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FACULTY OF BUSINESS AND ECONOMY
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Master Thesis

"Models of Prediction of Corporate Bankruptcy: The Predictive Power of Altman Z-Score Model in the Case of Financial Crisis in the USA"

Candidate: Maja Mitrevski

Mentor: Doc. Dr. Hyrije Abazi-Alili

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Declaration

I declare that this master thesis and the research reported here is my original work. Information taken from the published or unpublished work of other authors is cited in the text, and references are presented in the bibliography.

Tetovo, Maja Mitrevski

06/08/2018

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Contents

List of Figures

List of Tables

Abstract

The main objective of this thesis is by using a model analysis to predict insolvency and test accuracy of the model selected, rather than estimating future trends from historical data. As markets have developed and the availability of information has increased during the past, numerous attempts have been made to find patterns and generic methods to evaluate the potential risk of a company being insolvent and assess whether a company will continue to exist and produce a substantial return of investment. The predictive approach encourages the researchers to develop explanations for short term financial fluctuations and perhaps help management to predict the financial results in their firm for near future.

Many credit rating firms such as Standard and Poors, Moody's and Fitch have created large organizations or agencies concentrating on assessing and grading the creditworthiness of companies. Meanwhile there has also been extensive academic research on the subject, especially after the financial crisis of 2008 which brought up the need of use different assessment methods to minimize the risk of the investors.

One well-documented method is the Z-score developed by Edward Altman in the late 1960's. Although a purely quantitative approach excluding all types of soft factors and not taking in account the contextual conditions may incorporate significant weaknesses, the Z-score model has still gained popularity. This is probably due to being ground breaking and further due to its simplicity and proof of being fairly accurate in its predictions. Not many people with some knowledge in the area of credit assessment would argue against the statement that a numerical model is not enough to fully evaluate the default risk of a firm. However, a sufficient reliable approach may operate as a good complement to an overall evaluation.

The objective of this thesis is to test the accuracy of the Altman Z score model to a selected sample of US companies that were affected by the financial crisis in the US, to make a comparison of the results with another model and to provide recommendations for further research and analysis.

Abstrakt

Objektivi kryesor i kësaj teze është që duke përdorur një model analize të parashikohet falimentimi dhe testimi i saktesisë së provave të modelit të zgjedhur, në vend që të vlerësojnë tendencat e ardhshme nga të dhënat historike. Përderisa tregjet janë zhvilluar dhe disponueshmëria e informacionit është rritur gjatë periudhës, janë bërë përpjekje të shumta për të gjetur modele dhe metoda gjenerike për të vlerësuar rrezikun potencial të një kompanie të falimentoj dhe të vlerësojë nëse një kompani do të vazhdojë të ekzistojë dhe të prodhojë një kthim të konsiderueshëm të investimit. Qasja parashikuese inkurajon studiuesit për të zhvilluar shpjegime për luhatjet financiare afatshkurtra dhe ndoshta për të ndihmuar menaxhmentin për të parashikuar rezultatet financiare në firmën e tyre për një të ardhme të afërt.

Shumë firma të vlerësimit të kredisë si Standard dhe Poors, Moody's dhe Fitch kanë krijuar organizata apo agjenci të mëdha që përqendrohen në vlerësimin dhe notimin e aftësisë paguese të kompanive. Ndërkohë ka pasur gjithashtu një hulumtim të gjerë akademik mbi këtë temë, veçanërisht pas krizës financiare të vitit 2008 e cila solli nevojën për përdorim të metodave të ndryshme të vlerësimit për të minimizuar rrezikun e investitorëve.

Një metodë e mirë-dokumentuar është Z-score i zhvilluar nga Edward Altman në fund të viteve 1960. Megjithëse një qasje thjesht sasiore duke përjashtuar të gjitha llojet e faktorëve të butë dhe duke mos marrë parasysh kushtet kontekstuale mund të inkorporojë dobësi të rëndësishme, modeli Z-score akoma ka popullaritet. Kjo ndoshta është për shkak të thyerjes së akullit dhe më tej për shkak të thjeshtësisë së tij dhe provës për të qenë mjaft i saktë në parashikimet e tij. Jo shumë njerëz me disa njohuri në fushën e vlerësimit të kreditit do të argumentojnë kundër deklaratës se një model numerik nuk është i mjaftueshëm për të vlerësuar plotësisht rrezikun e parazgjedhur të një firme. Megjithatë, një qasje mjaftueshëm e besueshme mund të funksionojë si një plotësues i mirë për një vlerësim të përgjithshëm.

Qëllimi i kësaj teze është të provojë saktësinë e modelit Altman Z-score në një mostër të zgjedhur të kompanive amerikane që u prekën nga kriza financiare në SHBA, për të bërë një

krahasim të rezultateve me një model tjetër dhe për të dhënë rekomandime për hulumtime të mëtejshme dhe analiza.

Апстракт

Главната цел на оваа теза е преку користење на аналитички модел да се предвиди несолвентноста како и да се тестира точноста на избраниот модел, наместо да се проценат идните трендови базирани на историски податоци. Како што се развиваа пазарите и се зголемуваше достапноста на информациите низ минатото, се направија бројни обиди за изнаоѓање обрасци и генерички методи за да се процени потенцијалниот ризик од несолвентност на компанијата и да се процени дали компанијата ќе продолжи да постои и ќе произведе значителен поврат на инвестиција. Предвидливиот пристап ги поттикнува истражувачите да развијат објаснувања за краткорочните финансиски флуктуации и можеби да му помогнат на менаџментот да ги предвиди финансиските резултати на компанијата во блиска иднина.

Многу кредитни рејтинг фирми како што се Standard and Poors, Moody's и Fitch создадоа големи организации или агенции кои се концентрираат на рангирање и оценување на кредитната способност на компаниите. Во меѓувреме, исто така, беа опфатени детални академски истражувања на оваа тема, особено по финансиската криза од 2008 година, која ја наметна потребата од користење различни методи за проценка со цел да се минимизира ризикот на инвеститорите.

Еден добро документиран метод е Z-score моделот развиен од Едвард Алтман во доцните 1960-ти. Иако чисто квантитативниот пристап со исклучување на сите видови “меки” фактори и не земајќи ги во предвид останатите услови може да вклучи значителни слабости, моделот Z-score сепак добива популарност. Ова веројатно се должи на револуционерниот пристап и неговата едноставност како и доказите дека е прилично точен во своите предвидувања. Не многу луѓе со одредено знаење во областа на проценката на кредитен ризик ќе се изјаснуваат против дека нумерички модел не е доволен за целосно да го оцени ризикот од неуспешност на компанијата. Сепак, пристап со задоволително ниво на точност може да функционира како добар додаток на севкупната евалуација.

Целта на оваа теза е да ја тестира точноста на моделот Altman Z score на избран примерок на американски компании кои беа засегнати од финансиската криза во САД, да се направи споредба на резултатите со користење на друг модел како и да даде препораки за понатамошни истражувања и анализи.

1. CHAPTER 1: INTRODUCTION

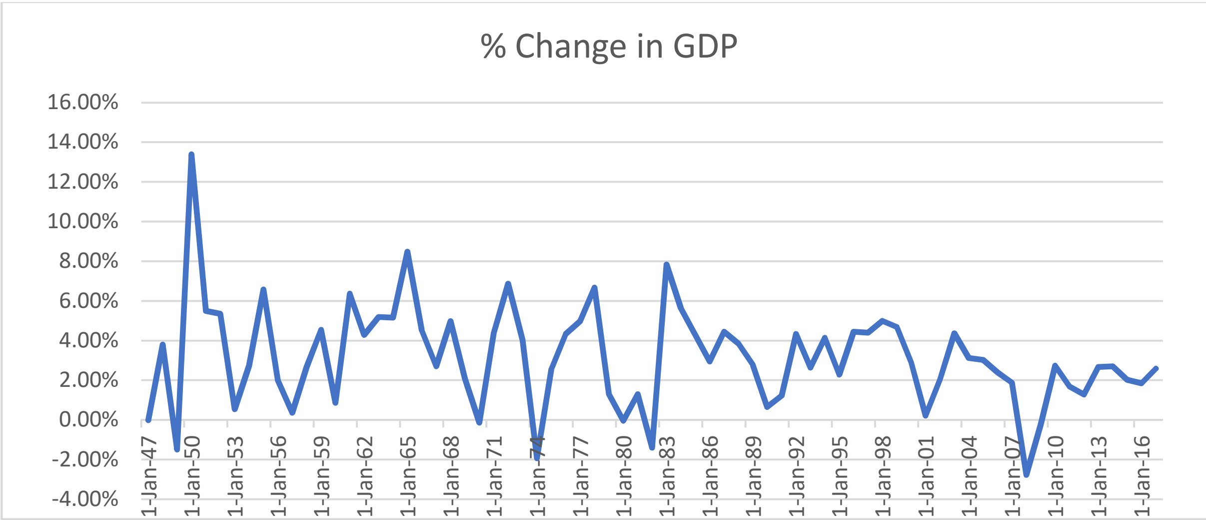
1.1.Introduction

The 2008 financial crisis has pushed the U.S. economy into its most severe recession since the Great Depression. The financial failures of many companies have had a devastating impact on world economy. According to the "2011 Financial Crisis Inquiry Commission report"[1] the US financial crisis affected the lives of millions of American citizens and could have been avoided if the regulatory agents had adequately monitored and managed the financial environment. At the time of the report 26 million individuals were unemployed with about 4 million homes being lost and the same amount entering the foreclosure process. It is an event that stands as testimony to the fickle nature of a system that was improperly monitored and regulated [2]. During 2008, United States alone experienced negative GDP growth for the first time since 1949 and the highest negative GDP growth number since 1938. The change in GDP per years can be seen in Exhibit 1 shown in this study.

[1] 2011 Financial Crisis Inquiry Commission report, retrieved from https://www.gpo.gov/fdsys/pkg/GPO-FCIC/pdf/GPO-FCIC.pdf

[2] Mitchell, T.R (2017, March). The Financial Crisis and Banking Sector Stability: The Case of USA and EURO Zone, retrieved from https://lra.le.ac.uk/bitstream/2381/39877/1/2017MitchellTRPhD.pdf

Figure 1.1 US GDP growth 1947-2017



(source: http://www.multpl.com/us-real-gdp-growth-rate/table/by-year)

Company failures negatively affect stakeholders and therefore prediction of corporate bankruptcy is an important aspect for the protection of the stakeholders' interests. The published annual report is the most important way for a firm to communicate with its external stakeholders. Even when the highlights of the annual report have been pre-announced to interested parties, the document remains as the key to reassurance on the financial position and past performance of the organization.

Therefore, it is necessary to use a tool or a model that could predict insolvency and can help creditors, investors, and managers answer the following questions: Can the company pay the interest and principal on its debt? Does the company rely too much on non-owner financing? Does the company earn an acceptable return on invested capital? Is the gross profit margin growing or shrinking? Does the company effectively use non-owner financing? Are costs under control? Is the company's market growing or shrinking? Do observed changes reflect opportunities or threats? Is the allocation of investment across different assets too high or too low?

There have been many models developed and used across the industries. Each model has its own limitations and financial institutions are always on the look-out for finding the best method to evaluate credit worthiness. There have been many studies in the past regarding the efficiency of the prediction models. During the financial crisis, the inability of the default prediction models to warn of the impending crisis has been the subject of many financial stability discussions and the need to review and re-evaluate them was evident.

The first multivariate bankruptcy prediction model was developed by Altman (1968) in the late 1960s. After this pioneering work, the multivariate approach to failure prediction spread worldwide among researchers in finance, banking and credit risk. The Z - Score measures how closely a firm resembles other companies that have filed for bankruptcy. It is a measure of corporate financial distress or economic bankruptcy. There is evidence that the Z-Score coefficients should be re-estimated for the prediction of corporate distress involving different time periods or different industries.

The primary focus of this study is to test the accuracy of corporate failures prediction in the U.S. from 2007-2011 using Altman's original model and a re-estimated model for both manufacturing and non-manufacturing companies. Z-Scores of the publicly held companies from these models are examined using financial data from one and two years prior to bankruptcy.

1.2. Objectives of the study

The main objective of this study is to research the benefits from using Altman Z-Score prediction model by analyzing the financial ratios based on the financial statements data that is publicly available. The ability to predict a financial failure of a company can significantly improve the decision-making process for investors, banks, asset managers, rating agencies and even distressed companies themselves, especially during a period of a financial crisis.

The Altman Z-score is a mathematical model for the creditworthiness of a company, both public and private. The model of the Altman Z-score is the result of a scientific investigation into the prediction of the possibility of a bankruptcy of a company. The Altman Z-score is used by different stakeholders interested in determining the creditworthiness of a company. The Altman Z-score is most commonly used by banks to determine the risk in issuing loans. In addition, the Altman Z-score an important tool for institutional investors to determine the risk of a company going bankrupt. Also, private investors can easily use this model as It is simple and the required data are easy to obtain. Altman Z-score model is used by companies in mergers and acquisitions as well as managers that use the model to determine the risks of the company and to create a strategy to get the company out of the danger of bankruptcy.

Research questions:

What is the likelihood of the company becoming insolvent?

What was the use of the Altman Z score model during the crisis?

Which industry groups were most affected by the crisis?

What are the implications of the financial crisis on the predictive ability of the Z-Score models?

What other models can be used in combination with the Altman Z Score model to give the best prediction results?

1.3.Thesis organization

The upcoming chapter will give an overview of previous research and literature and provide definition for bankruptcy, models of prediction of bankruptcy and review of the default prediction techniques, as well as outline the advantages and disadvantages related to their use. Chapter 3 will give a general overview of the original Altman Z Score model developed by Edward I. Altman in 1968, the characteristics of the sample companies that were part of the research, the results, as well as the re-estimated Altman Z score models with a detailed explanation for each of the variables used. The chapter describes how the original Altman Z Score model uses five variables or financial ratios and their overall weight in the final Z Score value depends on the characteristics of the selected sample. This chapter will provide the classification areas of the Altman's Z-score or the values and the ranges which will be used as cut-off values for the research in this thesis.

Chapter 4 includes the research methodology used on the selected sample. It describes the characteristics of the selected companies and describes the data collection process as well as the statistical model used. The hypotheses of the thesis are also given in this chapter.

Chapter 5 presents the results of the research. Using descriptive statistics, this chapter provides detailed analysis of the values gained with the calculation of each of the variables and the final Z Score for the manufacturing companies and non-manufacturing companies selected. An average Z score is calculated based on a four consecutive years financial data. A correlation matrix is built to show the correlation with the X-ratios as independent variables and the Z-Score as a dependent variable. We also test the predictive power of the model for the manufacturing and non- manufacturing companies and test the hypothesis showing percentage results for the accuracy of the model for the analyzed sample. The thesis will be finalized with a summary of the main findings of the thesis, the limitations and suggestions for further research on the topic.

2. CHAPTER 2: THEORETICAL ASPECT AND LITERATURE REVIEW

2.1.Introduction

At the end of the twentieth century, corporate distress reached levels not seen since the great depression of the 1930s. The number of business failures and bankruptcies increased together with the increase in corporate distress. Four generic terms that are generally found in literature for corporate distress are: (i) failure, (ii) insolvency, (iii) default and (iv) bankruptcy. Their individual economic meanings are described in the following paragraphs.

Failure means that the realized rate of return on invested capital, with allowances for risk consideration, is significantly and continually lower than prevailing rates on similar investments. Somewhat different criteria have also been utilized, including insufficient revenues to cover costs and cases of the average return on investment being below the firm's cost of capital. A firm could be an economic failure for many years without failing to cover its current obligations because of the absence of legally enforceable debt.

Insolvency is a term used in a more technical way. It indicates lack of liquidity, so it is more cash based, which happens when a company cannot meet its financial obligations. Technical insolvency most often is the cause of formal bankruptcy declaration.

Bankruptcy comes along when the insolvency of a company becomes critical, when the total liabilities of a company exceed a fair value valuation, for example stock based, of its total assets.

Default is another condition that is inescapably associated with distress. Defaults always occur between the debtor firm and a creditor class. A firm is not always immediately in default when it misses a loan payment or its interest payments. However, when a firm misses an interest payment or a principal repayment of publicly held bonds, and this problem is not fixed within 30 days, the security is immediately" in default". In the last few decades these defaults on publicly held indebtedness have become a commonplace event.

Finally, the term **bankruptcy** will be discussed. A firm can go bankrupt when the total liabilities exceed a fair value of the total assets of that firm, as discussed in the paragraph about insolvency. On the other hand, a firm can be declared bankrupt in the US by a Federal District Court. This Federal District Court can declare the firm bankrupt immediately or offer the firm to participate to a recovery program, which is called a “bankruptcy reorganization”. When a firm value is worth more than its liquidation value, the company has to participate to a recovery program.

