6.30: Altman sector failed and nonfailed results summary

	Failed			Nonfailed			N total	Total	Correct
Sector	N	Percentage	Rank	N	Percentage	Rank	prediction	sample	percentage*
Venture capital	5	100	1	10	32	4	8	15	0.53
Real estate	4	100	1	14	7	7	5	18	0.28
Leisure & hotels	3	100	1	6	17	6	4	9	0.44
Development cap.	2	75	2	4	25	5	2	6	0.33
Support services	3	67	3	6	59	1	6	9	0.67
Information tech.	3	42	5	16	53	2	10	19	0.53
Investment comp.	2	50	4	2	50	3	2	4	0.50

**** Total prediction divided by total sample***

N is number of sample companies

6.6.4 Springate's z-score sector classification for failed companies

The next section discusses the prediction results of failed venture capital, real estate, leisure and hotels, development companies, support services, information technology, specialty and other finance, insurance, and investment companies, using the Springate's z-score.

a. Venture capital

In table 31, the prediction result of failed venture capital is discussed. The companies are predicted 100 percent accurately using the Springate's Z-score.

Table 6.31: Predicting failure amongst venture capital companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	5	1.00	.25	.001
	Total		5	1.00		
Z2	Group 1	<= .86200	5	1.00	.25	.001
	Total		5	1.00		

b. Real Estate

The failed real estate companies are predicted accurately 75 percent in year one and two prior financial statements, as shown in table 6.32 below.

Table 6.32: Predicting failure amongst real estate companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	3	.75	.25	.051
	Group 2	> .86200	1	.25		
	Total		4	1.00		
Z2	Group 1	<= .86200	3	.75	.25	.051
	Group 2	> .86200	1	.25		

c. Leisure & Hotels

Table 6.33 shows the prediction accuracy of failed leisure and hotels. The companies are predicted accurately 50 percent for the years one and two prior financial statements.

Table 6.33: Predicting failure amongst leisure and hotels companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	2	.67	.25	.156
	Group 2	> .86200	1	.33		
	Total		3	1.00		
Z2	Group 1	<= .86200	1	.33	.25	.578
	Group 2	> .86200	2	.67		
	Total		3	1.00		

d. Development Capital

Failed development companies are predicted accurately 50 percent year one and zero percent years two prior financial statements as shown below in table 6.34.

Table 6.34: Predicting failure amongst development capital companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	1	.50	.25	.438
	Group 2	> .86200	1	.50		
	Total		2	1.00		
Z2	Group 1	<= .86200	0	.00	.25	.563
	Group 2	> .86200	2	1.00		
	Total		2	1.00		

E. Support Service

Table 6.35 shows the prediction rate of failed support services. The companies are predicted 83.5 percent accurate using the Springate's Z-score.

Table 6.35: Predicting failure amongst support service companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	1	.33	.25	.578
	Group 2	> .86200	2	.67		
	Total		3	1.00		
Z2	Group 1	<= .86200	0	.00	.25	.422
	Group 2	> .86200	3	1.00		
	Total		3	1.00		

f. Information Technology

Table 6.36 shows failed information technology Springate's z-score prediction result. The companies are predicted accurately zero percent for the two years prior financial statements.

Table 6.36: Predicting failure amongst information technology companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	0	.00	.25	.422
	Group 2	> .86200	3	1.00		
	Total		3	1.00		
Z2	Group 1	<= .86200	0	.00	.25	.563
	Group 2	> .86200	2	1.00		
	Total		2	1.00		

The Springate model z-score failed to predict accurately the specialty and other finance company in the sample. There was one insurance company in the sample of failed companies. But the model predicted correctly the company in the sample.

g. Investment Companies

Table 6.37 depicts the prediction result of Springate's model z-score. The investment companies are predicted accurately 50 percent, for years one and two.

Table 6.37: Predicting failure amongst investment companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	1	.50	.25	.438
	Group 2	> .86200	1	.50		
	Total		2	1.00		
Z2	Group 1	<= .86200	1	.50	.25	.438
	Group 2	> .86200	1	.50		
	Total		2	1.00		

6.6.5 Springate's z-score sector classification for nonfailed companies

In the next section, the prediction results of nonfailed venture capital, real estate, leisure and hotels, development companies, support services, information technology, specialty and other finance, insurance, and investment companies, using the Springate's z-score will be discussed below.

a. Venture capital

Table 6.38 shows the Springate accuracy rate for the nonfailed venture capital companies. The firms' classification result is 40 percent for years one and 22 percent year two, prior financial statements.

Table 6.38: Predicting nonfailure amongst venture capital companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	6	.60	.25	.020
	Group 2	> .86200	4	.40		
	Total		10	1.00		
Z2	Group 1	<= .86200	7	.78	.25	.001
	Group 2	> .86200	2	.22		
	Total		9	1.00		

b. Real estate

As shown in table 6.39, the accurate prediction results for the real estate companies are 64 percent in the first year, and 29 percent for year two prior financial statements.

Table 6.39: Predicting nonfailure amongst real estate companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	5	.36	.25	.258
	Group 2	> .86200	9	.64		
	Total		14	1.00		
Z2	Group 1	<= .86200	10	.71	.25	.000
	Group 2	> .86200	4	.29		
	Total		14	1.00		

c. Leisure and hotels

Leisure and hotels are predicted accurately 33 percent for the years one and two, as shown in table 6.40 below.

Table 6.40: Predicting nonfailure amongst leisure and hotels companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	4	.67	.25	.038
	Group 2	> .86200	2	.33		
	Total		6	1.00		
Z2	Group 1	<= .86200	4	.67	.25	.038
	Group 2	> .86200	2	.33		
	Total		6	1.00		

d. Development capital

Table 6.41 depicts the prediction results for the development capital, which is predicted accurately 25 percent for the years one and two, prior financial statements.

Table 6.41: Predicting nonfailure amongst development capital companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	3	.75	.25	.051
	Group 2	> .86200	1	.25		
	Total		4	1.00		
Z2	Group 1	<= .86200	3	.75	.25	.051
	Group 2	> .86200	1	.25		
	Total		4	1.00		

e. Support services

Springate's model prediction accuracy for nonfailed support services is 83 percent accurate for the year. And the model is accurate 100 percent for year two, as shown in table 6.42 below.

Table 6.42: Predicting nonfailure amongst support service companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	1	.17	.25	.534
	Group 2	> .86200	5	.83		
	Total		6	1.00		
Z2	Group 1	<= .86200	0	.00	.25	.178
	Group 2	> .86200	6	1.00		
	Total		6	1.00		

f. Information technology

As shown in table 6.43 below the model is accurate for the classification of nonfailed information technology companies 81 percent for the years one and 69 percent for the year two, prior financial statements.