It is important to identify the main reasons for corporate distress with bankruptcies as a consequence. Several studies about this subject have been done over the past decades. An example of these studies was done by a consulting firm, Buccino & Associates (1991). They surveyed over 1,300 managers, and the result pointed out that, by 88% of the respondents, the quality of management was identified as the primary difference in success or failure. Dun and Bradstreet (1980) identified earlier that lack of experience, unbalanced experience, or just plain incompetence was the cause of firm failures in more than 44% of the situations. Another important issue to consider is the relation between the age of a firm and the possibility to fail. Dun and Bradstreet (1980) showed that over 50% of all failures occur with firm with ages between two and five. After the age of five, companies tend to be more stabilized, experienced, established and as an indirect result of these reasons have better access to capital. Other, mainly financial reasons for firm failure which had the upper hand during the 80s are the following:

Industries - Some industries tend to be “sick”. Companies which are active in these industries
have a high possibility to fail soon;

Interest rates - Because of high interest rates some companies fall into the position in which they cannot obey to their obligations anymore;

Competition- International competition intensifies the charges for companies enormously. Scale advantages will bring with itself that small companies will take off against big companies, because these companies are more capable of doing business at a sharper price;

Debt to equity- Companies, particularly in the United States, increased their leverage. Because of that, a lot of companies put themselves in the situation of more obligations. In times of corporate distress these persisting obligations could lead to failure;

Deregulation- Deregulating of key industries leads to a far more competitive environment;

Formation rates- High new business formation rates will cause higher frequency of firm failures. New companies just have the characteristic to have a higher failure possibility than established companies**.**

2.2. Literature and research

Bankruptcy problem and companies not being successful have always been a big problem studied widely by the researchers (Bartual et al. 2012; Hernndez & Wilson 2013; Mendes 2014; Zaghdoudih 2013). Occurrence of bankruptcy with significance of 1960`s caused growth of interest on bankruptcy prediction models. World economy, especially after bankruptcy of huge organizations such as WorldCom and Enron became aware to the risk present in structure of companies` capital so that one of the most important goals of bankruptcy rules in most countries is reduction of credit risk.[3]

The amount of methods used for predicting bankruptcy is massive, starting from Beaver's (1966) method of using single-variable ratios and moving to the more recent studies such as logistic regression or hybrid models. For just one model there are countless articles, studies and even books made, for the main purpose of developing them, and nowadays mainly trying to bring the oldest models to the 21st century. Though new methods seem to surface consistently, it seems that the models developed in the mid-end 1900's keep their position in the top most popular.

Each one of these methods has their own limitations, but main assumption of most of them is that companies can be classified into two groups: 1. Companies with financial health, 2. Companies with financial inability. Anyway, some suggestions were provided on defining more than two groups based on the risk level, as well. But due general acceptance of the

[3] "A Review of Bankruptcy and its Prediction"; Ahmad Ahmadpour Kasgari, Seyyed Hasan Salehnezhad, Fatemeh Ebadi; October 2013

two classified groups the main attention is on two-grouped classification methods (Dimitras, et al, 1996).

The literature for bankruptcy prediction dates back to the 1930's beginning with the preliminary studies concerning the use of ratio analysis to predict future bankruptcies (Bellovary et al., 2007). Up until the 1960's the prediction methods were merely focused on single ratio studies and formulas. The most recognizable study for these is Beaver's (1966) original single-variable method. Beaver (1966) carried out univariate analysis, comparing the financial ratios of 79 failed companies and 79 non-failing companies. His utilization of the paired-sample approach and the use of a hold-out sample to validate the model has been a benchmark for later researchers (Moghadam, Zadeh, Fard, 2011, p.3). He examined the predictive power of thirty accounting ratios for five consecutive years leading up to the bankruptcy of the tested companies.

A misclassification rate was used as an index to gauge the predictive power of the variables. Misclassification could either be a Type I error (classifying a failing firm as non-failing), or Type II error (classifying a non-failing firm as failing) (Bunyaminu & Issah, 2012). The smaller the misclassification rate; the greater the accuracy. A limitation of Beaver's work is based primarily on the univariate nature of the model he developed. It only allows for one ratio used at a time, this can give inconsistent results for a firm should other ratios be utilized. Not only this, but the financial complexity of a firm cannot be captured by one single ratio. Lastly, the cut-off point determined is chosen post- failure of a company which means that, in reality, the failure status of a company must be predicted resulting in inaccurate classifications.

After that the models developed to multivariable methods, out of which the most recognizable is Altman's multivariable "Z-score" (1968). In 1968 Edward Altman advanced upon Beaver's work by incorporating four more variables into the model to give an overall more precise prediction of manufacturing corporate failure. Altman's multi-discriminant analysis (MDA) model differed to Beavers model in relation to the ratios chosen of highest prediction. Altman classifies the companies into two mutually exclusive groups; bankrupt and non-bankrupt (Altman, 1968, p.591). Altman's discriminate analysis became a dominant model used in corporate failure prediction literature due to its simplicity and accuracy. His multi-discriminant approach allowed him to develop the equation into a combination of five ratios consisting of liquidity, profitability, financial leverage, solvency, and sales activity (sales to total assets). This linear equation distinguished between failing and non-failing companies. The result of the combination of ratios gives rise to a discriminant score otherwise known as the 'Z score'.

Altman's model is not without criticisms. Gharghori et al. (2006) and Hillegeist et al. (2004) argue that the Altman's model comprises different measures of accounting variables that are derived from the financial statements which by nature are backward looking and may not provide predictive value for an entity's future. The same critics also argue the financial statements are prepared with a going concern assumption, in other words, companies are assumed not to file bankruptcy. In addition, Begley et al. (1996) indicate that the Altman's Z-Score model provides a more accurate prediction for U.S. companies in certain periods than others. Likewise, Grice and Ingram (2001) find that the Z-Score performs better with manufacturing companies than with companies in other industries.

In evaluating the performance of different default-risk models, Gharghori et al. (2006) find the option-based models outperform the accounting ratio models. Similarly, Black-Scholes-Merton option pricing model is found to be superior to accounting-based measures in bankruptcy prediction (Hillegeist et al. 2004). However, there is evidence that a hybrid approach, which combines a market-based model and an accounting-based model, provides better bankruptcy prediction than either model alone. A market-based model is found to be significant in predicting default of companies with high credit risk, while the accounting-based model is significant in default prediction of those with low credit risk. Thus, based on a company's credit risk, the prediction accuracy can be improved by placing more (less) emphasis on the market-based model while reducing (increasing) the emphasis on the accounting-based model (Li & Miu 2010). This is consistent with the finding of Das (2009) that a model that incorporates both accounting-based information and market-based information outperforms either model. A hybrid model appears to be also useful in predicting the bankruptcy of Japanese listed companies (Xu and Zhang 2009).

Credit Scoring and Default Prediction Techniques -Ganguin and Billardello (2005) suggest that there are two main lines of credit scoring and default probability approaches; credit rating agencies and quantitative default prediction models. The credit rating agencies work with specific case opinions that include soft factor assessments while the statistical methods have a purely numerical approach. In the definition of the models in this study, a further breakdown of these two techniques gives a general classification of the models based on the literature research.

2.3. Quantitative default prediction models definition

The formal studies on credit risk started in the 1930's (Altman, 1968). The early studies were univariate in nature, and single financial ratios were used to assess the financial position of the borrower. These studies set the platform for the further development of credit risk models. Some of the important univariate studies are Fitzpatrick (1932), Smith and Winaker (1935), Merwin (1942), Chudson (1945), Jackendoff (1962) and Beaver (1966). After seven decades of credit risk measurement, there is extensive development in the credit risk literature. The credit risk models can be classified into the following categories (Fejer-Kiraly, 2015):

1. Parametric Models (Accounting and market-based models), also known as *Statistical Prediction models;*

2. Non- parametric Models (Artificial Neural Networks (ANN), Hazard models, Fuzzy Models, Genetic Algorithms (GA) and Hybrid models, or models in which several of the former models are combined)[4], also known as *Artificial Intelligence Prediction models.*

2.3.1. Parametric models

The parametric models could be univariate and multivariate in nature which uses mainly financial ratios and focuses on the symptoms of bankruptcy (Andan & Dar, 2006). Further, parametric models can be classified into two categories: accounting based and market-based models. Market-based models are again divided into two parts: structural and reduced form models.

Accounting models- Beaver (1966) with his univariate default prediction study on US companies revolutionize the practice of credit risk assessment. The study compares the mean values of 30 financial ratios of 79 failed and 79 non-failed companies in 38 industries. Further, the study tests the ability of individual financial ratios to classify between bankrupt and non-bankrupt companies. Four financial ratios were found to have highest classification power, namely, net income to total debt (92 %), net income to net worth (91 %), cash flow to total debt (90 %), and cash flow to total assets (90 %). For future research, the study suggested multiple ratios considered simultaneously may have higher predictive ability than single ratios which created a platform for multiple ratio models.

Altman (1968) developed a first multivariate discriminant model for default prediction for US companies. The model uses five financial ratios to predict bankruptcy of the companies. The model can predict bankruptcy with 95 % of accuracy for the initial sample one year prior to bankruptcy. Altman et al. (1977) developed a model for US manufacturing and retailers, which had the effective classifying ability from 5 years prior to default. Since

[4] The non-parametric models are dependent on computer technology and mainly multivariate in nature (Andan & Dar, 2006). As the research mainly focuses on the use of the accounting models for bankruptcy prediction, it is relevant to include them in as part of the classification of the models per Fejer-Kiraly, 2015

Altman (1968), discriminant analysis is used by many researchers by making changes in financial ratios, study sample, and change in business culture. Some of the notable studies are Deakin (1972), Blum (1974), Springate (1978) and Fulmer (1984).

The limitations of discriminant analysis created space for the development of logit model. Ohlson (1980) introduced a logit model in the literature of bankruptcy prediction. The assumptions of logit model were different from Z-score models. Ohlson identified nine independent variables (financial and non-financial) based upon their frequent use in the bankruptcy prediction literature. The model was developed with the sample of 2163 companies (105 defaulted and 2058 non-defaulted) for the period 1970-1976. In line with Ohlson, Abdullah et al. (2008), applied the logistic model to foretell corporate failure of Malaysian companies. Further, Zmijewski (1984) applied probit technique using data of 40 bankrupt and 8000 non-bankrupt US companies for the period 1970-1978. The table below shows the explanatory variables of the accounting models described :

Table 2. 1 Accounting Models Explanatory Variables

Accounting model	Explanatory Variables
Altman Z Score	Net working capital/Total Assets
	Retained Earnings/ Total Assets
	EBIT/Total Assets
	Market Value of Equity/ Book value of Total Liabilities
	Sales/ Total Assets
Ohlson	Size-log (Total Assets/GNP Price level index)
	TLTA- Total Liabilities/ Total Assets
	WCTA- Working Capital/ Total Assets
	CLCA- Current Liabilities/ Current Assets
	ONENEG- 1IF Total Liabilities> Total Assets, 0 if otherwise
	NITA- Net Income/ Total Assets
	FUTL- Funds provided by operations/ Total Liabilities
	INTWO- 1 if net income was negative, 0 otherwise
	CHIN- (Nit-Nit-1)/(Nit- Nit-1) where NI is Net Income
Zmijewski	NITL= Net Income/ Total Liabilities
	TLTA- Total Liabilities/ Total Assets
	CACL- Current assets /Current Liabilities

(source: The Financial Crisis and Banking Sector Stability: The Case of USA and the EURO Zone; Tanisha Raeann Mitchell;2017; page 27)

Market based models- The market-based models are classified into structural and reduced form models. Black and Scholes (1973) option pricing theory which was extended by Metron (1974) is applied to model default in structural based models. In these model's companies can default on its debt obligation only at the time of maturity. Later, some models were developed by extension to allow a default to occur before the date of maturity. These models were familiarized by Black and Cox (1976), Lonfstaff and Schwartz (1995), Leland and Toft (1996). On the other hand, reduced form models focus over modeling default explicitly as an intensity or compensator process.

2.3.2. Non- parametric Models

Artificial Neural Networks (ANN), are networks existing of many layers of interconnected simple logic units or nodes. These networks have been invented in the 1950s and were inspired by the way scientists believed the human brain worked. The use of ANNs however, was limited strongly by the lack of suitable training methods. This changed in the mid-1980s with the reformulation of the backpropagation algorithm by Rumelhart et al. (1986). The logical units in feedforward neural networks - as opposed to recurrent ones - are called perceptrons. These perceptrons model a human brain's neuron that 'fires' on the output side when a certain threshold is reached. In perceptrons, the input x is a weighted linear combination of the outputs of perceptrons in the previous layer and a so called 'bias' (always equal to 1). The output is computed by using a nonlinear, differentiable activation function called a 'transfer function' or the identity function f(x) = x. The following activation functions are most commonly used:

Logistic function:

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

Hyperbolic tangent function:

$$f(x) = \tanh(\frac{x}{2}) = \frac{1 - e^{-x}}{1 + e^{-x}} \qquad (2)$$

The first attempt to use ANNs for bankruptcy prediction was done by Odom and Sharda (1990).

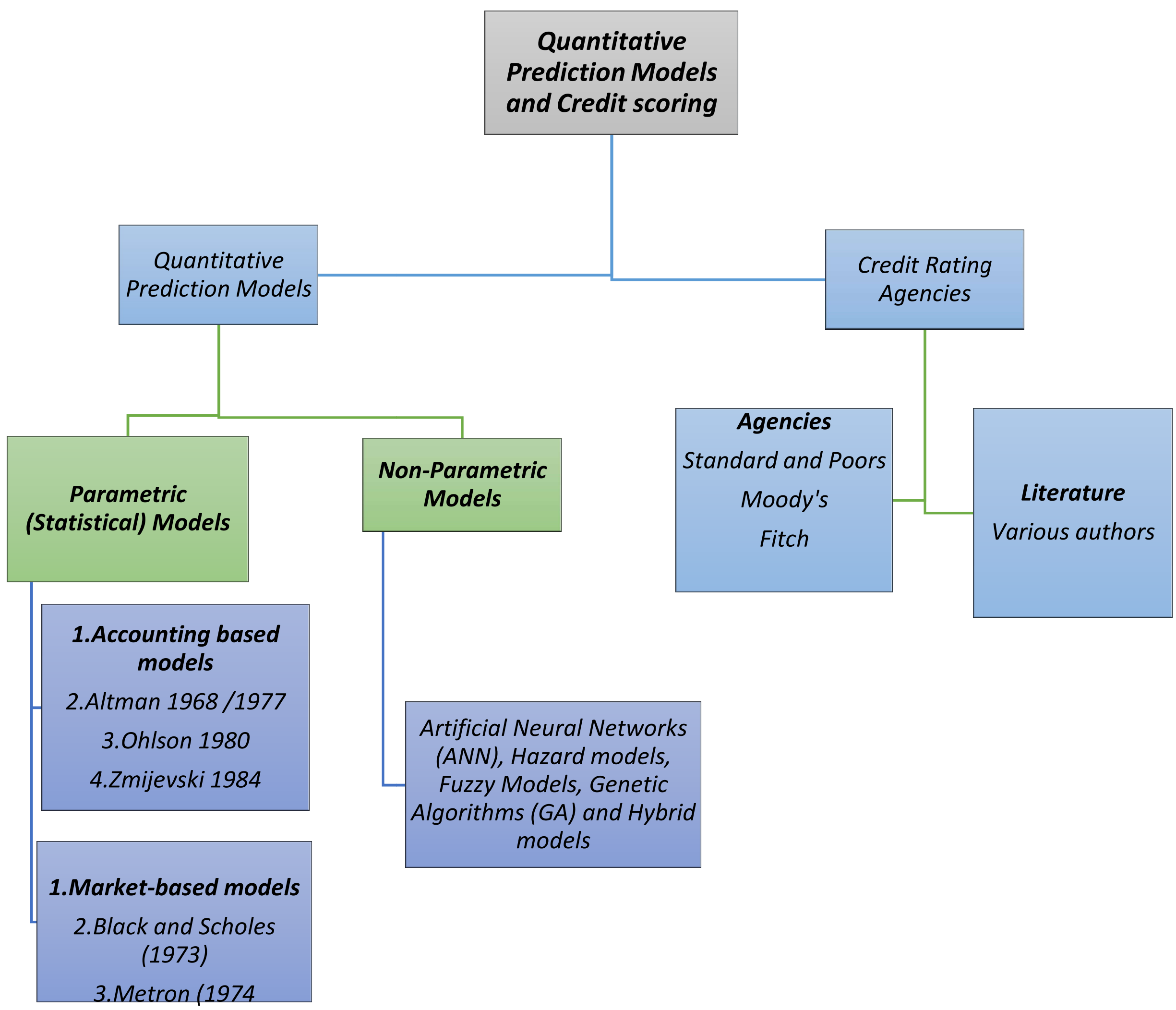
Genetic Algorithms (GAs) are stochastic derivative free optimization techniques which can search effectively through very large spaces, in many different ranges of applications. GAs are motivated by the analogy of biological evolution (Darwin's theory of evolution, survival of the fittest).