Table 6.43: Predicting nonfailure amongst information technology companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	3	.19	.25	.405
	Group 2	> .86200	13	.81		
	Total		16	1.00		
Z2	Group 1	<= .86200	5	.31	.25	.370
	Group 2	> .86200	11	.69		
	Total		16	1.00		

g. Speciality and other finance

Specialty and other finance are predicted accurately 100 percent for the years one and 50 percent for the year's two, prior financial statements, as shown in table 6.44.

Table 6.44: Predicting nonfailure amongst specialty and other finance companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	0	.00	.25	.563
	Group 2	> .86200	2	1.00		
	Total		2	1.00		
Z2	Group 1	<= .86200	1	.50	.25	.438
	Group 2	> .86200	1	.50		
	Total		2	1.00		

h. Insurance companies

Table 6.45 shows the prediction accuracy of the model for the nonfailed insurance companies. The prediction rate is zero percent for the years one and 50 percent for the years two, prior financial statements.

Table 6.45: Predicting nonfailure amongst insurance companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	2	1.00	.25	.063
	Total		2	1.00		
Z2	Group 1	<= .86200	1	.50	.25	.438
	Group 2	> .86200	1	.50		
	Total		2	1.00		

i. Investment companies

The prediction accuracy of the model for the nonfailed investment companies is 50 percent for the years one and two, as shown in table 6.46 below.

Table 6.46: Predicting nonfailure amongst investment companies using Springate z-score, 2004

Year		Category	N	Observed Prop.	Test Prop.	Exact Sig. (1-tailed)
Z1	Group 1	<= .86200	1	.50	.25	.438
	Group 2	> .86200	1	.50		
	Total		2	1.00		
Z2	Group 1	<= .86200	1	.50	.25	.438
	Group 2	> .862000	1	.50		
	Total		2	1.00		

6.6.6 Springate's model failed and nonfailed sector results summary

The following table 6.47 summarizes the prediction results of failed and nonfailed sampled companies using the Springate's model z-score results.

Table 6.47: Springate sector failed and nonfailed results summary, 2004

	Failed			Nonfailed			Total	Total	Correct
Sector	N	Percentage	Rank	N	Percentage	Rank	prediction	sample	percentage*
Venture capital	5	100	1	10	31	6	8	15	0.53
Real estate	4	75	2	14	47	4	10	18	0.56
Leisure & hotels	3	50	3	6	33	5	3	9	0.33
Development cap.	2	25	4	4	25	7	2	6	0.33
Support services	3	100	1	6	92	1	9	9	1.00
Information tech.	3	0	5	16	75	2	12	19	0.63
Investment comp.	2	50	3	2	50	3	2	4	0.50

Total prediction divided by total sample

N is number of sample companies

The Springate model seems to be better to predict failed venture capital (100 percent), support services (100 percent), real estate (75 percent), companies as failed. The model is significantly weak to classify failure correctly amongst development capital (25 percent), information technology (0 percent), and leisure and hotels (50 percent), and investment companies (50 percent).

The Springate model classification percentage for nonfailed venture capital, real estate, leisure and hotels, development capital, and investment companies shows significantly weak results. The results imply the model is not working in the prediction of these nonfailed venture capital, real estate, leisure and hotels, development capital, and investment companies. The model seems to be better in correctly predicting non-failure amongst support service (92 percent), and information technology (75 percent) companies.

6.6.7 Comparing Altman and Springate sector classification results

Table 6.48 depicts a comparison of Altman and Springate bankruptcy prediction models sector results. Best classified failed companies using both models correctly as failed are venture capital, real estate, and leisure and hotels. Altman model was stronger than Springate in predicting failed development companies and support services companies. Failed information technology companies are predicted significantly weak using both models. Both Altman and Springate models are not successful to classify nonfailed sampled companies. Only nonfailed support services, information technology, and real estate companies are classified best as non-failure using the Springate model.

Table 6.48: Summary of Altman and Springate sector classification results, 2004

	Companies		Altman model				Springate model			
			Failed		Nonfailed		Failed		Nonfailed	
Sector	Failed	Nonfailed	One	Two	One	Two	One	Two	One	Two
Venture Capital	5	10	100	100	30	33	100	100	40	22
Real estate	4	14	100	100	7	7	75	75	64	29
Leisure & hotels	3	6	100	100	17	17	67	33	33	33
Development Capital	2	4	100	50	25	25	50	50	25	25
Support services	3	6	67	67	50	67	33	0	83	100
Infor. Technology	3	16	33	50	50	56	0	0	81	69
Investment companies	2	2	50	50	50	50	50	50	50	50
Average			79	74	33	36	54	44	54	47

The Altman and Springate models results for the failed and nonfailed sampled companies of service and information technology are inconsistent in predicting failure and non-failure to the sub-sector companies. The 100 percent prediction results achieved using Altman model to venture capital, real estate, and leisure and hotels, is not consistent to the results of the same nonfailed companies to predicted as non-failure, the results were less than 30 percent correct classification. The same argument applies to the Springate model performance to predict non-failure amongst the support services and information technology, as it is inconsistent to the weak prediction results of failed support service and information technology companies.

6.7 Chapter Summary

The main goal of the chapter was the presentation and analysis of the empirical study to test the practical predictive ability of Altman's and Springate's z-scores in services and information technology companies. In the chapter the research results were presented, analysed, and discussed.

The analyses of empirical data are presented in three sections. The first part discussed the Altman's and Springate's z-score classification results to the failed and nonfailed sampled companies. The second part discussed the predictive results of these models from one to five years prior to bankruptcy. The success of these models depends not only on the ability to predict failure correctly, but also to correctly predict non-failure amongst the non-failure non-failed sampled companies. In the last section the predictive accuracy was discussed in relation to different sub-sectors in the service and information technology companies.

The first part of the analysis, focusing on the classification results for failed and nonfailed companies, shows the Altman and Springate models' failure to classify sampled companies as failed or nonfailed correctly. In the second part of the analysis, although the models seem to be improved in the predictive ability, it is inconsistent and invalid as the results of one and two years prior to failure are not satisfactory. Both models are also weak in the long-range predictive ability.

The analysis of Altman and Springate models to predict failure and non-failure in the services and information technology sub-sector companies was performed to investigate if the models are applicable to predict failure in some sub-sectors than the other. However, the results are inconsistent to predict the sampled companies correctly as failure or non-failure. Some sectors are predicted correctly in failure but are not predicted as nonfailed, which creates inconsistency and lack of generalizability of the models.

CHAPTER SEVEN

CONCLUSION

7.1 Introduction

The central theme of the study is to investigate the prediction ability of Altman (1968) and Springate (1978) bankruptcy prediction models in sampled services and information technology companies in South Africa. As financial analysts and researchers use bankruptcy prediction models routinely to evaluate the financial health of companies, testing the practical applicability of models is essential. Improper application of models may lead into mistaken managerial judgments and misunderstanding of actual facts that may lead to wrong conclusions and decisions. It is important for the business society such as creditors, customers, suppliers, employees, and government in general to know the financial well being of companies. Early awareness of financial distress may help finding immediate solutions to the problems, or the partners may know the consequences of the problems and be aware in advance. Failing to predict bankruptcy causes damage not only for the company failing but also affects all the creditors of the failing business as well as the economic environment of a society. The major reason why business failure has such a major impact on the economy of a country is the costs associated with going bankrupt.

There are sound theoretical and practical reasons for business failure to be an important interest to researchers from the fields of accounting, economics, and finance. Some of the main concerns to investigate bankruptcy are:

- The impact of bankruptcy on the economy of a country is not negligible.
- The long process of bankruptcy is costly, economically disastrous and requires involvement of legal proceedings.
- The substantial increase in business failures, and resultant losses of business partners, such as creditors, suppliers, financial institutions, customers, employees, and shareholders.
- The increase in the size of liabilities of failed companies and the proportion of large firms that file for bankruptcy.
- Successful and promising companies are seen going bankrupt.

There is, therefore, a need to create and explore all possible means by which business failures can be predicted in their early stages and thus permitting quick remedial action. Bankruptcy prediction is also a powerful tool to help identify and rectify financial problems before they reach a crisis. Hence, the losses associated with failure may be avoided or at least be minimized.

The Altman and Springate bankruptcy prediction models were developed using samples of predominantly manufacturing firms during 1968 and 1978, respectively. Even though these models were developed about three decades ago, they still seem to be popular and applied regularly by financial institutions and other companies today to predict failure. The models' coefficients were also developed using sample companies during the 1960's and 1970's, but these coefficients are continued to evaluate the financial health of companies at present. The models reliability when applied to current companies from various industries depend on the prediction ability of the models regardless the type of industry, time horizon and/or country. These models used to derive best discriminating variables using the original sample manufacturing companies. The problem is these variables may not be reliable predictors in other industries or time periods. As the relative importance of the variables changes over time, the coefficients may not be stable even if the variables included in the model were accurate predictors.

The main concern of the study is therefore to what extent these models are applicable to predict failure in the South African sample services and information technology companies. Hence the primary and secondary objectives of the study to investigate the models applicability are as follows:

- The primary objective is to test the practical applicability of Altman's and Springate bankruptcy prediction models to South African service and information technology companies listed on the Johannesburg Security Exchange during 1999 to 2003.
- The secondary objective is to comment on the application correctness to predict failure of the models according to the results derived from the empirical study.

With these objectives in mind, the study attempted to answer the following research questions using the South African sample services and information technology companies:

- Whether Altman's and Springate models z-score can be applied to predict bankruptcy using recent financial information.
- Whether the models are useful for predicting bankruptcy for non-manufacturing firms, such as service and information technology

companies, as they are for predicting bankruptcy of manufacturing firms.

- Whether the practical applicability of the models is still justifiable in the current South African economic environment.

The study attempted to address the objectives by employing a sample of 86 (24 failed and 62 nonfailed) service and information technology companies listed on the Johannesburg Security Exchange of South Africa. Two nonfailed companies are matched to each failed company by the similarity of sector and turnover. There are six real estate and ten information technology companies added to the first sample of companies, to evaluate the prediction ability of the models in these sectors using substantial samples, as the first sample results were inconsistent, specifically on the nonfailed companies (see paragraph 6.2). The main reasons for focusing on the services and information technology companies were threefold:

- The services and information technology industries are currently much more dominant than manufacturing, relative to 30 years ago.
- These industries are characterized by different sets of financial norms.
- The rapid change makes bankruptcy prediction more difficult in services and information technology companies.

7.2 Conclusions and recommendations

The conclusions and recommendations of the study to test the Altman and Springate bankruptcy prediction models in the service and information technology companies are presented in the next section.

7.2.1 Conclusions

The results on the failure prediction ability of Altman and Springate models to the services and information technology sampled companies are presented in chapter 6. The analysis was conducted in three steps. Firstly, the prediction ability of the models were tested on the total sample of failed and nonfailed service and information technology sampled companies up to five years prior to failure and the average prediction accuracy is analysed. Secondly, the models are tested on an annual basis prior to bankruptcy. The final analysis was the testing of the prediction ability of the models to the different sub-sectors of the service and information technology industry. The main conclusions of the study according to the analyses are:

a. Concluding results of total failed and nonfailed companies

- The Altman model shows average classification results of 74 percent accuracy rate in the failed sampled companies. This result is convincing that the Altman model is reasonably accurate to classify the failed companies correctly over five years, but it is still weaker than the Altman's original result (95 percent). Although an average accuracy rate of 74 percent over 5 years to bankruptcy seems to be reasonable, it is the opinion of the author that the success rate is too law, therefore, it invalidates the application of the Altman model in the services and information technology companies to predict failure.

- The average classification accuracy of the Altman model to the nonfailed sampled companies is 38 percent, which is significantly weaker than expected to classify nonfailed companies as non-failure compared to the Altman's 96 percent accuracy using the original sample. Although the model seems to predict failed companies reasonably well, the major problem with the model is the inability to predict the nonfailing sampled companies correctly. Therefore, failure to predict nonfailed companies correctly invalidates the general applicability of the Altman model in the service and information technology companies completely (see section 6.5.1.3).

- The results of the Springate model to classify sampled failed and nonfailed companies correctly is significantly weaker (47 percent failed and 52 percent nonfailed) compared to the original Springates' 92.5 percent accuracy rate, using the original sample reported by Springate (1978). The prediction results are too low to classify failed and nonfailed service and information technology companies correctly (see section 6.5.3). Hence, the results show that the model is not successful to classify the sampled companies correctly; as a result the application of the Springate model to the services and information technology companies of South Africa is not justifiable.

- When the classification results of Altman and Springate are compared, the Altman model seems to be more accurate in classifying the failed companies in comparison to the Springate model. But the prediction result of nonfailed companies using the Altman model is significantly weak, that invalidates the prediction ability of the model to the service and information technology sampled companies. The Springate model predicted nonfailed companies marginally more accurate than the Altman model, but as the model still failed to predict both failed and nonfailed companies accurately, the model is not successful to predict sampled companies correctly (see section 6.6). Therefore, both the Altman and Springate models are not accurate predictors of service and information technology companies of South Africa.

b. Concluding results on comparing failed and nonfailed companies on annual basis

- In the one year prior to failure, the Altman model was 45 percent accurate to classify sampled companies correctly, with type I and type II errors of 6 and 49 percent, respectively. These results indicate that the Altman model is significantly weak to classify the sampled companies correctly as failed and nonfailed.