Every GAs works with a collection of hypothesis, called a population, which is evaluated every generation. These hypotheses are represented by bit strings, called chromosomes. In each generation these chromosomes are evaluated according to their fitness value, which is usually equal to the output of the objective function. The chromosomes which have the highest fitness value immediately go, unaltered, to the new population. Others are used create offspring individuals by utilizing genetic operators such as crossover and mutation. GAs are heavily used for variable selection for example in neural networks within the bankruptcy prediction.

2.4.Credit Rating Agencies

Credit rating agencies such as Standard and Poors, Moody's and Fitch give what they call opinions on a firm's credit worthiness. These opinions have shown to be adequately related to the corporate default probabilities of the rated companies. A great advantage of the scoring of the credit rating agencies is that they do not expressively give an opinion on if a company is a good or bad investment. They extend the opinion by suggesting a rating in a rating range which indicates to what extent a firm is in good or bad condition. By having access to a rating of a particular firm the creditor can benchmark the rating against other investment with an equal rating in order to decide what spread it should demand to compensate for the risk of that firm. Another advantage is that credit rating agencies include recovery prospects and various soft factors which give the assessment robustness (Ganguin and Billardello 2005). What may be seen as a disadvantage of the ratings made by rating agencies is that rating migration tends to be very slow and not react as fast as some investors may prefer. However, a reason to this might be that credit rating agencies apply long term through the cycle assessments. Default risk is then consequently long term, measured and leads to stable ratings (Altman & Rijken 2004). Some adverse selection issues can be applied to the publication of certain ratings. The large credit rating agencies follow a code which obliges them to publish performed ratings of certain public companies. However, under some conditions the issuer of a security may be able to choose whether they want their private rating to be published or not. This gives them the potential of hiding "bad" ratings. Therefore, the outside investor will not know whether the firm has chosen to hide the investment or simply that the security has not been rated at all (Mahlmann 2008).

Figure 2.1: Review of the Default Prediction Techniques[5]



[5] The classification of the models of prediction is based on a combination of classification per Ganguin and Billardello (2005) and Fejer-Kiraly (2015

2.5.Advantages and disadvantages of the Models of Bankruptcy Prediction

This section describes the advantages and the disadvantages of the *Statistical Prediction models* and the *Artificial Intelligence Prediction models* mentioned above. It is difficult to make a clear comparison between the models having in mind that each application has different goals and circumstances that would need to be treated differently.

In this study a division is made between the different prediction models, resulting into discriminant analysis, decision trees, neural networks and genetic algorithms.

Discriminant analysis became popular with Beaver's approach for bankruptcy prediction in 1966. Based on his work Altman (1968) introduced his Z-score model, which also makes use of discriminant analysis and is seen as the basic tool for bankruptcy prediction mainly because of the simplicity in the use of accounting data from the financial reports.

Although discriminant analysis is so heavily used, there are some disadvantages connected to it such as:

Table 2. 2 Disadvantages of discriminant analysis

Discriminant analysis
Requires that the decision set used to distinguish between distressed and viable companies need to be linearly separable
Does not allow for a ratios signal to vacillate depending on its relationship to another ratio or set of ratios
Reduction of dimensionality
Difficulty in interpreting relative importance
Violations of normality and independence
Difficulty in specifying classification algorithm
Difficult to interpret time-series prediction test

(source: Bankruptcy Prediction using Classification and Regression Trees; M.A. Sprengers, 2005, page 19)

Decision trees or Recursive partitioning is a supervised learning technique which also gained popularity in the world of bankruptcy prediction. Mainly because decision trees are able to generate understandable rules and are capable to deal with continuous and categorial variables and cope with missing values in a data set. There are at least three demonstrable weaknesses, quoted in table 2.3 shown below.

ANNs are less used as the above-mentioned techniques, but they also gained popularity for bankruptcy prediction problems. ANNs can handle a wide range of problems and produce really good results for complicated problems, and is like decision trees capable of coping with continuous as well as with categorial variables.

Genetic algorithms: Most of the advantages of genetic algorithms can be seen in the following table that summarizes main disadvantages of the decision trees, ANNs and GAs:

Table 2. 3 Disadvantages of decision trees, Artificial Neural Networks and Genetic Algorithms

Decision trees	ANNs	Genetic algorithms
Error-prone with too many classes	Black boxes, difficult to understand	Difficulty in encoding
Computationally expensive to train	Cannot explain the results	No guarantee of optimality
Trouble with nonrectangular regions	May converge on an inferior solution	Computationally expensive

(source: Bankruptcy Prediction using Classification and Regression Trees; M.A. Sprengers, 2005, page 20)

3. CHAPTER 3: THE ALTMAN Z SCORE MODEL

3.1. Introduction

The widely popular Z-score function used for analyzing and predicting bankruptcies was first published in 1968 by Edward I. Altman (Altman, 1968). In Altman's study, the initial sample involved sixty-six corporations with thirty-three companies in each group in the time period of 1946 to 1965. The Z-score uses multiple inputs from corporate income statements and balance sheets to measure the financial status of a company. The inputs that Altman selected were from those financial reports that are one reporting period earlier than bankruptcies. The inputs that Altman used were twenty-two different financial ratios. Altman considered that these financial ratios were chosen to eliminate size effects. Those ratios were divided in five categories: liquidity, profitability, leverage, solvency, and activity. The reason for dividing the input variables in case 5 categories is ad-hoc. They are standard financial categories.

Altman applied linear multiple discriminant analysis (MDA) to find the best combination of five variables from an original set of variables. However, when applying the method of MDA, Altman could not avoid biased estimators. Altman himself admitted to the bias and tried the best way to minimize it. It is generally believed that the biased estimators come from two sources: sampling errors and searching (Frank etc., 1965). This is the first drawback of MDA – the biased estimators.

3.2. Predicting Financial Distress using the original Altman's (1968) Z-score Model - Z-Score Model for Public Companies

Altman's (1968) initial sample was composed of 66 corporations, with 33 companies in each of two groups. The bankrupt group (Group 1) consisted of manufacturers that filed bankruptcy petitions during the 1946–1965 period. The mean asset size of these companies was 6.4 million USD, ranging between 0.7 and 25.9 million USD. Altman recognized that this group was not homogenous with respect to size and industry, although all companies were relatively small and from manufacturing industries. He attempted to carefully select non-bankrupt companies (Group 2). Group 2 consisted of a paired sample of manufacturing companies chosen on a stratified random basis. These companies were stratified by industry and size, with the asset size range restricted to 1–25 million USD. Altman eliminated small companies (less than 1 million U.S.A. dollars in total assets) because of a lack of data and very large companies because of the rarity of bankruptcies among these companies in that period. He did not match the asset size of the two groups exactly, and therefore, the companies in Group 2 were slightly larger than those in Group 1. The data collected for the companies in both groups were from the same years. For Group 1, the data were derived from financial statements one reporting period prior to bankruptcy. Using financial statements, Altman compiled a list of 22 potentially important financial ratios for evaluation. He classified these variables into five standard ratio categories: liquidity, profitability, leverage, solvency, and activity. These ratios were chosen based on their popularity in the literature and their potential relevance to the study. The final discriminant function estimated by Altman (1968) is as follows:

$$Z= 1.2*X1 + 1.4*X2 + 3.3*X3 + 0.6*X4 + 0.999*X5$$

Where:

X1=Working capital/Total assets;

X2=Retained earnings/ Total assets;

X3=Earnings before interest and taxes/Total assets;

X4=Market value of equity/Book value of Total liabilities;

X5=Sales/Total assets.

Boundary values:

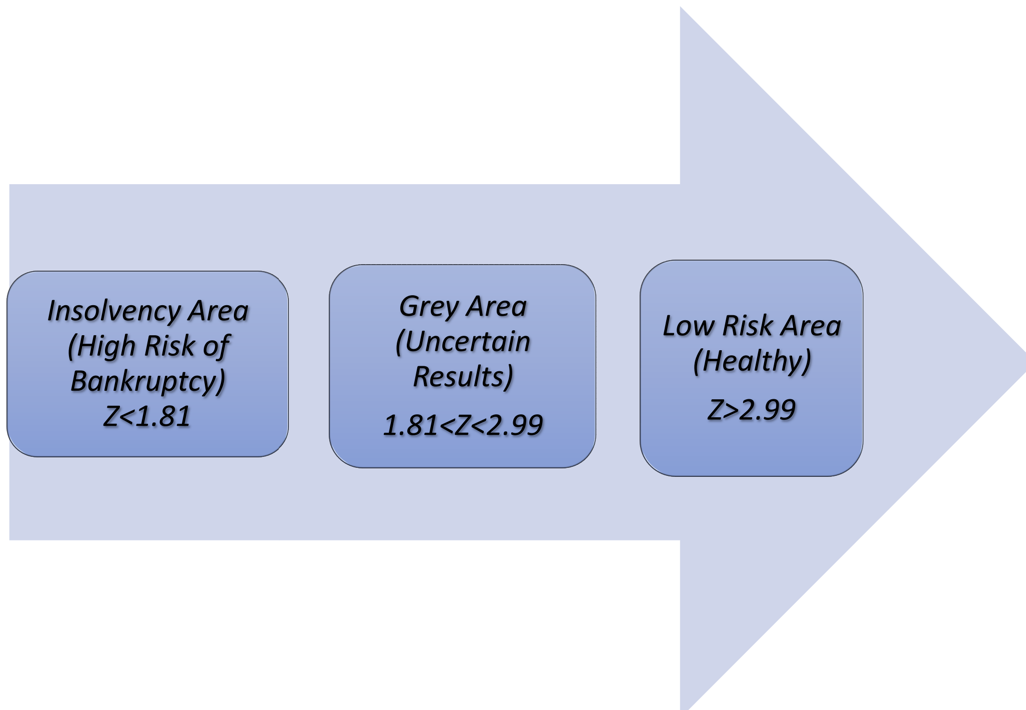
Z > 2.99 Safe Zone: Considered financially healthy

1.81 < Z < 2.99 Grey Zone: Could go either way

Z < 1.81 Distress Zone: Risk that company will go bankrupt within two years

Source: (Altman, 1968, p.594)

Figure 3.1: The Classification Areas of Altman's Z-score



(source: Models of Bankruptcy Prediction Since the Recent Financial Crisis: KMV, Naïve, and Altman's Z- score; I Ting Hsiao & Lei Gao; June 2016)

X1, 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 assets 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 many authors 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.

X2, 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, thus it is conceivable that a bias would be created by a by this kind of readjustments in the company's financials. A relatively young firm will show some 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 companies that failed did so in the first five years of their existence."

X3, 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 companies 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.

X4, 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 X4 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.

X5, 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 X5. This seeming irregularity is due to the format of the different variables.

After obtaining the parameters of the Z-score model, Altman conducted a test to assess the model's performance. The test was used to evaluate the prediction accuracy. He believed that the "measure of success of the MDA in classifying companies is analogous to the coefficient of determination (R2) in regression analysis".

A misclassification rate was used as an index to measure the predictive power of the variables. Misclassification could either be a Type I error (classifying a bankrupt firm as non-bankrupt), or Type II error (classifying a non-bankrupt firm as bankrupt). The smaller the misclassification rate; the greater the accuracy.

The initial sample of 33 companies 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 companies were classified using a discriminant function, which in fact, was based upon the individual measurements of these same companies. The result of his test to the initial sample is shown in the following:

Table 3. 1 Test results - Altman, Edward I. (1968)

	Number Correct	Percent Correct	Percent error	n
Type I	31	94	6	33
Type II	32	97	3	33
Total	63	95	5	66

(source: "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy"; Altman, Edward I. (1968); Journal of Finance: 189–209)

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.

3.3.Z'-Score and Z"-Score Models for Private Companies

The original Z-Score model was based on the market value of the firm and was thus applicable only to publicly traded companies. Altman (1983) emphasized that the Z-Score model is intended for publicly traded companies and that ad hoc adjustments are not scientifically valid.

Altman (1983) advocated a complete re-estimation of the model, substituting the book value of equity for the market value in X4. Using the same data, Altman extracted the following revised Z'-Score model:

$$Z' = 0.717*X1 + 0.847*X2 + 3.107*X3 + 0.420*X4 + 0.998*X5$$

where X4 = Book value of equity/Book value of total liabilities, with the other variables the same as those in the original (1968) Z-Score model. Due to the lack of a private firm database, Altman did not test the Z'-Score model on a secondary sample. However, he analyzed the accuracy of a four-variable Z"-Score model that excluded the Sales/ Total assets ratio, X5, from the revised model because of a potential industry effect that is more likely to take place when this kind of industry-sensitive variable (asset turnover) is included in the model. Altman then estimated the following four-variable Z"-Score model (Altman, 1983):

$$Z'' = 6.56*X1 + 3.26*X2 + 6.72*X3 + 1.05*X4$$

The EBIT/Total assets ratio, X3, contributed most to the discrimination power in this version of the model. The classification results for the Z"-Score model were identical to the revised five-variable Z'-Score model.

3.4. Problems and limitations of the Z-Score models

The Z Score is not intended to predict when a firm will actually file for legal bankruptcy. It is instead a measure of how closely a firm resembles other companies that have filed for bankruptcy, i.e. it tries to assess the likelihood of economic bankruptcy. The model has also drawn several statistical objections over the years. The original model uses unadjusted accounting data; it uses data from relatively small companies; and it uses data that is around 60 years old. Nevertheless, despite these flaws, the original Z Score model is still the most widely used measure of corporate financial distress.

4. CHAPTER 4: RESEARCH METHODOLOGY

4.1.Sampling design

On order to make the selection to a firm to be included in this research, it must fulfill the requirement to supply the independent variables needed to calculate the Z-Score. The companies included in this research are American companies that were facing with bankruptcy risk or submitted bankruptcy during the period of the financial crisis 2008-2010. Also, in the data selected I include 2007 financials, as the major of the analyzed companies went bankrupt in 2008 but 2007 was a year when the early signs of the financial crisis started. The list of companies included in this research can be seen as part of Exhibit 2 in the thesis.

The reason for selecting American companies for this research is not only that Altman Z score model was developed by using American companies as a sample, but because the definition of bankruptcy may vary depending on which country the companies that are being studied are located.

4.2.Data Collection

The companies that are being selected for this research are collected from Bankruptcy Data Research Database[6]. The sample includes both manufacturing and non-manufacturing companies.[7] The ratios for the companies that were selected for the sample have been calculated in a previous research ("*Predicting Corporate Default-An assessment of the Z-Score Model on the US Market 2007-2010*", Therese Johansson & Jonna Kumbaro, 2011) which uses different statistical techniques for interpreting the results. The sample companies filled an annual report (called Form 10-K) at the Securities and Exchange Commission at least three

[6] The database can be found on the following website: http://bankruptcydata.com

[7] In USA classification of companies as manufacturing and non-manufacturing is most often made by viewing each firm's SIC, Standard Industrial Classification (http://www.osha.gov/pls/imis/sic_manual.html)

years prior to bankruptcy. The sample that was selected for the research has the following characteristics:

- American public company
- Listed on the American stock exchange (NYSE)[8]
- Filed for Bankruptcy 2007-2010
- Had at least $100 million of assets in the balance sheet data prior to the bankruptcy filing.

The reasons for selecting this sample for conducting the research are:

- Data availability- the selected list of companies had financial data that was available for me to obtain and analyze within the selected period of the financial crisis. Most of the research conducted in the US is done through obtaining databases from specialized database research companies that charge certain fee for obtaining a database with certain characteristics of the sample based on the purpose of the research. This is also described as a limitation of the study in section 6.1. During analyzing of the results, the original sample that I was able to provide was approximately 18-24 companies per each category from a database used for a previous research (ex. 18 manufacturing bankrupt; 18 manufacturing non-bankrupt), but for some of the companies there was either no financial data available to calculate some of the ratios for previous years or the size of the company based on the assets size would not fall into the range of over $1,000 billion in assets. Therefore, several companies were dropped out during the analysis. The remark and recommendation is that including larger number of companies would certainly be more representable and give more supported results especially for such a large and developed economy such as USA where the financial crisis had the biggest impact. The lack of information is again described as limitation in section 6.1 of the study.
- Analyzed period- All the selected companies submitted annual report Form 10-K within the analyzed period of the financial crisis. Year 2005 was taken as a staring lower limit

[8] NYSE-New York Stock Exchange

year to analyze the financial ratios for the companies that were actually bankrupt and 2011 was taken as an upper limit year for the companies that had not bankrupt. The purpose of selecting a lower limit of 2005 is to expand the period analyzed in order to see the development of the ratios over the years and draw conclusions based on the results. Including 2011 as a year would show the trend of the ratios for the non-bankrupt companies and see if there's a trend of improvement in the financials after the crisis. The section 5.5.1 in the thesis will provide the results from 2010 and 2011 financials for the non-bankrupt companies to see the trend of the Z-Scores.

- Characteristics of the sample- by selecting the companies shown in Exhibit 2 of the thesis, an attempt to include multiple similar characteristics of the sample was made. The selection was made mainly to distinguish manufacturing and non- manufacturing companies and include both types in the research to compare the predictive power of Altman Z Score model. Furthermore, in the non- manufacturing list of companies, an attempt to include different types of non- manufacturing businesses was made to include to compare the ratios and give availability to draw conclusions or maybe give ideas for further research. The companies selected were also widely known for the public in the US and their bankruptcy was announced in all large media during the financial crisis.

No financial institutions were included in the research since they have certain characteristics that cannot be captured with Z'-Score and Z''-score models.[9] Furthermore, the sampling is narrowed according to the following characteristics that were also applied in Altman's 1968 model:

a) Industry to where the company belongs (based on Standard Industrial Classification two-digit codes)
b) Size (Total Assets)

[9] There have been attempts on modifying the Z-score in order to use it on financial institutions. One of these studies can be found here: http://trap.ncirl.ie/865/1/jasminechieng.pdf

The average asset size of the bankrupt manufacturing companies is $1,258 billion and $2,848 billion for manufacturing companies that not filed for bankruptcy during the analyzed period. [10]

The average size of the bankrupt non-manufacturing companies is $1,200 billion and $1,048 billion for the non-bankrupt ones.

Most of the companies have been established 30-60 years, while some of the companies included were founded even more than 100 years ago. The average number of employees ranges from 496 to 202k.

Table 4. 1 Sample statistics – companies selected

Group	Manufacturing companies	Non-manufacturing companies
Bankrupt	13	13
Non-bankrupt	13	13
Total	26	26

(source: Derived from database available on http://bankruptcydata.com)

4.3. Data Analysis and Statistical model

By using discriminant analysis[11], each company gets a value, as Z score or Z''-Score that classifies the firm in one of the two groups, bankrupt or non- bankrupt. The Z-score range consists of a grey area which refers to the range where the incorrectly classified companies from the original sample were located (Altman 1968). Table 4.2 in this research can be seen for the grey area ranges.

[10] During the analyzed period General Motors Co and Ford Motor Company filed bankruptcy but since they are very large companies, including them in the average would cause deviance and influence the results. Statistically, the more the similar the sample is, the more consistent and representable the results should be.

[11] Discriminant analysis works by creating one or more linear combinations of predictors, creating a new latent variable for each function. These functions are called discriminant functions. The number of functions possible is either *Ng*-1 where *Ng* = number of groups, or *p* (the number of predictors), whichever is smaller.

The lower and the upper boundaries of the grey area are used as cut off values (range 1.8 to 2.99).

The study has followed the descriptive quantitative method by applying Altman's model to the sample of study. The data is extracted from the company's financial statements for four years prior to the bankruptcy or to the current fiscal year relative to the non-bankrupt (surviving) group. From the data, the ratios composed of Altman's models for manufacturing and non-manufacturing companies were calculated to derive the appropriate Z-score:

- For Manufacturing Companies: $Z= 1.2*X1 + 1.4*X2 + 3.3*X3 + 0.6*X4 + 0.999*X5$
- For Non-Manufacturing Companies $Z'' = 6.56*X1+ 3.26*X2+ 6.72*X3+1.05*X4$

Table 4. 2 Sample statistics- Z Score and Z" score ranges

	Bankruptcy Area	Grey Area	Non-Bankrupt Area
Z-score	<1.8	1.8-2.99	>2.99
Z''-Score	<1.1	1.1-2.6	>2.6

(source: Derived from database available on http://bankruptcydata.com)

As the objective of this study is to test the accuracy in prediction of the Altman Z Score model, the hypotheses of the study can be stated as follows:

H1: Altman's Z-Score model can accurately predict the financial health or the failure of the US <u>manufacturing</u> companies; sample of the study.

H2: Altman's Z" model can accurately predict the financial health or the failure of the <u>non-manufacturing</u> companies; sample of the study.

The analysis method can be summarized as follows:

- Computations have been made using Excel programs;
- Descriptive statistics of the model variables for each of the two groups under the study have been provided;

- Z score values were computed for each company for four consecutive years, and an overall index has been used to calculate the predictive power for both of the two groups (the bankrupt group and the non-bankrupt group).

5. CHAPTER 5: RESULTS OF THE RESEARCH

5.1. Data and methodology

The ratios for each of the components of the **Z-score** were calculated for 13 bankrupt and 13 non-bankrupt manufacturing companies selected from the sample based on financial data for four consecutive years prior to filing for bankruptcy. The companies selected can be seen in Exhibit 3. The average asset size of the bankrupt manufacturing companies is $1,258 billion and for the non- bankrupt companies the average is $2,848 billion.

As shown in section 3.2, we use the following formula to calculate the Z-Score values for the manufacturing companies:

Z= 1.2*X1 + 1.4*X2 + 3.3*X3 + 0.6*X4 + 0.999*X5

Also, following the same sampling method, 13 bankrupt and 13 non-bankrupt non-manufacturing companies are selected. The average assets for the selected non-manufacturing companies is $1,200 billion for the bankrupt and $1,048 billion for the non-bankrupt companies. The list of selected non – manufacturing companies can be seen in Exhibit 3. Following the same approach as for the manufacturing companies, we analyze the data for four consecutive years prior to filing for bankruptcy. The following formula for calculating the Z" score is used:

Z" =6.56*X1+ 3.26*X2+ 6.72*X3+1.05*X4

5.2. Descriptive statistics-Manufacturing Companies

Using the descriptive statistics method, in the table 5.1 below we show the minimum and maximum values of each ratio and then calculate the mean and standard deviation for each value based on the tested sample size (N=13).

First, we calculate the ratios for the *Bankrupt Manufacturing companies* (the companies that filed the form 10-k to declare bankruptcy and did bankrupt during the analyzed period):

Table 5. 1 The descriptive statistics of the bankrupt manufacturing companies- four consecutive years prior to bankruptcy

DESCRIPTIVE STATISTICS- BANKRUPT COMPANIES-MANUFACTORING (USED FINANCIAL DATA FOR FOUR CONSECUTIVE YEARS PRIOR TO BANKRUPTCY)					
Variable	N	Minimum	Maximum	Mean	Std.Deviation
X1	13	-0.328	0.593	0.065	0.2455
X2	13	-1.243	0.225	-0.323	0.5107
X3	13	-0.999	0.653	-0.039	0.4091
X4	13	0.013	0.736	0.178	0.2210
X5	13	0.674	2.746	1.243	0.5911
Z-SCORE	13	0.252	2.745	1.147	0.739
VALID N (LISTWISE)	13				

Table 5. 2 The descriptive statistics of minimum values for each ratio from the Altman Z Score model- bankrupt manufacturing companies

DESCRIPTIVE STATISTICS- ANALYSIS OF MINIMUM VALUES PER EACH RATIO FOR ALTMAN Z-SCORE						
	N	Value (Y-1)	Value (Y-2)	Value (Y-3)	Value (Y-4)	Average

X1	13	-1.036	-0.103	-0.096	-0.0756	-0.328
X2	13	-1.433	-1.303	-1.147	-1.0899	-1.243
X3	13	-1.129	-1.052	-0.917	-0.8978	-0.999
X4	13	0.006	0.002	0.002	0.0409	0.013
X5	13	0.453	0.697	0.761	0.7839	0.674
Z-SCORE	13	-0.369	0.276	0.507	0.5938	0.252
VALID N (LISTWISE)	13					

Table 5. 3 The descriptive statistics of maximum values for each ratio from the Altman Z Score model- bankrupt manufacturing companies

DESCRIPTIVE STATISTICS- ANALYSIS OF MAXIMUM VALUES PER EACH RATIO FOR ALTMAN Z-SCORE						
	N	Value (Y-1)	Value (Y-2)	Value (Y-3)	Value (Y-4)	Average
X1	13	0.355	0.580	0.673	0.7646	0.593
X2	13	0.154	0.172	0.192	0.3820	0.225
X3	13	0.496	0.630	0.699	0.7866	0.653
X4	13	1.046	0.622	0.629	0.6478	0.736
X5	13	2.654	2.730	2.730	2.8716	2.746
Z-SCORE	13	2.676	2.444	2.706	3.1518	2.745
VALID N (LISTWISE)	13					

From the tables 5.1, 5.2 and 5.3 above that show the ratios calculated based on the financial data for four consecutive years prior to filing for bankruptcy, the results are as follows:

The first variable (X1) has an average of 0.065 value with 25% standard deviation. The minimum value for this ratio based on the analyzed four years results is -0.328 and in table 5.2 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for this ratio is 0.593 and in table 5.3 we can see that the biggest influence has Y-4 analyzed period or four years prior to bankruptcy.

The second variable (X2) has an average of -0.323 value with a 51% standard deviation. The minimum value for this ratio based on the analyzed four years results is -1.243 and in table 5.2

we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 0.225 and in table 5.3 we can see that the biggest influence has Y-4 analyzed period or four years prior to bankruptcy.

The third variable (X3) has an average of -0.039 and standard deviation of 41%. The minimum value for this ratio based on the analyzed four years results is -0.999 and in table 5.2 we can see that the biggest influence has Y-1 and Y-2 analyzed period or one year and two years prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 0.653 and in table 5.3 we can see that the biggest influence has Y-4 analyzed period or four years prior to bankruptcy.

The fourth variable (X4) has an average of 0.178 and standard deviation of 22%. The minimum value for this ratio based on the analyzed four years results is 0.013. Based on the analyzed data in table 5.2 we can see that the biggest influence has Y-2 and Y-3 analyzed period or two and three years prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 0.736 and in table 5.3 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy.

The last variable (X5) has an average of 1.243 with a 59% standard deviation. The minimum value for this ratio based on the analyzed four years results is 0.674. Based on the analyzed data in table 5.2 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 2.746 and in table 5.3 we can see that the biggest influence has Y-4 analyzed period or four years prior to bankruptcy.

The dependent variable (Z) has an average of 1,147 with standard deviation of 74%. The minimum value of the overall Z Score based on the analyzed four years results is 0.252 and in table 5.2 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for the overall Z Score based on the analyzed four years results is 2.745 and based on the analyzed data in table 5.3 we can see that the biggest influence has Y-4 analyzed period or four years prior to bankruptcy.

As described in part 4.2 in the study, in order to classify the manufacturing company as bankrupt (*Z-Score values*), the value of the Z-Score should be <1.8. From Table 5.1 above, we can see that variables X2 (Retained earnings/ Total assets**)** and X3 (Earnings before interest and taxes/Total assets) both have a negative mean value of -0.323 and -0.039 consecutively, which shows that the generated losses of the analyzed companies compared to the value of assets have the most significant influence on the overall Z-Score of the bankrupt manufacturing companies.

Also, when analyzing the separate year's results, we can draw a conclusion that Y-1 had the biggest influence for obtaining the minimum values that would drive the decrease Z Score ratio and thus classify the company as bankrupt. When analyzing Y-4 results we can see the opposite effect- the biggest impact over the maximum values that drive the Z-Score results had Y-4. This clearly shows that the closer we get to the year when the company files for bankruptcy, the Z Score shows a lower value and clearly classifies the company in the "grey area" or bankrupt. The individual Z score values for the bankrupt manufacturing companies and the analyzed financial periods Y-1 through Y-4 can be seen in Exhibit 3 of this study.

Going forward with the analysis, we calculate the ratios for the *Non-Bankrupt Manufacturing companies* (the companies that filed the form 10-k to declare bankruptcy and <u>did not bankrupt</u> during the analyzed period):

Table 5. 4 The descriptive statistics of the non-bankrupt manufacturing companies- four consecutive years prior to bankruptcy

DESCRIPTIVE STATISTICS- NON-BANKRUPT COMPANIES-MANUFACTORING (USED FINANCIAL DATA FOR FOUR CONSECUTIVE YEARS PRIOR TO BANKRUPTCY)					
Variable	N	Minimum	Maximum	Mean	Std.Deviation
X1	13	-0.023	0.591	0.252	0.1749
X2	13	-0.197	0.771	0.372	0.3082

X3	13	-0.347	0.445	0.120	0.2188
X4	13	0.191	3.960	1.743	1.1272
X5	13	0.045	1.753	1.011	0.4091
Z-SCORE	13	0.512	4.902	3.499	0.8972
VALID N (LISTWISE)	13				

Table 5. 5 The descriptive statistics of minimum values for each ratio from the Altman Z Score model- non-bankrupt manufacturing companies

DESCRIPTIVE STATISTICS- ANALYSIS OF MINIMUM VALUES PER EACH RATIO FOR ALTMAN Z-SCORE						
	N	Value (Y-1)	Value (Y-2)	Value (Y-3)	Value (Y-4)	Average
X1	13	-0.330	0.078	0.079	0.0800	-0.023
X2	13	-0.562	-0.094	-0.075	-0.0560	-0.197
X3	13	-0.810	-0.161	-0.181	-0.2370	-0.347
X4	13	0.236	0.239	0.050	0.2390	0.191
X5	13	0.001	0.001	0.089	0.0900	0.045
Z-SCORE	13	1.867	1.944	2.174	2.6685	2.163
VALID N (LISTWISE)	13					

Table 5. 6 The descriptive statistics of maximum values for each ratio from the Altman Z Score model-non-bankrupt manufacturing companies

DESCRIPTIVE STATISTICS- ANALYSIS OF MAXIMUM VALUES PER EACH RATIO FOR ALTMAN Z-SCORE						
	N	Value (Y-1)	Value (Y-2)	Value (Y-3)	Value (Y-4)	Average
X1	13	0.563	0.580	0.600	0.6196	0.591
X2	13	0.713	0.647	0.776	0.9490	0.771
X3	13	0.552	0.454	0.409	0.3640	0.445
X4	13	4.208	3.883	3.864	3.8830	3.960
X5	13	1.565	1.734	1.812	1.9010	1.753

Z-SCORE	13	4.593	4.973	4.992	5.0500	4.902
VALID N (LISTWISE)	13					

From the Tables 5.4, 5.5 and 5.6 above that show the ratios calculated based on the financial data for four consecutive years prior to filing for bankruptcy the results are as follows:

The first variable (X1) has an average of 0.252 value with 17% standard deviation. The minimum value for this ratio based on the analyzed four years results is -0.023 and in table 5.5 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 0.591 and in table 5.6 we can see that the biggest influence has Y-4 analyzed period or four years prior to filing for bankruptcy.

The second variable (X2) has an average of 0.372 value with a 31% standard deviation. The minimum value for this ratio based on the analyzed four years results is -0.197 and based on the analyzed data in table 5.5 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 0.771 and in table 5.6 we can see that the biggest influence has Y-4 analyzed period or four years prior to filing for bankruptcy.

The third variable (X3) has an average of 0.120 and standard deviation of 22%. The minimum value for this ratio based on the analyzed four years results is -0.347 and in table 5.5 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 0.445 and based on the analyzed data in table 5.6 we can see that the biggest influence has Y-1 analyzed period or one year prior to filing for bankruptcy.

The fourth variable (X4) has an average of 1.743 and standard deviation of 112%. The minimum value for this ratio based on the analyzed four years results is 0.191 and table 5.5 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 0.467 and in table 5.6

we can see that the biggest influence has Y-1 analyzed period or one year prior to filing for bankruptcy.

The last variable (X5) has an average of 1.01 with a 41% standard deviation. The minimum value for this ratio based on the analyzed four years results is 0.045 and based on the analyzed data in table 5.5 we can see that the biggest influence has Y-1 and Y-2 analyzed period or one year and two years prior to bankruptcy. The maximum value for this ratio based on the analyzed four years results is 1.753 and based on the analyzed data in table 5.6 we can see that the biggest influence has Y-1 analyzed period or one year prior to filing for bankruptcy.

The dependent variable (Z) has an average of 3.499 with standard deviation of 90%. The minimum value of the overall Z Score based on the analyzed four years results is 0.512 and based on the analyzed data in table 5.2 we can see that the biggest influence has Y-1 analyzed period or one year prior to bankruptcy. The maximum value for the overall Z Score based on the analyzed four years results is 4.092 and based on the analyzed data in table 5.3 we can see that the biggest influence has Y-4 analyzed period or four years prior to bankruptcy.

As described in part 4.2 in the study, in order to classify the company as non-bankrupt, the value of the Z-Score should be >2.99. From Table 5.4 above, we can see that mean values of variables X4 (Market value of equity/Book value of Total liabilities**)** and X5 (Sales/Total assets) have the biggest influence on the overall Z-Score for the non- bankrupt manufacturing companies.

Same as in the case for the bankrupt manufacturing companies, we can draw a conclusion that Y-1 had the biggest influence for obtaining the minimum values that would drive the decrease Z Score ratio. When analyzing Y-4 results we can see the opposite effect- the biggest impact over the maximum values that drive the Z-Score results had Y-4. This clearly shows that the closer we get to the year when the company files for bankruptcy, the Z Score shows a lower value. The individual Z score values for the bankrupt manufacturing companies and the analyzed financial periods Y-1 through Y-4 can be seen in Exhibit 3 of this study.