- The classification accuracy two years prior to failure is 45 percent. The results achieved for years three to five prior to failure are 50 percent third year, 57 percent fourth year, and 59 percent fifth year. Although the predictive accuracy of the Altman model is improving on the three to five years prior to failure, the weak results of one and two years prior to failure invalidates the predictive ability of the model.

- The Springate model classification result one year prior to failure is 59 percent accurate to classify sampled companies correctly. The type one and type two errors of the Springate model is 12 and 29 percent, respectively. The prediction accuracy is too weak to classify sample companies correctly as failed and nonfailed; therefore the model is not successful to predict failure in the sampled companies.

- The two years prior to failure prediction accuracy of Springate model is 48 percent. In the three, four and five years prediction result, the model achieved a 44 percent, 51 percent, and 54 percent accurate classification results, respectively. Which is significantly weak to predict failure accurately on the sampled companies.

- Comparing the Altman and Springate models, the results on the annual basis for failed and nonfailed sampled companies show the Altman model is better in classifying the failed companies correctly than the Springate model. On the other hand, the Springate model is better in classifying the nonfailed companies correctly. Springate model correct total classification ability is relatively better in the first and second years, but it is weaker in the other years, than the Altman's model. However, the weak performance of the Altman model in the first two years prior to failure invalidates the Altman model even more than the Springate model (see section 6.7.7).

c. Concluding results of sub-sector sampled companies

- In the sub-sector classification test, the findings indicate that the Altman (1968) model was more reliable when used to predict failed sample venture capital, real estate, leisure and hotels, and development capital companies, which is 100 percent; and support service 67 percent predicted correctly as failed; than when used to predict information technology (42 percent) and investment companies (50 percent) in the one and two years prior to failure. The specialty and other finance and insurance sample companies results are ignored in the conclusion as the sample size of the sub-sectors are not substantial enough to deduct conclusion on the sub-sector.

- The Altman model is not successful in classifying the nonfailed companies as nonfailed in the one and two years prior to failure; the accuracy rate for venture capital is 32 percent, 7 percent for real estate, 17 percent for leisure and hotels, 25 percent for development capital, 59 percent for support services, 53 percent for information technology, and 50 percent for investment companies. Hence, it can be deducted that failure to predict nonfailed sample companies as nonfailed invalidates the accuracy results achieved on the failed sample companies to classify as failed, as the model expected to predict both failed and nonfailed sample companies correctly (see section 6.8.3). Although certain sub-sectors achieved slightly better results, not one of these sub-sectors had results justifying the application of the Altman model.

- The Springate's model sub-sector classification seems successful in the prediction of failure to the failed venture capital (100 percent), and real estate (75 percent) companies. The model was not successful to predict failure correctly to the failed leisure and hotels (50 percent), development capital (25 percent), information technology (0 percent), support services (33 percent), and investment companies (50 percent).

- Nonfailed support services and information technology sample companies are classified correctly best using the Springate as nonfailed with a prediction rate of 92 percent and 75 percent. The Springate model was not successful to predict nonfailed real estate (47 percent), leisure and hotels (33 percent), development capital (25 percent), and investment companies (50 percent) correctly as nonfailure. Hence, the model is successful only to predict four failed and four nonfailed sample companies correctly, which is less than 50 percent of the sample companies.

- Therefore, it can be concluded that both Altman and Springate models are inconsistent to predict failure and non-failure at the same time on one sub-sector. The Altman model only predicted support services 67 percent as failed and 59 percent as nonfailed correctly, which is slightly better although it is significantly low compared to Altman's original accuracy rate. This results show that the models are not applicable to predict a specific sub-sector correctly in the service and information technology companies.

It is generally assumed bankruptcy prediction models are useful regardless of the industry and time horizon. The findings reported in the study for each model indicates that the overall accuracy rate of the Altman and Springate models were reduced when used on the South African sample. These results suggest that the Altman and Springate z-score models are not accurate predictors, and consequently, the models are not advised to be used in predicting failure in the non-manufacturing firms, especially, in current South African services and information technology companies.

7.2.2 Recommendations

It is important researchers and analysts understand prediction models during their application. That is, practitioners should not assume that a model's predictive accuracy could transcend to industries other than those used in the development of the model. Models developed using firms from one set of industries may not be highly accurate in predicting bankruptcies for firms in other industries. The findings discussed above indicated that the use of Altman's and Springate's models to predict failure for service and information technology companies is questionable. Hence, applications of these models to South African services and information technology companies are not advisable.

According to the empirical results the research study recommendations are as follows:

- The development of a practically applicable bankruptcy prediction model is recommended to the services and information technology companies of South Africa. Identifying reliable and representative sample companies is important during the development of the models.

- In the implementation of bankruptcy prediction models, the incorporation of other important indicators of financial soundness of business organizations, such as stock ratings, current legal affairs, government policies, and economic environment, are recommended.

- It is recommended the practical applicability of bankruptcy prediction models should be checked after some period of time as the economy changes. Therefore, the identification of reliable models will help analysts to predict financial distress precisely.

7.3 Limitations of the research study

The purpose of this section is to suggest some problems that were not adequately covered in this study. The study deliberately excluded some important data because of the availability of financial statements was insufficient to address the issues on hand. For example, in the transport sector, there was one failed company but the problem was to find matching nonfailed companies. The data collection was more of a problem in this study.

The problem was lack of sufficient sampled companies in some sectors such as in the specialty and other finance and insurance service companies. The limited number of failed companies was another limitation to test the models using more companies in the industry.

7.4 Further research

The study tried to strengthen the position of existing work in bankruptcy prediction, particularly based on the Altman and Springate models. A number of research areas could be provided from the practical application of bankruptcy prediction models. Presented below are few suggestions researchers might extend this research in several directions.

a) Testing the application of other models to the firms in the database developed in this study would be a useful extension.

b) Developing new bankruptcy prediction models using service and information technology sample companies.

c) Testing the application of Altman and Springate models in the manufacturing and retailing companies in South Africa.

d) Researchers should also investigate development of bankruptcy prediction models using different statistical methodology other than multivariate discriminant analysis, such as artificial neural networks (ANNs), logit or probit analysis, to compare and select the most efficient model.

e) Another research area that could be extended is to test bankruptcy prediction models to the non-listed, relatively smaller turnover sized firms where the incidence of business failure is greater than larger corporations.