5.3. Descriptive statistics- Non -Manufacturing Companies

The ratios for each of the components of the **Z"-score** were calculated for 13 non-manufacturing companies selected from the sample for four consecutive years prior to filing for bankruptcy that can be shown in Exhibit 3. As shown in section 3.3, we use the following formula to calculate the Z"-Score values:

$$Z'' = 6.56*X1 + 3.26*X2 + 6.72*X3 + 1.05*X4$$

Using the same approach as in section 5.1, we present a table that shows the minimum and maximum values of each ratio and then calculate the mean and standard deviation for each value based on the tested sample size (N=13).

The ratios for the *Bankrupt Non-Manufacturing companies* (the companies that filed the form 10-k to declare bankruptcy and did bankrupt during the analyzed period) are shown in the table below:

Table 5. 7 The descriptive statistics of the bankrupt non-manufacturing companies- four consecutive years prior to bankruptcy

DESCRIPTIVE STATISTICS- BANKRUPT COMPANIES-NON MANUFACTORING (USED FINANCIAL DATA FOR FOUR CONSECUTIVE YEARS PRIOR TO BANKRUPTCY)					
Variable	N	Minimum	Maximum	Mean	Std.Deviation
X1	13	-4.968	2.013	0.089	1.7953
X2	13	-6.067	10.569	-0.022	3.7704
X3	13	-1.384	2.552	0.098	1.0478
X4	13	-0.700	1.251	0.335	0.5561
Z"-SCORE	13	-6.276	7.086	0.500	3.1754
VALID N (LISTWISE)	13				

Table 5. 8 The descriptive statistics of minimum values for each ratio from the Altman Z" Score model- bankrupt non-manufacturing companies

DESCRIPTIVE STATISTICS- ANALYSIS OF MINIMUM VALUES PER EACH RATIO FOR ALTMAN Z"-SCORE						
	N	Value (Y-1)	Value (Y-2)	Value (Y-3)	Value (Y-4)	Average
X1	13	-3.462	-5.565	-5.477	-5.3660	-4.968
X2	13	-3.208	-7.610	-7.561	-5.8900	-6.067
X3	13	-1.609	-1.335	-1.301	-1.2899	-1.384
X4	13	-0.818	-0.785	-0.697	-0.4981	-0.700
Z"-SCORE	13	-3.368	-7.969	-7.763	-6.0024	-6.276
VALID N (LISTWISE)	13					

Table 5. 9 The descriptive statistics of maximum values for each ratio from the Altman Z" Score model bankrupt non-manufacturing companies

DESCRIPTIVE STATISTICS- ANALYSIS OF MAXIMUM VALUES PER EACH RATIO FOR ALTMAN Z"-SCORE						
	N	Value (Y-1)	Value (Y-2)	Value (Y-3)	Value (Y-4)	Average
X1	13	1.921	1.983	2.003	2.1430	2.013
X2	13	3.031	13.919	12.564	12.7630	10.569
X3	13	2.828	2.475	2.495	2.4110	2.552
X4	13	0.704	1.344	1.434	1.5230	1.251
Z"-SCORE	13	4.050	8.650	7.559	8.0859	7.086
VALID N (LISTWISE)	13					

The results presented in tables 5.7; 5.8 and 5.8 are as follows:

The first variable (X1) has an average of 0.089 value with 179% standard deviation. The minimum for this ratio is-4.968 and based on the results presented in table 5.8, the biggest influence has Y-2 result. The maximum for this ratio is 2.013 and based on the results presented in table 5.9, the biggest influence has Y-4 result.

The second variable (X2) has an average of -0.022 value with a 377% standard deviation. . The minimum for this ratio is-6.067 and based on the results presented in table 5.8, the biggest influence has Y-2 result. The maximum for this ratio is 10.569 and based on the results presented in table 5.9, the biggest influence has Y-2 result.

The third variable (X3) has an average of 0.098 and standard deviation of 105%. The minimum for this ratio is-1.384 and based on the results presented in table 5.8, the biggest influence has Y-1 result. The maximum for this ratio is 2.552 and based on the results presented in table 5.9, the biggest influence has Y-1 result.

The fourth variable (X4) has an average of 0.335 and standard deviation of 56%. %. The minimum for this ratio is-0.700 and based on the results presented in table 5.8, the biggest influence has Y-1 result. The maximum for this ratio is 1.251 and based on the results presented in table 5.9, the biggest influence has Y-4 result.

The dependent variable (Z”) has an average of 0.50 with standard deviation of 317%.%. The minimum for the Z” Score is-6.276 and based on the results presented in table 5.8, the biggest influence has Y-1 result. The maximum for this ratio is 7.086 and based on the results presented in table 5.9, the biggest influence has Y-1 result.

As described in part 4.2 in the study, in order to classify the non-manufacturing company as bankrupt (*Z”-Score values*), the value of the Z-Score should be <1.1. From Table 5.7 above, we can see that variables X2 (Retained earnings/ Total assets**)** has a negative mean value of -0.022 which shows that the generated losses of the analyzed companies compared to the value of assets have a significant influence on the overall Z-Score of the bankrupt non-manufacturing companies.

Going further with the analysis, we calculate the ratios for the *Non-Bankrupt Non-Manufacturing companies* (the companies that filed the form 10-k to declare bankruptcy and did not bankrupt during the analyzed period):

Table 5. 10 The descriptive statistics of the non-bankrupt non-manufacturing companies- four consecutive years prior to bankruptcy

DESCRIPTIVE STATISTICS- NON- BANKRUPT COMPANIES-NON MANUFACTORING (USED FINANCIAL DATA FOR FOUR CONSECUTIVE YEARS PRIOR TO BANKRUPTCY)					
Variable	N	Minimum	Maximum	Mean	Std.Deviation
X1	13	-0.145	3.831	1.369	1.3669
X2	13	-0.474	2.020	0.529	0.8235
X3	13	-0.832	2.609	0.582	0.8964
X4	13	0.218	5.290	1.569	1.3275
Z-SCORE	13	0.542	7.795	4.049	2.2954
VALID N (LISTWISE)	13				

Table 5. 11 The descriptive statistics of minimum values for each ratio from the Altman Z" Score model -non-bankrupt non-manufacturing companies

DESCRIPTIVE STATISTICS- ANALYSIS OF MINIMUM VALUES PER EACH RATIO FOR ALTMAN Z"-SCORE						
	N	Value (Y-1)	Value (Y-2)	Value (Y-3)	Value (Y-4)	Average
X1	13	-0.143	-0.165	-0.145	-0.1250	-0.145
X2	13	-0.985	-0.467	-0.278	-0.1650	-0.474
X3	13	-1.361	-0.657	-0.656	-0.6550	-0.832
X4	13	0.093	0.172	0.260	0.3459	0.218
Z"-SCORE	13	0.128	0.364	0.714	0.9610	0.542
VALID N (LISTWISE)	13					

Table 5. 12 The descriptive statistics of maximum values for each ratio from the Altman Z" Score model- non-bankrupt non-manufacturing companies

DESCRIPTIVE STATISTICS- ANALYSIS OF MAXIMUM VALUES PER EACH RATIO FOR ALTMAN Z"-SCORE						
	N	Value (Y-1)	Value (Y-2)	Value (Y-3)	Value (Y-4)	Average
X1	13	3.755	3.811	3.856	3.9010	3.831
X2	13	2.105	1.908	1.991	2.0740	2.020
X3	13	1.635	2.845	2.934	3.0230	2.609
X4	13	4.453	5.552	5.569	5.5855	5.290
Z"-SCORE	13	9.586	7.125	7.199	7.2705	7.795
VALID N (LISTWISE)	13					

From the Tables 5.10, 5.11 and 5.12 above that show the ratios calculated based on the financial data for four consecutive years prior to filing for bankruptcy the results are as follows:

The first variable (X1) has an average of 1.369 value with 136% standard deviation. The minimum for this ratio is-1.145 and based on the results presented in table 5.10, the biggest influence has Y-2 result. The maximum for this ratio is 3.831 and based on the results presented in table 5.11, the biggest influence has Y-1 result.

The second variable (X2) has an average of 0.529 value with an 82% standard deviation. The minimum for this ratio is -0.474 and based on the results presented in table 5.10, the biggest influence has Y-1 result. The maximum for this ratio is 2.020 and based on the results presented in table 5.11, the biggest influence has Y-1 result.

The third variable (X3) has an average of 0.582 and standard deviation of 90%. The minimum for this ratio is -0.832 and based on the results presented in table 5.10, the biggest influence has Y-1 result. The maximum for this ratio is 2.609 and based on the results presented in table 5.11, the biggest influence has Y-4 result.

The fourth variable (X4) has an average of 1.569 and standard deviation of 133%. The minimum for this ratio is 0.218 and based on the results presented in table 5.10, the biggest influence has Y-1 result. The maximum for this ratio is 5.29 and based on the results presented in table 5.11, the biggest influence has Y-4 result.

The dependent variable (Z") has an average of 4.049 with standard deviation of 229%. The minimum value of the overall Z" score is 0.542 and based on the results presented in table 5.10, the biggest influence has Y-1 result. The maximum value of the Z" score is 7.795 and the biggest influence has Y-1.

As described in part 4.2 in the study, in order to classify the non-manufacturing company as non-bankrupt, the value of the Z-Score should be >2.6. From Table 5.10 above, we can see that mean values of variables X1(Working capital/Total assets) and X4 (Market value of equity/Book value of Total liabilities**)** have the biggest influence on the overall Z-Score.

5.4. Correlation results

Manufacturing companies- Based on the results of the each of the variables for all four consecutive years we have calculated the correlation results using Data analysis tool in excel.

For the bankrupt manufacturing companies, the correlation results for each of the variables are shown in the correlation matrix below:

Table 5. 13 Correlation matrix Altman-bankrupt manufacturing companies

	X2	*X3*	*X4*	*X5*	*Z-Score*
X2	1				
X3	0.1528	1			
X4	0.3012	0.08016	1		
X5	-0.5196	-0.3265	-0.1010	1	
Z-Score	0.5025	0.5174	0.4731	0.4314	1

From the table above, we observe that all the independent variables of the model, are significantly correlated with the dependent variable Z. This assures the appropriateness and reliability of Altman's Z Score model for the bankrupt manufacturing companies.

Table 5. 14 Correlation matrix Altman- non -bankrupt manufacturing companies

	X1	*X2*	*X3*	*X4*	*X5*	*Z-Score*
X1	1					
X2	0.3475	1				
X3	0.2373	0.6776	1			
X4	-0.3303	-0.6721	-0.3792	1		
X5	0.2643	0.2387	0.1858	-0.2998	1	
Z-Score	0.0982	-0.1210	0.1648	0.6957	0.2678	1

In table 5.14 we can observe that for the non-bankrupt manufacturing companies, there is a strong correlation between the independent variable X4 (Market Value of Equity/Book value of Total Liabilities) during the analyzed 4- year period. The other variables show moderate to low and even a negative correlation (X2) with the dependable variable Z.

Non-Manufacturing companies- For the bankrupt non-manufacturing companies, the correlation results for each of the variables are shown in the correlation matrix below:

Table 5. 15 Correlation matrix Altman- bankrupt non- manufacturing companies

	X1	*X2*	*X3*	*X4*	*Z"-Score*
X1	1				
X2	-0.6069	1			
X3	-0.4118	0.1129	1		
X4	0.5286	-0.1455	-0.3679	1	
Z"-Score	-0.2209	0.8723	0.1645	0.1705	1

From the table 5.15 we can observe that there is a strong positive correlation between independent variable X2 and dependent Z”-Score for the bankrupt non-manufacturing companies.

Table 5. 16 Correlation matrix Altman- non- bankrupt non- manufacturing companies

	X1	*X2*	*X3*	*X4*	*Z"-Score*
X1	1				
X2	0.2464	1			
X3	0.0070	0.4010	1		
X4	-0.0385	-0.1282	-0.1244	1	
Z"-Score	0.6342	0.5847	0.4703	0.4318	1

From the table above, we observe that all the independent variables of the model, are significantly correlated with the dependent variable Z. This assures the appropriateness and reliability of Altman’s Z Score model for the non-bankrupt non-manufacturing companies.

5.5. Predictive Power Calculation

We use the following formula to calculate the predictive power of the model:

The Predictive Power = TCA ÷ NO

Where:

TCA: Total correct attempts to predict the status using Z' model

NO: Number of observations

From Exhibit 3, we analyze the results from the **Z Scores** for the **manufacturing companies**. As shown in Table 4.2, in order to classify the manufacturing company as bankrupt the value of the Z score needs to be <1.8. If the value of the Z score is in the range of 1.8- 2.99 then the company belongs in the "Grey area".

As presented in Table 5.13 below, from the analyzed manufacturing companies, the Altman Z score correctly predicted the bankruptcy for 10 companies out of 13 when analyzing the data one year prior to filing for bankruptcy. Only 3 companies were classified in the "Grey area".

When analyzing the data two years prior to filing for bankruptcy, the Altman Z score correctly predicted the bankruptcy for 9 companies out of 13.

When analyzing the data three years prior to filing for bankruptcy, the Altman Z score correctly predicted the bankruptcy for 8 companies out of 13. Five companies were classified in the "Grey area".

When analyzing the data four years prior to filing for bankruptcy, the Altman Z score correctly predicted the bankruptcy for 6 companies out of 13. Five companies were classified in the "Grey area".

Table 5. 17 Test result of Z Scores for manufacturing companies

Manufacturing Companies	Z-score one reporting period prior to bankruptcy (13 bankrupt/13 non-bankrupt)	Z-score two reporting periods prior to bankruptcy (13 bankrupt/13 non-bankrupt)	Z-score three reporting periods prior to bankruptcy (13 bankrupt/13 non-bankrupt	Z-score four reporting periods prior to bankruptcy (13 bankrupt/13 non-bankrupt
Bankrupt Companies Classified Bankrupt	10	9	8	6
Bankrupt companies Classified within Grey Area	3	4	5	5
Bankrupt Companies Classified as Non-Bankrupts	0	0	0	2
Total number Bankrupt Companies Not Classified as Bankrupt	**3**	**4**	**5**	**7**
Non-Bankrupt Companies Classified as Non-Bankrupt	9	8	9	10
Non-Bankrupt Companies Classified within Grey Area	4	5	4	3

Non-Bankrupt Companies Classified as Bankrupt	0	0	0	0
Total number Non-Bankrupt Companies Not Classified as Non-Bankrupt	**4**	**5**	**4**	**3**

Therefore, the predictive power of the Altman Z score model for the manufacturing companies is calculated as follows:

- TCA= 10 ÷ 13= 0.769 when analyzing the data one year prior to filing for bankruptcy and
- TCA= 9 ÷ 13= 0.692 when analyzing the data two years prior to filing for bankruptcy.
- TCA= 8 ÷ 13= 0.615 when analyzing the data three years prior to filing for bankruptcy
- TCA= 6 ÷ 13= 0.462 when analyzing the data four years prior to filing for bankruptcy

This result shows that in 76.9% of the analyzed sample one year prior or 69.2% of the of the analyzed sample two years prior to filing for bankruptcy, the Altman Z score could successfully predict the result. However, when analyzing the predictive power of year three and year four prior to filing for bankruptcy, we notice a decrease in the predictive power percentage but we can see that total 5 out of 13 companies are classified in the “grey” area, which still is a signal that the companies are facing insolvency and a possible bankruptcy. That later can be seen in the results from year one and two prior to filing for bankruptcy.

As far as calculating the predictive power for the Non- Bankrupt Manufacturing companies the predictive power of the Altman Z score shows a result of the following results:

- TCA= 9 ÷ 13= 0.692 when analyzing the data one year prior to filing for bankruptcy and
- TCA= 8 ÷ 13= 0.615 when analyzing the data two years prior to filing for bankruptcy
- TCA= 9 ÷ 13= 0.692 when analyzing the data three years prior to filing for bankruptcy.
- TCA= 10 ÷ 13= 0.769 when analyzing the data four years prior to filing for bankruptcy.

This result shows that in 69.2% of the analyzed sample one year prior or 62.5% of the of the analyzed sample two years prior to filing for bankruptcy, the Altman Z score could successfully predict the result. However, when analyzing the predictive power of year three and year four prior to filing for bankruptcy, we notice an increase in the predictive power percentage. Similar to the previous conclusion regarding the results of the bankrupt manufacturing companies, we can draw a conclusion that the analyzed sample of companies were "healthy" four and three years before filing for bankruptcy and later the number of the companies classified in the "grey" area increased.

Subsequent, we analyze the results from the **Z" Scores** for the **non -manufacturing companies**. As shown in Table 4.2, in order to classify the manufacturing company as bankrupt, the value of the Z" score needs to be <1.1. If the value of the Z" score is in the range of 1.1-2.6 then the company belongs in the "Grey area".

As presented in Table 5.18, from the analyzed non-manufacturing companies, the Altman Z'' score correctly predicted the bankruptcy for 11 companies out of 13 one year prior to filing for bankruptcy Only 2 companies were classified in the "Grey area". Whereas, two years prior to filing for bankruptcy the Altman Z'' score correctly predicted the bankruptcy of 7 companies out of 3.