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APPENDICES

Appendix A: Failed and nonfailed sampled companies financial information

Failed sampled companies

	Venture Capital					Real Estate				Leisure & Hotels		
	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**	**F12**
Year 1	**2002**	**2003**	**2000**	**2000**	**2003**	**2003**	**2001**	**2002**	**2003**	**2002**	**1999**	**1999**
Turnover	5,278	5,297	1,607	60,602	261	35,562	95,850	116,397	85466	42,365	1,167,617	90,185
EBIT	-12,998	-941	-8,073	-1,367	-92	3,300	68,815	63,395	68703	-679	213672	-6,497
WC	-6,298	-5,170	332	-11,888	-11,803	61,809	-342,050	-20,105	-7671	-14,457	525,882	-17,530
RE	-57,680	-23,699	1,799	31,087	-15,335	-53,683	379	10,204	401223	5,321	240,301	202,932
Total Liab.	13,407	20,096	168	644	11,835	264,471	797,842	488,067	13838	23,518	883,113	4000
Mkt v.of eq.	2561	113	-19,207	-18,171	118	408	25011	6,478	5267	354	73,009	417
Totla Assets	7,112	9,119	796	37,702	23,418	405,941	869,192	649,819	394738	50,234	1,484,684	45,404
EBT	-14,188	-1,685	-8,112	-4364	-92	-30,114	9695	-4,116	18032	-754	159,038	-16,565
CL	6,324	5,675	636	32,140	11,835	153,619	363,860	23,182	16,892	17,020	415,448	28,363
Year 2	**2001**	**2002**	**1999**	**1999**	**2002**	**2002**	**2000**	**2001**	**2002**	**2001**	**1998**	**1998**
Turnover	2,031	4,988	1,568	56,126	215	51,866	62,927	113,050	61835	43,076	879,874	77,362
EBIT	-10194	-919	-11,057	-12,155	-2026	28,045	40,098	82,019	31522	-1,098	138975	23,137
WC	-3,000	-5,239	2,456	-5,175	-11,711	84,500	-48,707	-13,217	-10789	-3,018	244,730	-2,003
RE	-43,719	-17,406	10,349	24,584	-13,228	-23,569	354	20,358	335220	6,075	116,507	213,165
Total Liab.	14,495	18,813	880	23167	11,749	235,948	-48,707	491,843	13678	17,735	598,711	11300
Mkt v.of eq.	3801	113	-11,095	-18,399	103	1362	26382	6,478	-9271	839	58,014	-79,889
Totla Assets	14,574	11,330	2,148	27,840	23,425	407,532	371,924	662,449	343944	45,205	899,767	38,754
EBT	-11,065	-1,725	-11,095	-13810	-2026	1,082	299	12,743	-8677	-1,177	97,734	15,137
CL	3,113	5,680	1934	21,603	11,749	124,822	62,129	18,906	24,311	11,225	304,500	18,335
Year 3	**2000**	**2001**			**2001**	**2001**	**1999**	**2000**		**2000**	**1997**	
Turnover	0	5,948			257	14,482	51,245	91,362		45,702	643,536	48,733
EBIT	-229	-367			-4553	27,923	38,036	68,016		6180	123,976	17,328
WC	28,208	-6,174			-12,082	273,544	-58,124	-13,444		11,291	268,298	88,902
RE	-39,737	-15,681			-8,675	-24,650	288	13,549		58,905	107,575	177,465
Total Liab.	40,484	17,383			12,259	166,816	356,284	501,587		18,959	373,085	23,800
Mkt v.of eq.	534	97			410	2179	23509	10,006		1,219	74,922	-90,404
Totla Assets	46,768	11,625			25,298	337,318	357,225	664,859		125,397	614,680	15,792
EBT	-4,414	-1,266			-4,553	14,474	770	3,520		6,165	98,687	9,667
CL	2,144	6,543			12,259	5,536	72,399	17,807		10,358	176,950	5,257
Year 4	**1999**	**2000**			**2000**	**2000**	**1998**	**1999**		**1999**	**1998**	
Turnover	2,089	7,999			412	28,252	44,122	34,136		42,236	322,285	
EBIT	-5068	-252			-30	15966	34,597	25656		6,138	60232	
WC	28,400	-7,147			-1,623	207,092	-21,091	-3,592		30,551	152,644	
RE	-35,323	-14,415			-8,645	-39,124	237	-396		78,934	35,084	
Total Liab.	35,596	17,648			1,648	156,473	354,023	189,433		31,243	228,438	
Mkt v.of eq.	1,425	129			9450	1362	20113	10149		5,296	61,045	
Totla Assets	45,045	13,156			19,613	312,502	354,913	309,491		131,572	402,804	
EBT	-10,627	-1,517			-30	6,744	811	6,571		6,068	49,311	
CL	1,559	7,704			1,648	10,842	70,159	6,877		8,822	119,890	

Year 5		**1999**			**1999**	**1999**	**1997**	**1998**		**1998**	**1997**	
Turnover		8,416			356	44,813	39,642	26,629		70,028	178,586	
EBIT		-4,666			-979	30905	32,575	20,963		67824	35906	
WC		-8,070			-1,594	193,292	-3,924	-5,031		28,527	52,933	
RE		-12,898			-7,666	-6,642	194	1,022		62,635	5,883	
Total Liab.		16,651			1,640	178,868	310,565	158,816		63,553	118,227	
Mkt v.of eq.		354			9000	10893	28406	8,625		13,014	16,369	
Totla Assets		13,676			19,616	367,378	311,412	243,771		159,634	159,340	
EBT		-6,829			-979	10,237	767	1,023		65,812	29,450	
CL		8,643			1,640	30,992	26,628	7,567		34,285	44,210	

Where:
EBIT = Earnings before interest and taxes
WC = Net working capital
RE = Retained earnings
EBT = Earnings before tax
CL = Current liabilities
F = Failed company
NF = Nonfailed company