When analyzing the data three years prior to filing for bankruptcy, the Altman Z score correctly predicted the bankruptcy for 8 companies out of 13. Five companies were classified in the "Grey area".

When analyzing the data four years prior to filing for bankruptcy, the Altman Z score correctly predicted the bankruptcy for 6 companies out of 13. Five companies were classified in the "Grey area".

Table 5. 18 Test result of Z" Scores for non-manufacturing companies

Non-Manufacturing Companies	Z''-score one reporting period prior to bankruptcy (13 bankrupt/13 non-bankrupt)	Z''-score two reporting periods prior to bankruptcy (13 bankrupt/13 non-bankrupt)	Z"-score three reporting periods prior to bankruptcy (13 bankrupt/13 non-bankrupt	Z"-score four reporting periods prior to bankruptcy (13 bankrupt/13 non-bankrupt
Bankrupt Companies Classified Bankrupt	11	7	7	6
Bankrupt companies Classified within Grey Area	1	3	4	4
Bankrupt Companies Classified as Non-Bankrupts	1	3	2	3
Total number Bankrupt Companies Not Classified as Bankrupt	**2**	**6**	**6**	**7**
Non-Bankrupt Companies Classified as	6	10	10	11

Non-Bankrupt				
Non-Bankrupt Companies Classified within Grey Area	4	1	1	0
Non-Bankrupt Companies Classified as Bankrupt	3	2	2	2
Total number Non-Bankrupt Companies Not Classified as Non-Bankrupt	**7**	**3**	**3**	**2**

The calculation of the predictive power would be as follows:

- TCA= 11 ÷ 13= 0.846 when analyzing the data one year prior to filing for bankruptcy or 84.6%;
- TCA= 7 ÷ 13= 0.538 when analyzing the data two years prior to filing for bankruptcy or 53.8%.;
- TCA= 7 ÷ 13= 0.538 when analyzing the data three years prior to filing for bankruptcy;
- TCA= 6 ÷ 13= 0.461 when analyzing the data four years prior to filing for bankruptcy.

As far as calculating the predictive power for the Non-Bankrupt Non-Manufacturing companies the predictive power of the Altman Z score shows the following results:

- TCA= 6 ÷ 13= 0.461 when analyzing the data one year prior to filing for bankruptcy;
- TCA= 10 ÷ 13= 0.769 when analyzing the data two years prior to filing for bankruptcy;
- TCA= 10 ÷ 13= 0.769 when analyzing the data three years prior to filing for bankruptcy;
- TCA= 11 ÷ 13= 0.846 when analyzing the data four years prior to filing for bankruptcy.

According to the overall results shown above, we can accept the first hypothesis which states "*Altman's Z-Score model can accurately predict the financial health or the failure of the US manufacturing companies; sample of the study*". Although the results of year four prior to filing for bankruptcy for the bankrupt manufacturing companies show a predictive power of 46.2%, the overall result from the research is still above 50% (average 66.32% for both bankrupt and non-bankrupt manufacturing companies). As far as testing the second hypothesis, the overall result from the research is still above 50% (average 65.35 % for both bankrupt and non-bankrupt non-manufacturing companies) which means we can still accept that "*Altman's Z" model can accurately predict the financial health or the failure of the <u>non-manufacturing</u> companies; sample of the study".*

By looking at the results from the selected sample of companies in table 5.13 and 5.14, we can answer one of the research questions in section 1.2 of this study - Which industry groups were most affected by the crisis? We can see that over the analyzed four-year period, the Altman Z Score successfully predicted bankruptcy or non-bankruptcy of 19 manufacturing companies out of 26 and 17 out of 26 non-manufacturing companies. By looking at the results from the Altman Z Score of the bankrupt companies, looks like that in this specific sample the manufacturing companies were more affected over the analyzed four-year period.

The size of the sample is a limitation described in section 6.1, but this research can confirm the general outcome that was analyzed after the crisis that the manufacturing companies were significantly affected by the financial crisis.

5.5.1. Non- Bankrupt companies -results for 2010 and 2011

In the previous sections, the Z Scores of the selected manufacturing and non-manufacturing companies were calculated in order to observe the trend of the scores over four consecutive years prior to filing for bankruptcy. In this section we have expanded the analysis with including 2010 and 2011 as reporting periods based on which we calculate the Z Score ratios for the manufacturing and the Z" score ratios for the non-manufacturing companies that "survived" or did not bankrupt. The analysis is done in order to observe if the companies classified as non-bankrupt had some better financial performances after the financial crisis peak of year 2008.

The Z scores for each company are presented in Exhibit 4 and can be summarized as follows:

Table 5. 19 2010 and 2011 Z Score results for the non-bankrupt companies

Manufacturing Companies	**Z-score 2010 (13 non-bankrupt)**	**Z-score 2011 (13 non-bankrupt)**
Non-Bankrupt Companies Classified as Non-Bankrupt	11	12
Non-Bankrupt Companies Classified within Grey Area	2	1
Non-Bankrupt Companies Classified as Bankrupt	0	0
Total number Non-Bankrupt Companies Not Classified as Non-Bankrupt	**2**	**1**
Non-Manufacturing Companies	Z''-score 2010 (13 non-bankrupt)	Z''-score 2011 (13 non-bankrupt)
Non-Bankrupt Companies Classified as Non-Bankrupt	8	10
Non-Bankrupt Companies Classified within Grey Area	5	3
Non-Bankrupt Companies Classified as Bankrupt	0	0
Total number Non-Bankrupt Firms Not Classified as Non-Bankrupt	**5**	**3**

As the results show, for the manufacturing companies shown in section 5.17, for Z-score one reporting period prior to bankruptcy, we had 9 companies classified as non-bankrupt and 4 companies classified in the grey area. In 2010 we see an increase in the number of the “survived” or non-bankrupt companies by moving 2 companies from the grey area into the non-bankrupt area. As for 2011, we again see an improvement with 12 companies classified as non-bankrupt vs. only 1 manufacturing company placed in the grey area.

For the non- manufacturing companies shown in section 5.18, for Z”-score one reporting period prior to bankruptcy we had 6 companies classified as non-bankrupt, 4 companies in the grey area and 3 companies classified as bankrupt. In 2010 we see an increase in the number of the "survived" or non-bankrupt companies to 8 and, we have no companies classified as bankrupt but see an increase of the number of companies to 5 in the grey area. As for 2011, we again see an improvement with 10 companies classified as non-bankrupt vs. only 3 non-manufacturing company placed in the grey area. This shows that for the sample taken for the study, the surviving companies had shown better financial performances after the period of the crisis.

5.6. Comparison-Taffler Model for Bankruptcy prediction

Formulated in 1977, this model is another frequently used bankruptcy model. Its basic idea is similar to the Altman Z score model, while this one used only four partial indicators, namely:

$$\mathbf{T = 0.53*R1 + 0.13*R2 + 0.18*R3 + 0.16*R4}$$

where:

- R1 = earnings before taxes / current liabilities
- R2 = current assets / total liabilities
- R3 = current liabilities / total assets
- R4 = sales / total assets

Zones of discrimination of this model are 0.3 and 0.2. That means that if the overall result is higher than 0.3, the company is in the "safe zone" with no significant risk of bankruptcy. The result between 0.2 and 0.3 presents "grey zone" with some potential risk of bankruptcy and the necessity to make some decisions for improving of the position of the company. Results below 0.2 present "bankrupt zone" with significant risk of bankruptcy (Taffler 1983).

Using the sample from Exhibit 3, the T scores have been calculated for the whole sample of 26 manufacturing and non-manufacturing companies for four consecutive years.

The individual results for each company over the period can be seen in Exhibit 5 of this study. The table below shows the summarized results for Atman's Z score and Taffler's T score for the selected sample:

Table 5. 20 Summary of results- Altman vs Taffler classification scores

Manufacturing Bankrupt	Y-1		Y-2		Y-3		Y-4	
Classification	Altman	Taffler	Altman	Taffler	Altman	Taffler	Altman	Taffler
bankrupt	10	8	9	10	8	8	6	9
grey	3	5	4	3	5	5	5	4
safe	0	0	0	0	0	0	2	0
N	13	13	13	13	13	13	13	13
Predictive power%	77%	62%	69%	77%	62%	62%	46%	69%
Manufacturing Non-Bankrupt	Y-1		Y-2		Y-3		Y-4	
Classification	Altman	Taffler	Altman	Taffler	Altman	Taffler	Altman	Taffler
bankrupt	0	0	0	0	0	0	0	0
grey	4	6	5	6	4	4	3	3
safe	9	7	8	7	9	9	10	10
N	13	13	13	13	13	13	13	13
Predictive power%	69%	54%	62%	54%	69%	69%	77%	77%
Non-Manufacturing Bankrupt	Y-1		Y-2		Y-3		Y-4	
Classification	Altman	Taffler	Altman	Taffler	Altman	Taffler	Altman	Taffler
bankrupt	11	9	7	10	7	9	6	9
grey	1	2	3	2	4	2	3	2
safe	1	2	3	1	2	2	4	2
N	13	13	13	13	13	13	13	13
Predictive power%	85%	69%	54%	77%	54%	69%	46%	69%
Non-Manufacturing Non-Bankrupt	Y-1		Y-2		Y-3		Y-4	
Classification	Altman	Taffler	Altman	Taffler	Altman	Taffler	Altman	Taffler
bankrupt	3	0	2	1	2	0	2	0
grey	4	7	1	4	1	7	0	7
safe	6	6	10	8	10	6	11	6
N	13	13	13	13	13	13	13	13
Predictive power%	46%	46%	77%	62%	77%	46%	85%	46%

The results from table 5.19 show that overall Altman Z score shows a better prediction power when we analyze Y-1 results or one year prior to filing for bankruptcy. However, in classifying the Non- Manufacturing companies as bankrupt, in Y-2 to Y-4 the Taffler model shows a better prediction power of 69%-77% compared to Altman's Z score model results of 46%-54%.

Thus, by analyzing these results we may partially answer one of the research questions mentioned in section 1.2 - What other models can be used in combination with the Altman Z Score model to give the best prediction results? The results show that even though Altman Z Score Model has relatively strong predictive power for the analyzed sample, it is a better approach if we take into consideration the results obtained with the Taffler bankruptcy prediction model as an addition to the research to be able to draw some useful conclusions. In the study we mentioned Ohlson and Zmijewski models as some of the suggested models to use. As Taffler model has a very similar approach to Altman's Z Score model, it was decided to use this model in order to obtain the results and make a comparison.

6. CHAPTER 6: CONCLUSIONS

6.1. Limitations of the study

The sample used for this thesis is small and focuses only on the companies that are existing on the US market. For the research a sample of 26 manufacturing and 26 non-manufacturing companies was selected. The results would be even more reliable if a larger number of companies was selected (for example at least 50-80 from each industry) and therefore the size of the selected sample for this study should be seen as a limitation. The size of the selected sample would not be a full representation of the full US market, but are a good sample to analyze and test the Altman Z Score model predictive power in a period of a financial crisis. Due to lack of financial information, some of the original sample companies that were selected for analysis, were excluded from the study. Thus, another important limitation of this study was the availability of the data.

While the original Altman Z Score model works reasonably well for the US market, for most countries, the classification accuracy may be somewhat improved with country-specific estimation. In a country model, the information provided even by simple additional variables may help boost the classification accuracy to a much higher level. Based on the empirical tests in this study, the original Z-Score model works consistently well and it's easy to implement and interpret. Thus, this kind of accounting-based model can be used by all interested parties.

Further research should focus on other modifications and extensions than those presented in this paper, such as using alternative modeling techniques (e.g., panel data analysis), introducing new variables (e.g., macroeconomic data), and testing its usefulness with data from other countries (e.g., emerging markets).

The objective of this study was to test the predictive power of the Altman Z score for manufacturing and Z" score Non-manufacturing companies listed on the US market. As many different authors have already concluded during their research, the best representable results would be gathered if it is used in combination with some other bankruptcy prediction models (market based, Artificial Neural Networks-ANN etc.). In this study, a comparison was made with the Taffler bankruptcy prediction model results for the selected sample due to the similarity in the research approach with the Altman Z Score model. The results would be even more reliable if we incorporate another accounting based model or maybe a market based model or a credit agency's analysis of the sample that would serve as a support to incorporate the "soft" factors of the analysis, which are often seen as a disadvantage of the accounting based models by different authors.

6.2.Concluding remarks

The testing of the Z-score model has been an interesting and challenging experience where the outcome has shown dissimilar results. Unfortunately, it is not easy to clarify whether the Z-score and Z''-score models give a satisfying prediction of bankrupt companies since this varies with the preferences and requirements of the user applying the model. Moreover, since the model is developed using empirical evidence it is highly dependent on the history having a reliable predictive ability. However, since there is no default prediction model showing 100%, a 66.32 % average accuracy for the Z-score and a 65.35 % accuracy for the Z''-score in identifying bankrupt companies is good news. The comparison with the Taffler model shows that the Taffler model had a better prediction power for period Y-2 to Y-4 of 69%-77% compared to Altman's Z score model results of 46%-54% for the selected sample of non-manufacturing companies in classifying them as bankrupt. Therefore, adding another model to compare with the Altman Z score results was very useful to make the results more reliable. The lower percentage of the predictive power of Altman Z Score for the non- manufacturing bankrupt companies can probably be seen as a disadvantage in this case. But we can add that the predictive power is stronger as the results are being analyzed closer to the year of filing the bankruptcy. Namely, in the case of classifying of Bankrupt Non-Manufacturing companies as Bankrupt, the change in the percentage from 46.1% based on the financial data calculated four years before filing for bankruptcy to 84.6% based on the financial data calculated one year before filing for bankruptcy is a significant increase of 38.5%. This increase for the manufacturing companies over the four years was 30.7%.

As for classifying the Non- Bankrupt Non-Manufacturing companies as Non -Bankrupt we see a decrease in the predictive power of the Z" score as coming closer to the date of filing the bankruptcy from 84.6% based on the financial data calculated four years before filing for bankruptcy to 46.1% based on the financial data calculated one year before filing for bankruptcy.

Furthermore, when applying the optimal cut off value suggested by Altman (1968) which is 50 years ago and getting an average accuracy of 66.32% and 65.35% for four reporting periods prior to bankruptcy indicates that a financial ratio model still has a fairly reliable ability to predict default even though it is not as accurate as in the initial sample. It is an affirmation that business logics to some extent still apply irrespectively of changes in the economic environment and the corporate world.

There is reason to believe that the Z-score model have gained popularity much due to the fact of its simplicity and cost-efficiency. The model does not require the user to have extensive knowledge in advanced finance for him or her to understand how the model functions and moreover how to actually apply it. When deciding on whether to invest in a security or not there will always be a tradeoff where the actual costs in terms of time and money of applying the model must be stated in relation to what costs may be realized in case of the security defaulting. In some situations, the accuracy of the Z-score may be sufficient together with a sober evaluation of other factors affecting the firm whereas in other cases concerning large investments may require a more exhaustive assessment by for example engaging a credit rating agency. Still, in many situations the model can be a very useful tool for getting an indication whether a firm may face financial distress or not. In any of the circumstances stated above it is important for the affected party to understand the potential outcomes resulting from errors, bias and weaknesses of the models, many of them discussed in this paper.

6.3. Suggestions for further research

The literature review section summarizes recent articles in prominent academic journals that have utilized Altman's Z-Score or Z''-Score models, or re-estimated versions of them, in empirical analyses. These models are typically used as benchmarks in failure prediction modeling studies, where one or several alternative methods or approaches (hazard models, contingent-claims, intelligent algorithms etc.) have been tested. However, in a considerable number of the reviewed studies failure prediction is not the primary focus. Instead, these models have been largely used as measures of financial strength. As to the failure prediction studies, the results have been somewhat uneven so that in some studies the models have performed well, whereas in others they have been outperformed by competing models.
In this study, the classification performance of the Z Score and Z''-Score model is assessed using very small data set from US listed companies. A suggestion would be to expand the sample to include a larger number of companies in order to get more reliable results. It would be also very useful to do an in-depth analysis of the structure of each analyzed company to observe the structure of the ratios and their influence and make a correlation with the results obtained when applying the Z Score model.

In the conclusion part, our evidence thus indicates that the original Z-Score Model performs well in a US context. It is, however, possible to extract a more efficient country model for most European countries and for non-European countries using the four original variables, accompanied with a set of additional background variables. Considering practical applications, it is obvious that while a general US based model works reasonably well, for most countries the classification accuracy may be somewhat improved with country-specific estimation. It would be useful to make a similar analysis on the Macedonian market for the manufacturing and non-manufacturing companies listed on the Macedonian Stock exchange. As the Macedonian stock exchange market is very small compared to the US market it would be hard to make some kind a parallel comparison to analyze the effect of the 2008 crisis for the both economies. However, the availability of data can be a good starting point to make some efforts or preliminary research by applying the Altman Z score model, especially due to the simplicity of the model itself. During the research on the Altman Z Score model, I have found very little literature and similar research papers by Macedonian authors which was one of the reasons to conduct a research by using this model.

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Exhibit 1: GDP growth in United States

US GDP growth 1947-2017	
Year 1947-2017	% change in GDP
31-Dec-17	2.58%
31-Dec-16	1.84%
31-Dec-15	2.02%
31-Dec-14	2.70%
31-Dec-13	2.66%
31-Dec-12	1.28%
31-Dec-11	1.68%
31-Dec-10	2.73%
31-Dec-09	-0.24%
31-Dec-08	-2.77%
31-Dec-07	1.87%
31-Dec-06	2.39%
31-Dec-05	3.03%
31-Dec-04	3.12%
31-Dec-03	4.36%
31-Dec-02	2.04%
31-Dec-01	0.21%
31-Dec-00	2.89%
31-Dec-99	4.69%
31-Dec-98	5.00%
31-Dec-97	4.39%
31-Dec-96	4.45%
31-Dec-95	2.28%
31-Dec-94	4.13%
31-Dec-93	2.63%
31-Dec-92	4.33%
31-Dec-91	1.22%
31-Dec-90	0.65%
31-Dec-89	2.78%
31-Dec-88	3.84%
31-Dec-87	4.45%
31-Dec-86	2.94%
31-Dec-85	4.28%
31-Dec-84	5.63%
31-Dec-83	7.83%

31-Dec-82	-1.40%
31-Dec-81	1.29%
31-Dec-80	-0.04%
31-Dec-79	1.30%
31-Dec-78	6.68%
31-Dec-77	4.98%
31-Dec-76	4.33%
31-Dec-75	2.56%
31-Dec-74	-1.93%
31-Dec-73	4.02%
31-Dec-72	6.86%
31-Dec-71	4.38%
31-Dec-70	-0.15%
31-Dec-69	2.07%
31-Dec-68	4.97%
31-Dec-67	2.70%
31-Dec-66	4.51%
31-Dec-65	8.48%
31-Dec-64	5.15%
31-Dec-63	5.18%
31-Dec-62	4.28%
31-Dec-61	6.37%
31-Dec-60	0.86%
31-Dec-59	4.54%
31-Dec-58	2.67%
31-Dec-57	0.36%
31-Dec-56	1.99%
31-Dec-55	6.57%
31-Dec-54	2.74%
31-Dec-53	0.53%
31-Dec-52	5.35%
31-Dec-51	5.49%
31-Dec-50	13.40%
31-Dec-49	-1.50%
31-Dec-48	3.80%
31-Dec-47	-0.01%

Exhibit 2: Sample Companies and Corresponding Peers

Bankrupt					Non Bankrupt	
	Year filed	Corp. Name	BV Total Assets	Year filed	Corp. Name	BV Total Assets
Mining			(mill)			(mill)
	2009	Edge Petroleum Corp	$357.60	2009	StillWater Min ina	$724.80
	2009	TXCO Resources Inc.	$486.90			
Transportation						
Communications	2007	In Phonic Inc.	$264.40	2007	USA Mobility Inc	$241.40
Electric				2008	Atlantic Tele-Network	$344.60
Gas	2008	Frontier Airlines Holdings, Inc.	$1,250.00	2008	Pinnacle Airlines Corp	$1,133.10
	2009	Citadel Broadcasting Corp	$2,433.00	2009	Otelco Inc	$355.50
	2009	Primus Telecommunications Group	$460.40			
	2010	Trico Marine Services Inc.	$1,202.60			
Retail Trade						
	2007	Tweeter Home Entertainment Group	$258.60	2007	Bombay Co.	$238.10
	2008	Circuit City Stores Inc.	$3.745.90	2009	Duckwall-ALCO Stores	$208.80
	2009	Eddie Bauer Holdings Inc.	$596.90	2007	BioScrip Inc	$305.50
Services						
	2008	Bally Total Fitness Holding Corp	$396.80	2008	Cedar Fair L.P.	$2,510.90
	2009	Six Flags Inc.	$2,945.30	2009	FTI Consulting	$2,088.20

				2009	Gaylord Entertainment	$2,560.40
				2008	Hunt (J.B.)	$1,862.80
Manufacturing						
	2008	Constar Intemational Inc.	$472.30	2007	Schweitzer-Mauduit Intl Inc	$696.60
	2008	Lenox Group,Inc .	$352.10	2008	Apogee Enterprises	$527.70
	2009	Accuride Corp	$808.50	2009	Domtar Corp.	$7,748.00
	2009	Asyst Technologies Inc.	$445.70	2009	Federal Signal	$834.00
	2009	Champion Enterprises,In c.	$1,022.20	2009	Alamo Group	$384.40
	2009	Dayton Superior Corp	$300.10	2009	FMC Corp.	$2,993.90
	2009	Lear Corp	$6,872.90	2009	Northwest Pipe Co	$509.40
	2008	Chesapeake Corp.	$1,114.80	2009	Cooper Inds.	$6,164.90
	2008	MPC Corp	$122.40	2009	Temple-Inland	$5,869.00
	2008	VeraSun Energy	$1,863.50	2009	Oshkosh Corp.	$6,081.50
	2009	Fleetwood Enterprises	$625.60	2008	Georgia Gulf	$1,610.40
	2009	Hayes Lemmerz Inti Inc	$1,096.20	2009	Intemational Tex tile Group	$761.30
	2010	General Motors	$136,295.00	2010	Ford Motor Co	$194,850.00

Exhibit 3: Z-score and Z" score for Sample Companies

Manufacturing Companies:

Bankrupt Manufacturing firms- Z-score- One reporting period prior to bankruptcy							
Company	**Filing date 10.K**	**1.2*X1**	**1.4*X2**	**3.3*X3**	**0.6*X4**	**0.999*X5**	**Z-Score**
Constar International Inc.	12/31/2007	0.098	-0.976	0.105	0.057	1.867	**1.151**
Lenox Group, Inc.	12/31/2007	0.355	0.154	-0.069	0.173	1.284	**1.897**
Accuride Corporation	12/31/2008	0.270	-0.533	-1.129	0.006	1.152	**-0.234**
Asyst Technologies, Inc.	3/31/2008	0.142	-1.258	-0.099	0.174	1.026	**-0.015**
Champion Enterprises, Inc.	12/31/2008	-0.070	-0.382	-0.178	0.047	1.602	**1.019**
Dayton Superior Corporation	12/31/2008	-1.036	-1.433	0.496	0.018	1.586	**-0.369**
Lear Corporation	12/31/2008	-0.163	-0.037	-0.144	1.046	1.974	**2.676**
Chesapeake Corp.	12/31/2007	0.093	0.137	0.073	0.071	0.873	**1.247**
MPC Corporation	12/31/2007	-0.172	-0.494	-0.177	0.050	1.370	**0.577**
VeraSun Energy	12/31/2007	0.147	0.087	0.095	0.089	0.453	**0.871**
Fleetwood Enterprises	4/27/2008	0.207	-1.066	0.094	0.071	2.654	**1.960**
Hayes lemmerz Inti Inc	1/31/2009	-0.509	-0.002	-0.760	0.040	1.737	**0.506**
GMCo	12/31/2008	-0.431	-1.086	-0.771	0.665	1.636	**0.013**

Bankrupt Manufacturing firms- Z-score- Two reporting periods prior to bankruptcy							
Company	**Filing date 10.K**	**1.2*X1**	**1.4*X2**	**3.3*X3**	**0.6*X4**	**0.999*X5**	**Z-Score**
Constar International Inc.	12/31/2006	0.1575	-0.8363	0.1768	0.0962	1.8394	**1.434**
Lenox Group, Inc.	12/31/2006	0.0971	0.1063	-0.3031	0.3868	1.3443	**1.631**
Accuride Corporation	12/31/2007	0.1761	0.0260	0.0877	0.1986	0.9103	**1.399**
Asyst Technologies, Inc.	3/31/2007	-0.0697	-0.3816	-0.1776	0.0468	1.6018	**1.020**
Champion Enterprises, Inc.	12/21/2007	0.0494	0.0324	0.0750	0.6224	1.2458	**2.025**
Dayton Superior Corporation	12/31/2007	0.2347	-1.3032	0.4428	0.1096	1.5223	**1.006**
Lear Corporation	12/31/2007	0.0176	-0.0050	0.2382	0.0020	2.0505	**2.303**
Chesapeake Corp.	12/31/2006	0.0343	0.1720	0.0009	0.2295	0.8929	**1.330**
MPC Corporation	12/31/2006	-0.1031	-0.9442	-1.0523	0.0482	2.3277	**0.276**
VeraSun Energy	12/31/2006	0.5801	0.1579	0.6298	0.3791	0.6973	**2.444**
Fleetwood Enterprises	4/29/2007	0.2802	-0.9461	-0.2712	0.3615	2.7296	**2.154**

Hayes lemmerz Inti Inc	1/31/2008	0.1136	-0.7200	-0.0707	0.1331	1.1776	**0.634**
GMCo	12/31/2007	-0.0756	-0.3704	-0.0955	0.4585	1.2089	**1.126**

Bankrupt Manufacturing firms- Z-score- Three reporting periods prior to bankruptcy

Company	Filing date 10.K	1.2*X1	1.4*X2	3.3*X3	0.6*X4	0.999*X5	Z-Score
Constar International Inc.	12/31/2005	0.1652	-0.7920	0.1500	0.1253	1.8670	**1.516**
Lenox Group, Inc.	12/31/2005	0.1231	0.1433	-0.2995	0.4200	1.4290	**1.816**
Accuride Corporation	12/31/2008	0.1811	0.0259	0.0822	0.2129	0.9411	**1.443**
Asyst Technologies, Inc.	3/31/2008	-0.0631	-0.3269	-0.1322	0.0462	1.7103	**1.234**
Champion Enterprises, Inc.	12/31/2008	0.0551	0.0261	0.0691	0.6288	1.1912	**1.970**
Dayton Superior Corporation	12/31/2008	0.1899	-1.1467	0.4589	0.0987	1.4551	**1.056**
Lear Corporation	12/31/2008	0.0192	-0.0043	0.2019	0.0019	1.9984	**2.217**
Chesapeake Corp.	12/31/2005	0.0431	0.1920	0.0008	0.2144	0.7829	**1.233**
MPC Corporation	12/31/2005	-0.0955	-0.8776	-0.9167	0.0689	2.3277	**0.507**
VeraSun Energy	12/31/2005	0.6730	0.1766	0.6987	0.3967	0.7611	**2.706**
Fleetwood Enterprises	4/27/2006	0.2980	-0.8767	-0.1894	0.3615	2.7296	**2.323**
Hayes lemmerz Inti Inc	1/31/2007	0.1387	-0.6981	-0.0564	0.1265	1.1899	**0.701**
GMCo	12/31/2006	-0.0612	-0.3019	-0.0932	0.4329	1.1988	**1.175**

Bankrupt Manufacturing firms- Z-score- Four reporting periods prior to bankruptcy

Company	Filing date 10.K	1.2*X1	1.4*X2	3.3*X3	0.6*X4	0.999*X5	Z-Score
Constar International Inc.	12/31/2004	0.2630	-0.6975	0.3490	0.3143	1.9570	**2.186**
Lenox Group, Inc.	12/31/2004	0.1393	0.1601	-0.2827	0.4367	1.4458	**1.899**
Accuride Corporation	12/31/2007	0.1934	0.0404	0.1167	0.4429	0.9756	**1.769**
Asyst Technologies, Inc.	3/31/2007	0.1265	-0.1413	-0.0432	0.1242	1.7993	**1.865**
Champion Enterprises, Inc.	12/31/2007	0.0740	0.0395	0.0889	0.6478	1.2110	**2.061**
Dayton Superior Corporation	12/31/2007	0.2577	-1.0899	0.5111	0.1477	1.5073	**1.334**
Lear Corporation	12/31/2007	0.0348	0.0114	0.2469	0.0409	2.0434	**2.377**
Chesapeake Corp.	12/31/2004	0.2297	0.3820	0.0978	0.3024	0.7839	**1.796**
MPC Corporation	12/31/2004	-0.0756	-0.8653	-0.8978	0.0859	2.3466	**0.594**
VeraSun Energy	12/31/2004	0.7646	0.2689	0.7866	0.4827	0.8490	**3.152**
Fleetwood Enterprises	4/27/2005	0.4320	-0.7207	-0.0474	0.4945	2.8716	**3.030**
Hayes lemmerz	1/31/2008	0.2067	-0.6791	-0.0364	0.1455	1.2099	**0.847**

Inti Inc							
GMCo	12/31/2005	0.0238	-0.2239	-0.0042	0.5159	1.2878	**1.599**

Non-Bankrupt Manufacturing firms - Z-score -One reporting period prior to bankruptcy							
Company	**Filing date 10.K**	**1.2*X1**	**1.4*X2**	**3.3*X3**	**0.6*X4**	**0.999*X5**	**Z-Score**
Schweitzer- Mauduit Inti Inc	12/31/2006	0.119	0.546	0.025	0.236	0.941	**1.867**
Domtar Corp.	12/31/2008	0.179	-0.121	-0.236	2.377	1.048	**3.247**
Federal Signal	12/31/2008	0.229	0.380	0.220	0.330	1.150	**2.309**
Apogee Enterprises	3/1/2008	0.174	0.452	0.389	0.711	1.565	**3.291**
Alamo Group	12/31/2008	0.563	0.481	0.183	1.281	1.450	**3.958**
Northwest Pipe Co	12/31/2008	0.526	0.517	0.379	1.307	0.863	**3.592**
Cooper Inds.	12/31/2008	0.143	0.667	0.470	2.135	1.058	**4.473**
Temple-Inland	1/3/2009	0.128	0.223	0.046	3.055	0.001	**3.453**
Oshkosh Corp.	9/30/2008	0.136	0.249	0.220	2.814	1.174	**4.593**
Georgia Gulf	12/31/2007	0.109	0.028	-0.125	1.203	1.434	**2.649**
FMC Corp.	12/31/2008	0.270	0.713	0.552	1.149	1.041	**3.725**
International Textile Group	12/31/2008	-0.330	-0.562	-0.810	4.208	1.307	**3.813**
Ford Motor Co	12/31/2008	0.301	-0.104	-0.179	1.407	0.592	**2.017**

Non-Bankrupt Manufacturing firms - Z-score -Two reporting periods prior to bankruptcy							
Company	**Filing date 10.K**	**1.2*X1**	**1.4*X2**	**3.3*X3**	**0.6*X4**	**0.999*X5**	**Z-Score**
Schweitzer- Mauduit Inti Inc	12/31/2005	0.123	0.571	0.188	0.239	0.970	**2.091**
Domtar Corp.	12/31/2007	0.140	0.009	0.115	2.717	0.770	**3.751**
Federal Signal	12/31/2007	0.098	0.400	0.212	0.435	0.799	**1.944**
Apogee Enterprises	12/31/2008	0.205	0.459	0.351	1.674	1.734	**4.423**
Alamo Group	12/31/2007	0.580	0.493	0.224	1.200	1.439	**3.936**
Northwest Pipe Co	12/31/2007	0.480	0.481	0.287	1.184	0.844	**3.276**
Cooper Inds.	12/31/2007	0.131	0.647	0.454	1.975	0.962	**4.169**
Temple-Inland	1/3/2008	0.078	0.233	0.001	3.097	0.001	**3.410**
Oshkosh Corp.	9/30/2007	0.121	0.227	0.304	3.001	0.986	**4.639**
Georgia Gulf	12/31/2006	0.099	0.185	0.210	1.239	0.988	**2.721**
FMC Corp.	12/31/2007	0.194	0.643	0.275	0.879	0.963	**2.954**
International Textile Group	12/31/2007	0.296	-0.094	-0.161	3.883	1.049	**4.973**
Ford Motor Co	12/31/2007	0.276	-0.007	-0.059	1.633	0.553	**2.396**

Non-Bankrupt Manufacturing firms - Z-score -Three reporting periods prior to bankruptcy							
Company	**Filing date 10.K**	**1.2*X1**	**1.4*X2**	**3.3*X3**	**0.6*X4**	**0.999*X5**	**Z-Score**
Schweitzer- Mauduit Inti Inc	12/31/2004	0.213	0.760	0.098	0.050	1.159	**2.280**
Domtar Corp.	12/31/2006	0.157	0.026	0.098	2.700	0.787	**3.768**
Federal Signal	12/31/2006	0.133	0.630	0.178	0.205	1.029	**2.174**
Apogee Enterprises	12/31/2007	0.294	0.537	0.262	1.596	1.812	**4.501**
Alamo Group	12/31/2006	0.600	0.512	0.204	1.181	1.458	**3.955**
Northwest Pipe Co	12/31/2006	0.532	0.530	0.235	1.135	0.893	**3.325**
Cooper Inds.	12/31/2006	0.176	0.686	0.409	1.936	1.001	**4.208**
Temple-Inland	1/3/2007	0.079	0.321	0.000	3.009	0.089	**3.498**
Oshkosh Corp.	9/30/2006	0.140	0.244	0.285	2.984	1.003	**4.656**
Georgia Gulf	12/31/2005	0.187	0.271	0.122	1.153	1.074	**2.807**
FMC Corp.	12/31/2006	0.336	0.776	0.133	0.746	1.096	**3.087**
International Textile Group	12/31/2006	0.316	-0.075	-0.181	3.864	1.068	**4.992**
Ford Motor Co	12/31/2006	0.365	0.076	-0.148	1.550	0.636	**2.479**