Nonfailed sampled companies continued

Dev't Capital		Support Service			Info. Tech.			Spe. & O. F.	Insurance	Inves. Comp.	
F13	**F14**	**F15**	**F16**	**F17**	**F18**	**F19**	**F20**	**F21**	**F22**	**F23**	**F24**
2003	2002	1999	2002	2001	2000	2000	2000	2002	2002	2003	1999
62,987	99,604	404,557	2,385,878	68,321	3,495,072	107,183	83,056	634,179	391,563	508,559	3,038,800
-11,358	6485	101934	74274	-18,324	104764	52,937	10,263	277163	-21741	-795792	566000
1,446	-16,523	-7,587	67,552	-5,116	355,666	34,247	27,873	916,765	58,164	410,922	664,900
-29,169	-85,088	-414,704	91,849	15,609	294,058	81,997	82,364	969,956	18,317	-602,655	816,700
29,748	53,764	321,122	484,207	892	955,389	66,880	13,356	139,547	347,195	552,663	533,300
4058	1122	21,636	27,900	-16,823	34,792	-2,881	-3,273	431,826	2,062	42258	51,862
20,384	49,305	412,569	625,057	21,058	1,272,384	45,904	44,255	1,170,802	383,455	1,097,682	1,390,200
-8,995	4,887	74,109	50,302	-18,469	57,635	52,906	9,013	269,794	-22,882	-833,487	554,800
18,402	51,943	171,810	467,761	19,918	809,548	43,400	22,162	126,463	75,038	233,236	508,000
18mnth	**2001**	**1998**	**2001**	**2000**	**1999**		**1999**	**2001**	**2001**	**2002**	**1998**
192,344	73,478	309,375	586,087	326,981	2,646,933		24,703	762,649	382,376	390,266	16,374,700
-10,062	12927	83383	79674	29,532	69379		10,307	400089	5960	-537055	639500
27,238	-27,972	53,521	100,161	14,986	221,345		12,513	643,221	59,585	193,075	586,700
-10,076	-64,741	24,163	81,739	113,677	97,939		38,863	744,500	37,881	-721,056	319,800
52,960	66,719	180,340	319,061	7,535	575,250		17,290	84,096	341,201	1,229,817	1,770,300
13005	1215	51,164	40,951	37,385	52,640		-36,639	745,573	6,349	80489	87,457
62,642	48,813	294,196	468,169	99,648	877,533		51,385	879,674	396,305	3,281,669	3,287,100
-12,950	11,454	73,497	73,265	29,283	69,379		9,759	388,963	4,629	-563,675	546,000
33,307	64,313	76,741	314,544	97,148	560,998		3,698	65,735	71,024	470,070	1,494,400
	2000	**1997**	**2000**	**1999**	**1998**			**2000**	**2000**	**2001**	**1997**
	106,265	212,663	242,013	110,195	1,936,161			520,366	241,350	2,133	16,802,500
	11,022	35534	53267	16,910	104785			283340	18,024	-122146	727600
	24,798	77,337	49,017	16,220	298,541			259,505	72,445	-153,258	1,155,000
	-45,186	-51,278	-282,904	60,137	288,340			459,676	33,833	-267,350	1,137,200
	6,500	126,138	226,723	185	332,343			259,265	347,570	635,035	4,327,500
	1560	39268	32,860	-52,649	47,374			346,192	10,473	157004	652,018
	31,339	193,992	296,318	43,019	708,711			783,367	398,058	3,500,216	6,887,900
	8,293	35,419	49,905	16,415	104,785			277,979	15,567	-133,214	599,200
	6,500	60,897	223,358	42,452	319,353			508,423	73,077	167,425	3,329,300
16mnth	**1999**	**1996**	**1999**		**1997**			**1999**	**1999**	**2000**	**1996**
72,439	295,203	22,057	493		1,919,575			213,425	221,542	3,006	15,999,086
-229	-51047	2,539	493		125603			158,692	35,051	459073	1196575
29,698	-6,558	1,497	697		250,736			171,713	89,170	-99,060	826,117
-12,666	-70,146	681	691		383,312			181,708	32,246	-52,976	1,245,277
38,510	104,303	8,291	13		360,652			40,870	332,007	211,768	4,711,402
11757	2214	978	352		107,795			215,053	35,666	309447	536,660
86,359	116,450	12,195	710		880,340			216,424	380,496	3,611,157	6,196,757
-1,698	-59,319	2,076	389		125,603			109,228	31,310	453,617	980,597
22,653	96,844	7,865	13		345,736			34,176	66,185	110,608	3,452,605

999	1998	1995	1998		1996			1998	1998	1999	1995
27,221	277,559	19,563	0		1,911,948			122,328	164,044	0	16,406,788
9,696	25840	748	-73		258541			34971	24,324	28805	754060
55,401	1,812	143	-3,910		224,587			50,215	55,711	-270,226	2,040
8,643	-136,263	-339	302		329,355			72,480	26,521	-31,188	-59,045
31,235	111,858	21,165	3,911		400,829			81,592	312,045	628,767	5,346,232
32,136	44764	346	14179		115,818			153,061	91,318	251341	413673
71,370	132,461	24,049	106,998		845,692			167,068	352,078	1,806,851	6,114,811
9,554	20,880	412	-387		258,541			32,467	20,996	15,320	557,255
14,426	91,382	14,779	3,911		388,475			77,937	67,010	275,414	3,990,358

Normalised sampled companies

	Venture Capital										Real Estate														Leisure & Hotels			
	NF1	NF2	NF3	NF4	NF5	NF6	NF7	NF8	NF9	NF10	NF11	NF12	NF13	NF14	NF15	NF16	NF17	NF18	NF19	NF20	NF21	NF22	NF23	NF24	NF25	NF26	NF27	NF28
Year 1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Turnover	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBIT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
WC	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RE	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total Liabilities	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Mkt value of equity	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
CL	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Totla Assets	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Year 2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Turnover	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBIT	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
WC	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RE	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total Liabilities	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Mkt value of equity	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBT	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
CL	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Totla Assets	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Year 3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Turnover	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBIT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
WC	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RE	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total Liabilities	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Mkt value of equity	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
CL	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Totla Assets	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Year 4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Turnover	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBIT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
WC	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RE	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total Liabilities	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Mkt value of equity	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
CL	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Totla Assets	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Year 5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Turnover	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBIT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RE	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
WC	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total Liabilities	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Mkt value of equity	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
EBT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
CL	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Totla Assets	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Nonfailed sampled companies continued

		Development Capital				Support Service						Information Technology															
NF29	NF30	NF31	NF32	NF33	NF34	NF35	NF36	NF37	NF38	NF39	NF40	NF41	NF42	NF43	NF44	NF45	NF46	NF47	NF48	NF49	NF50	NF51	NF52	NF53	NF54	NF55	NF56
2002	2002	2003	2003	2003	2003	2003	2003	2002	2002	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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2001	2001	2002	2002	2002	2002	2002	2002	2001	2001	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2000	2000	2001	2001	2001	2001	2001	2001	2000	2000	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001	2001
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1999	1999	2000	2000	2000	2000	2000	2000	1999	1999	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1998	1998	1999	1999	1999	1999	1999	1999	1998	1998	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999	1999
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Nonfailed sample companies continued

Bp. & Other Fin.		Insurance		Inves. Companies	
NF57	NF58	NF59	NF60	NF61	NF62
2003	2002	2003	2003	2003	2003
[illegible]	447,435	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	61,526	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	121,299	-11,959	[illegible]	[illegible]	1,419,000
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
0	[illegible]	[illegible]	[illegible]	0	8,417,540
[illegible]	[illegible]	[illegible]	[illegible]	27,110	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	7,099,000
2002	2001	2002	2002	2002	2002
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	-14,000
64,138	64,734	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	111,510	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2001	2000	2001	2001	2001	2001
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	-144	[illegible]	28,716	1,099,900
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	72,240	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	8,482	[illegible]
[illegible]	[illegible]	[illegible]	4,247,000	39,463	46,500
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	6,945,500
2000	1999	2000	2000	2000	2000
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	6,044,000
[illegible]	72,100	[illegible]	[illegible]	[illegible]	1,344,000
[illegible]	[illegible]	140	-42,000	-8,119	1,828,000
[illegible]	-154,156	[illegible]	[illegible]	-2713	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	-7,654	[illegible]
[illegible]	97,829	[illegible]	2,113,000	23,021	1,150,000
[illegible]	[illegible]	144,723	[illegible]	167,445	18,797,000
1999		1999	1999	1999	1999
[illegible]		[illegible]	1,564,000	41,629	[illegible]
61,529		[illegible]	300,000	[illegible]	[illegible]
[illegible]		[illegible]	[illegible]	[illegible]	723,000
[illegible]		-1,590	-153,000	[illegible]	[illegible]
[illegible]		45,111	[illegible]	[illegible]	[illegible]
[illegible]		[illegible]	[illegible]	[illegible]	[illegible]
[illegible]		[illegible]	[illegible]	[illegible]	[illegible]
58,181		[illegible]	2,000,000	27,333	[illegible]
158,467		109,779	2,631,000	-26,504	16,271,000

Appendix B: Failed and nonfailed sampled comlpanies z-score summary

Failed sampled companies Altman's z-score summary

Z1	-17.5314	-4.0750	-28.5144	0.5373	-1.5174	0.1129	-0.0813	0.4939	0.7946	0.6107	1.9626	0.2908	-0.5851	-0.3515	0.4070	4.5792	-1.3738	3.6994	4.7636	1.9511	5.2790	1.0865	-2.2026	4.9842
Z2	6.6077	-2.5297	-4.3446	-0.1497	-1.6467	0.5300	0.4087	0.6103	0.4413	1.0194	2.1156	0.3601	3.0202	-0.0213	2.5070	2.4016	4.3977	3.8217		0.7792	5.2313	1.3468	-0.5098	6.0643
Z3	-0.4749	-2.1159			-1.6169	1.1948	0.3403	0.4912		1.3314	2.6016	1.2396		3.6264	1.9956	0.3568	23.0011	4.3805			3.8781	1.1112	-0.1257	3.3108
Z4	-0.6421	-1.6367			2.7401	0.8842	0.4097	0.4003		1.6952	2.0306		1.2206	0.1903	2.7920	21.7725		3.7820			8.6905	1.3506	1.2436	3.7287
Z5	0.0009	-2.5262			2.5015	1.0422	0.5131	0.4067		2.7274	2.3976		2.5481	1.5565	0.9133	2.1331		4.3069			3.5166	1.1648	0.0688	3.1234

Failed companies Springate's z-score summary

Z1	[illegible]	-0.8644	-21.7139	-0.1347	-0.5319	0.0874	-0.1006	0.2221	0.9080	-0.0298	1.3739	-0.5473	-0.7241	0.9288	1.4165	2.0739	-2.8313	1.6864	3.7384	1.3563	3.1580	0.1894	-4.0133	3.3377
Z2	-4.6436	-0.7496	-1.7227	-1.0306	0.8906	0.4815	0.2669	0.6727	0.8267	0.1686	1.3573	0.9206	0.9263	0.9424	2.1102	1.3973	1.1245	1.7907		14.3213	6.4015	0.6300	-1.1857	3.0148
Z3	-0.7526	-0.5670			-1.2855	2.8322	0.2237	0.4787		0.7827	1.8556	19.6443		4.0931	1.7953	1.1964	13.5352	2.1971			2.0782	0.7096	-0.6771	1.5916
Z4	-4.1764	-0.5051			-0.0935	1.2861	0.2954	0.9173		0.9648	1.4409		0.6321	-0.7940	1.6633	23.1698		1.8433			5.5721	1.0693	3.0691	1.9503
Z5		-1.9305			-0.6236	1.0670	0.3781	0.3757		2.9308	1.9219		1.6063	1.6019	0.4454	-0.1050		2.5557			1.5200	0.7682	-0.0684	1.5443

Nonfailed sampled companies Altman's z-scores summary

	Venture Capital										Real Estate									
Z1	-8.6010	-0.6014	2.0258	-3.6920	4.8210	-41.1937	6.3299	2.4277	0.5048	4.8210	0.7987	1.3158	0.8084	0.8590	-3.6463	0.8001	1.2952	0.9568	0.5501
Z2	-115.322387	0.0000	-6.9614	-1.3701	5.7412	-7.3997	8.0751	-1.0419	0.7236	5.7412	1.1555	1.1488	1.0958	0.7941	2.6615	0.7935	1.0231	0.6755	0.5706
Z3	-1072.49245	-1.2424	-21.4746	-1.2489	3.1438	1.7269	6.9317	2.4767	0.4971	3.1438	3.8748	1.2667	1.2221	0.6823	3.6446	0.7476	0.5416	0.8909	0.4429
Z4	-716.849479	0.2979	2.4271	1.7768	2.3940	2.9507	4.4576	6.2428	-2.0018	2.3940	1.9519	1.4621	0.7706	0.6827	104.5787	0.7388	0.9614	0.7655	2.0022
Z5	-1459.01274	2.0230	7.9276	9.9435	3.4014	3.1090	0.6711	9.7187	0.0431	3.4014	1.2945	2.0902		0.6168		0.7723	0.9700	0.5189	2.6372

Nonfailed sampled companies Altman's z-scores summary continued

					Leisure & Hotels						Development Capital				Support Service				
0.3237	0.5857	0.8846	0.8320	3.6967	1.4280	0.7097	5.5619	2.1775	-6.0378	-4.3319	0.1396	-2.4629	3.2493	-0.7373	2.4489	6.3753	5.8340	11.0784	1.7553
0.3824	0.4472	0.9393	0.3961	4.4394	1.0121	0.6630	4.6609	1.7684	-6.2419	-5.2210	1.9273	-2.5095	2.7505	1.5587	2.0346	4.9977	8.6991	7.8943	3.0322
0.4971	0.9602	0.9112	0.5679	1.8736	-0.1358	1.9123	4.2158	2.1563	-4.2435	-1.6716		-3.1598	5.8660	1.9869	2.0750	6.5296	6.8536	8.1931	
0.7217	0.9353	0.7871	0.4707	1.7309	0.3743	2.6039	1.8964	1.5503	-7.2133	-0.0632	1.6823	2.8496	2.6842	2.5441	2.2568	7.7749	5.4615	4.9032	2.9198
0.6715	0.8657	0.4193	0.4322	1.3187	0.7656	1.6268	4.2539	1.4484	0.0243	6.1288	5.3226	5.6613	3.2338	1.6183	2.1927	6.1898	6.1202	4.5686	13.0403

Nonfailed sampled companies Altman's z-scores summary continued

Information Technology															Speci. & Other Fin.		
3.9643	5.3423	6.1700	-1.0500	2.7459	1.8600	3.5640	-5.3591	4.5833	3.6590	2.0992	-0.3766	5.3126	1.8023	2.9463	1.7629	1.6943	3.1113
3.8478	-0.5795	6.8014	-8.7489	-6.3805	3.1844	3.0035	-2.4633	3.3930	3.3281	-0.2461	2.3721	7.2030	-0.2446	3.7870	2.5220	1.6707	5.1852
3.3166	6.2559	5.2815	-0.4455	4.4700	3.3564	3.3808	-7.6942	3.7963	2.8546	-0.1268	1.7697	6.0449	2.8467	3.8192	2.6050	2.9877	5.1606
3.3166	29.6708	3.2763	13.6309	8.0039	3.2690	2.6348	-12.5422	4.0763	3.4963	2.8410	2.2776	3.6583	0.2822	3.8615	0.9221	3.7070	6.3581
6.8337	4.6544		8.5919		2.8257	1.6060	-6.2763	3.5134	3.7718	-0.8688	5.6919	2.2791	2.5338	4.4128	2.5429		7.8928

Nonfailed sampled companies Altman's z-scores summary continued

Life Assurance			Investment Comp.	
3.1113	0.2448	0.2448	0.9151	102.5586
5.1852	0.2419	0.2419	2.2906	98.2858
5.1608	1.7710	1.7710	1.8468	122.5187
6.3581	2.7502	2.7502	2.1461	8.8241
7.8928	2.0695	2.0695	5.4772	4.9821

Normalised sampled companies Springate's Z-score summary

	Venture Capital									
Z1	[illegible]	-0.9020	2.3041	0.3586	0.3426	-35.0625	5.5702	1.3882	0.8971	0.2970
Z2	-31.3958	0.0000	-6.9123	0.7582	0.0238	-17.8734	4.2887	-1.8213	1.2264	0.1454
Z3	-267.8630	-1.0597	-31.4967	0.3469	-0.3403	-3.3472	4.0151	-0.9850	1.0341	0.0612
Z4	-20.9449	-1.2750	1.3514	-4.9590	-0.6324	1.5944	2.0643	1.9486	-1.9831	-0.0077
Z5	-251.4114	-1.4122	23.9370	-0.3291	0.1178	1.6252	-2.9528	0.4496	-0.7555	0.4754

	Real Estate														
Z1	0.3513	0.9313	1.0622	0.8936	6.0593	0.3824	1.3112	1.4732	0.3568	0.2904	1.0085	0.5023	1.1475	4.3061
Z2	1.2023	0.4901	0.6177	0.5615	3.0247	0.4198	0.9535	0.6091	0.4310	0.3263	0.2970	0.4681	0.2154	7.8356
Z3	2.8835	0.8022	1.4735	0.2800	2.8912	0.3548	0.1834	0.3640	0.3096	0.4667	0.6247	0.3775	0.3368	2.3533
Z4	1.2985	0.9814	0.4654	0.4393	-65.8125	0.1565	0.3729	0.2933	-2.6411	1.2241	0.7178	0.6923	0.3001	2.3782
Z5	0.3225	1.2581		0.4269		0.4407	0.3780	0.0803	0.3633	0.5380	0.6974	0.4353	0.3183	2.2123

Nonfailed Springate z-score summary continued

Leisure & Hotels						Development Capital			
0.9238	0.4607	2.3186	0.6127	0.1332	-1.0442	-1.0775	-0.9107	1.4981	-1.1214
0.9691	-0.7719	1.8669	0.6111	-0.7567	-12.6339	0.5122	-1.8930	1.1364	0.5600
-3.1988	0.3623	1.7948	0.7601	-0.6556	-0.2927	0.0000	-4.4772	1.6351	0.7652
-0.2269	0.7892	1.6497	0.7284	-8.7743	-1.3356	0.1721	2.0184	1.4310	1.2195
0.5497	1.0807	1.6107	0.6101	-3.0271	1.6771	1.7442	2.4908	1.4044	0.5646

Support Service					Information Technology									
1.1028	2.6270	1.8225	4.2708	0.4306	2.0280	0.8667	2.7977	2.7033	2.3906	0.4360	1.4786	1.1758	2.4057	1.3232
1.0201	2.0955	3.4954	2.0864	1.1642	1.9754	0.9050	2.9285	-4.8588	-7.1762	1.6946	1.4186	1.2299	1.7877	1.7382
0.8714	2.6960	2.7955	3.5752		1.5920	1.2207	2.7420	-3.4437	1.4441	1.9414	1.8309	-0.4995	2.1784	1.4938
1.2837	3.0271	2.4749	2.3797	0.2408	1.3862	1.2054	2.4991	3.3094	2.8862	2.2291	1.3949	-5.3498	2.7492	1.7861
1.0335	2.3010	2.2993	2.2584	0.2376	2.4193	1.8087	0.0000	2.6576		1.8234	1.2891	-5.9109	3.4427	3.0323

Nonfailed Springate z-score summary continued

					Speci. & Other Fin.			Insurance			Inves. Comp.	
1.6404	-0.5651	2.9266	1.0019	1.3718	1.3946	0.7612	2.2988	2.2988	0.2562	0.4477	0.4477	6.9687
-1.1529	1.0856	4.2051	-1.0432	2.0575	1.5733	0.8049	3.3212	3.3212	0.2120	0.9028	0.9028	-0.6577
-1.7918	0.7246	3.6011	1.4590	2.6793	1.7331	1.5181	2.1333	2.1333	0.8074	0.7676	0.7676	0.2257
3.1475	1.3624	2.0869	0.2320	2.7099	0.4776	2.0755	1.9971	1.9971	1.0056	-0.2632	-0.2632	1.1990
0.8551	5.1782	1.9881	1.6707	3.5633	1.6264		1.9115	1.9115	0.6344	3.0184	3.0184	1.2510