Non-Bankrupt Manufacturing firms - Z-score -Four reporting periods prior to bankruptcy							
Company	**Filing date 10.K**	**1.2*X1**	**1.4*X2**	**3.3*X3**	**0.6*X4**	**0.999*X5**	**Z-Score**
Schweitzer- Mauduit Inti Inc	12/31/2003	0.303	0.949	0.188	0.239	1.249	**2.928**
Domtar Corp.	12/31/2005	0.174	0.042	0.115	2.717	0.804	**3.852**
Federal Signal	12/31/2005	0.167	0.860	0.212	0.435	1.064	**2.738**
Apogee Enterprises	12/31/2006	0.383	0.615	0.351	1.674	1.901	**4.924**
Alamo Group	12/31/2005	0.620	0.531	0.224	1.200	1.478	**4.052**
Northwest Pipe Co	12/31/2005	0.584	0.579	0.287	1.184	0.945	**3.580**
Cooper Inds.	12/31/2005	0.221	0.725	0.454	1.975	1.046	**4.421**
Temple-Inland	1/3/2006	0.080	0.409	0.001	3.097	0.090	**3.677**
Oshkosh Corp.	9/30/2005	0.159	0.261	0.304	3.001	1.022	**4.747**
Georgia Gulf	12/31/2004	0.275	0.357	0.210	1.239	1.162	**3.243**
FMC Corp.	12/31/2005	0.478	0.909	0.275	0.879	1.238	**3.779**
International Textile Group	12/31/2005	0.336	-0.056	-0.161	3.883	1.088	**5.090**
Ford Motor Co	12/31/2005	0.454	0.159	-0.059	1.633	0.725	**2.912**

Non-Manufacturing Companies:

Bankrupt Non-Manufacturing firms- Z"-score- One reporting period prior to bankruptcy						
Company	**Filing date 10-K**	**6.56*X1**	**3.26*X2**	**6.72*X3**	**1.05*X4**	**Z"-score**
Edge Petroleum Corporation	12/31/2008	-0.991	-1.874	-0.192	-0.063	**-3.120**
TXCO Resources Inc.	12/31/2008	-3.462	0.021	0.270	0.494	**-2.677**
In Phonic, Inc.	12/31/2006	1.500	-2.816	-1.607	0.405	**-2.518**
Frontier Airlines Holdings, Inc.	3/31/2008	-0.751	-0.112	-0.188	0.145	**-0.906**
Citadel Broadcasting Corporation	12/31/2008	0.286	-3.208	2.828	-0.115	**-0.209**
Primus Telecommunications Group, Inc.	12/31/2008	-1.185	-1.085	0.789	-0.612	**-2.093**
Tweeter Home Entertainment Group	9/30/2006	0.998	3.031	-0.355	0.376	**4.050**
Circuit City Stores, Inc.	2/29/2008	1.461	0.854	-0.665	0.704	**2.354**
Eddie Bauer Holdings, Inc.	1/3/2009	0.838	-2.743	-1.609	0.146	**-3.368**
Bally Total Fitness Holding Corporati	12/31/2006	-1.461	-1.702	1.933	-0.818	**-2.048**
Six Flags, Inc.	12/31/2008	-0.316	-1.930	0.319	-0.169	**-2.096**
Finlay Enterprises Inc	1/31/2009	1.921	-0.354	-1.266	0.013	**0.314**
Trico Marine Services Inc	12/31/2009	0.064	0.068	-0.713	0.211	**-0.370**

Bankrupt Non-Manufacturing firms- Z"-score- Two reporting periods prior to bankruptcy						
Company	**Filing date 10-K**	**6.56*X1**	**3.26*X2**	**6.72*X3**	**1.05*X4**	**Z"-score**
Edge Petroleum Corporation	12/31/2007	0.019	0.053	0.186	1.344	**1.602**
TXCO Resources Inc.	12/31/2007	-0.442	0.033	0.197	1.020	**0.808**
In Phonic, Inc.	12/31/2005	1.881	-2.737	-1.335	1.089	**-1.102**
Frontier Airlines Holdings, Inc.	3/31/2007	-0.119	0.054	-0.063	0.264	**0.136**
Citadel Broadcasting Corporation	12/31/2007	0.554	-1.208	2.475	0.205	**2.026**
Primus Telecommunications Group, Inc.	12/31/2007	-0.304	-7.610	0.463	-0.518	**-7.969**
Tweeter Home Entertainment Group	9/30/2005	0.904	2.531	-1.114	0.433	**2.754**

Circuit City Stores, Inc.	2/28/2007	1.914	1.087	-0.009	0.849	**3.841**
Eddie Bauer Holdings, Inc.	12/29/2008	0.581	-1.353	-0.235	0.485	**-0.522**
Bally Total Fitness Holding Corporati	12/31/2005	-5.565	13.919	1.081	-0.785	**8.650**
Six Flags, Inc.	12/31/2007	-0.216	-1.836	0.087	-0.106	**-2.071**
Finlay Enterprises Inc	2/2/2008	1.983	0.202	0.047	0.191	**2.423**
Trico Marine Services Inc	12/31/2008	0.064	0.068	-0.713	0.211	**-0.370**

Bankrupt Non-Manufacturing firms- Z"-score- Three reporting periods prior to bankruptcy						
Company	**Filing date 10-K**	**6.56*X1**	**3.26*X2**	**6.72*X3**	**1.05*X4**	**Z"-score**
Edge Petroleum Corporation	12/31/2006	0.109	0.242	0.276	1.434	**2.061**
TXCO Resources Inc.	12/31/2006	-0.425	0.050	0.214	1.037	**0.875**
In Phonic, Inc.	12/31/2004	1.916	-2.507	-1.301	1.124	**-0.769**
Frontier Airlines Holdings, Inc.	3/31/2006	-0.030	0.132	0.026	0.353	**0.481**
Citadel Broadcasting Corporation	12/31/2006	0.574	-1.189	2.495	0.225	**2.104**
Primus Telecommunications Group, Inc.	12/31/2006	-0.252	-7.561	0.515	-0.466	**-7.763**
Tweeter Home Entertainment Group	9/30/2004	0.949	1.879	-1.069	0.478	**2.237**
Circuit City Stores, Inc.	2/28/2006	1.915	1.175	-0.008	0.850	**3.932**
Eddie Bauer Holdings, Inc.	12/29/2007	0.600	-1.336	-0.216	0.504	**-0.448**
Bally Total Fitness Holding Corporati	12/31/2004	-5.477	12.564	1.169	-0.697	**7.559**
Six Flags, Inc.	12/31/2006	-0.074	-1.703	0.229	0.036	**-1.512**
Finlay Enterprises Inc	2/2/2007	2.003	0.221	0.067	0.211	**2.502**
Trico Marine Services Inc	12/31/2007	0.153	0.151	-0.624	0.300	**-0.020**

Bankrupt Non-Manufacturing firms- Z"-score- Four reporting periods prior to bankruptcy						
Company	**Filing date 10-K**	**6.56*X1**	**3.26*X2**	**6.72*X3**	**1.05*X4**	**Z"-score**
Edge Petroleum Corporation	12/31/2006	0.108	0.189	0.465	1.523	**2.285**
TXCO Resources Inc.	12/31/2006	-0.427	0.198	0.890	1.052	**1.713**
In Phonic, Inc.	12/31/2004	1.926	-1.987	-1.290	1.169	**-0.182**
Frontier Airlines Holdings, Inc.	3/31/2006	0.070	0.298	0.078	0.542	**0.988**

Citadel Broadcasting Corporation	12/31/2006	0.572	-1.090	2.411	0.243	**2.136**
Primus Telecommunications Group, Inc.	12/31/2006	-0.237	-5.890	0.523	-0.399	**-6.002**
Tweeter Home Entertainment Group	9/30/2004	0.948	1.819	-1.034	0.522	**2.255**
Circuit City Stores, Inc.	2/28/2006	1.943	1.189	-0.003	0.879	**4.008**
Eddie Bauer Holdings, Inc.	12/29/2007	0.759	-1.158	-0.190	0.682	**0.093**
Bally Total Fitness Holding Corporati	12/31/2004	-5.366	12.763	1.187	-0.498	**8.086**
Six Flags, Inc.	12/31/2006	-0.083	-1.570	0.217	0.169	**-1.267**
Finlay Enterprises Inc	2/2/2007	2.143	0.381	0.089	0.371	**2.984**
Trico Marine Services Inc	12/31/2007	0.154	0.241	-0.629	0.390	**0.156**

Non- Bankrupt Non-Manufacturing firms- Z"-score- One reporting period prior to bankruptcy

Company	**Filing date 10-K**	**6.56*X1**	**3.26*X2**	**6.72*X3**	**1.05*X4**	**Z"-score**
StillWater Mining	12/31/2008	2.087	-0.985	-1.061	1.470	**1.511**
USA Mobility Inc	12/31/2008	0.454	0.105	0.766	4.453	**5.778**
Atlantic Tele-Network	12/31/2006	1.399	1.026	0.330	2.024	**4.779**
Pinnacle Airlines Corp	12/31/2007	0.476	0.206	0.494	0.093	**1.269**
Otelco Inc	12/31/2008	0.350	-0.035	0.412	0.410	**1.137**
Bombay Co.	2/3/2007	1.314	-0.399	-1.361	0.574	**0.128**
Duckwall-ALCO Stores	2/1/2009	3.755	0.990	-0.165	1.004	**5.584**
BioScrip Inc	12/31/2006	0.795	-0.742	-0.357	1.183	**0.879**
PharMerica Corp.	12/31/2008	2.627	-0.103	-0.299	0.903	**3.128**
Cedar Fair	1/31/2008	2.684	2.105	1.635	3.162	**9.586**
FTI Consulting	12/31/2007	-0.143	-0.046	0.587	0.245	**0.643**
Gaylord Entertainment	12/31/2007	0.501	0.752	0.249	0.591	**2.093**
Hunt J B Transport Service Inc	12/31/2007	-0.125	2.087	1.330	0.237	**3.529**

Non- Bankrupt Non-Manufacturing firms- Z"-score- Two reporting periods prior to bankruptcy

Company	Filing date 10-K	6.56*X1	3.26*X2	6.72*X3	1.05*X4	Z"-score
StillWater Mining	12/31/2007	1.665	-0.467	-0.147	2.405	**3.456**
USA Mobility Inc	12/31/2007	0.192	0.060	0.288	5.552	**6.092**
Atlantic Tele-Network	12/31/2005	1.216	0.858	1.489	1.917	**5.480**
Pinnacle Airlines Corp	12/31/2006	2.690	0.115	2.845	0.499	**6.149**
Otelco Inc	12/31/2007	0.450	-0.057	0.618	1.828	**2.839**
Bombay Co.	1/28/2006	2.296	0.323	1.028	1.384	**5.031**
Duckwall-ALCO Stores	2/1/2008	3.811	1.203	0.042	1.439	**6.495**
BioScrip Inc	12/31/2005	1.483	-0.341	-0.657	1.998	**2.483**
PharMerica Corp.	12/31/2007	3.787	1.883	0.305	1.150	**7.125**
Cedar Fair	12/31/2008	-0.163	-0.074	0.429	0.172	**0.364**
FTI Consulting	12/31/2008	0.404	0.760	0.768	1.224	**3.156**
Gaylord Entertainment	12/31/2008	-0.165	0.299	0.098	0.572	**0.804**
Hunt J B Transport Service Inc	12/31/2006	-0.028	1.908	1.415	0.790	**4.085**

Non- Bankrupt Non-Manufacturing firms- Z"-score- Three reporting periods prior to bankruptcy						
Company	**Filing date 10-K**	**6.56*X1**	**3.26*X2**	**6.72*X3**	**1.05*X4**	**Z"-score**
StillWater Mining	12/31/2006	1.755	-0.278	-0.057	2.495	**3.915**
USA Mobility Inc	12/31/2006	0.209	0.077	0.305	5.569	**6.159**
Atlantic Tele-Network	12/31/2004	1.251	1.088	1.524	1.952	**5.814**
Pinnacle Airlines Corp	12/31/2005	2.779	0.193	2.934	0.588	**6.494**
Otelco Inc	12/31/2006	0.470	-0.038	0.638	1.848	**2.917**
Bombay Co.	1/28/2005	2.348	0.372	1.080	1.436	**5.237**
Duckwall-ALCO Stores	2/1/2007	3.856	1.242	0.087	1.484	**6.669**
BioScrip Inc	12/31/2004	1.484	-0.253	-0.656	1.999	**2.574**
PharMerica Corp.	12/31/2006	3.806	1.900	0.324	1.169	**7.199**
Cedar Fair	12/31/2007	-0.075	0.012	0.517	0.260	**0.714**
FTI Consulting	12/31/2007	0.546	0.893	0.910	1.366	**3.715**

Gaylord Entertainment	12/31/2007	-0.145	0.318	0.118	0.592	**0.883**
Hunt J B Transport Service Inc	12/31/2005	0.061	1.991	1.504	0.879	**4.435**

Non- Bankrupt Non-Manufacturing firms- Z"-score- Four reporting periods prior to bankruptcy						
Company	**Filing date 10-K**	**6.56*X1**	**3.26*X2**	**6.72*X3**	**1.05*X4**	**Z"-score**
StillWater Mining	12/31/2005	1.845	-0.089	0.033	2.684	**4.473**
USA Mobility Inc	12/31/2005	0.226	0.093	0.322	5.586	**6.226**
Atlantic Tele-Network	12/31/2003	1.285	1.318	1.558	2.182	**6.343**
Pinnacle Airlines Corp	12/31/2004	2.868	0.271	3.023	0.666	**6.828**
Otelco Inc	12/31/2005	0.490	-0.019	0.658	1.867	**2.995**
Bombay Co.	1/28/2004	2.400	0.421	1.132	1.485	**5.439**
Duckwall-ALCO Stores	2/1/2006	3.901	1.281	0.132	1.523	**6.837**
BioScrip Inc	12/31/2003	1.485	-0.165	-0.655	2.087	**2.752**
PharMerica Corp.	12/31/2005	3.825	1.917	0.343	1.186	**7.271**
Cedar Fair	12/31/2006	0.013	0.098	0.605	0.346	**1.062**
FTI Consulting	12/31/2006	0.688	1.026	1.052	1.499	**4.265**
Gaylord Entertainment	12/31/2006	-0.125	0.337	0.138	0.611	**0.961**
Hunt J B Transport Service Inc	12/31/2004	0.150	2.074	1.593	0.962	**4.779**

Exhibit 4: Z-score and Z" score for Sample Non Bankrupt Companies 2010 and 2011 financial data

Surviving (Non- Bankrupt) Companies 2010 and 2011 financial data:

Non-Bankrupt Manufacturing firms- Z"-score- 2010 as a reporting year

Company	Reporting period	6.56*X1	3.26*X2	6.72*X3	1.05*X4	Z"-score
Edge Petroleum Corporation	12/31/2010	0.590	0.895	0.278	0.265	0.850
TXCO Resources Inc.	12/31/2010	0.307	-0.104	-0.219	2.394	1.065
In Phonic, Inc.	12/31/2010	0.791	0.610	0.450	0.365	1.185
Frontier Airlines Holdings, Inc.	12/31/2010	0.378	0.530	0.467	0.800	1.654
Citadel Broadcasting Corporation	12/31/2010	1.010	0.500	0.202	1.301	1.470
Primus Telecommunications Group, Inc.	12/31/2010	0.683	0.566	0.428	1.359	0.915
Tweeter Home Entertainment Group	12/31/2010	0.493	0.706	0.509	2.180	1.103
Circuit City Stores, Inc.	12/31/2010	0.981	0.311	0.134	3.146	0.092
Eddie Bauer Holdings, Inc.	12/31/2010	0.255	0.266	0.237	2.833	1.193
Bally Total Fitness Holding Corporati	12/31/2010	0.297	0.114	-0.039	1.291	1.522
Six Flags, Inc.	12/31/2010	0.462	0.846	0.685	1.241	1.133
Finlay Enterprises Inc	12/31/2010	-0.010	-0.543	-0.791	4.328	1.427
Trico Marine Services Inc	12/31/2010	0.491	-0.021	-0.096	1.597	0.782

Non-Bankrupt Manufacturing firms- Z"-score- 2011 as a reporting year

Company	Reporting period	6.56*X1	3.26*X2	6.72*X3	1.05*X4	Z"-score
Edge Petroleum Corporation	12/31/2011	0.760	0.951	0.278	0.294	1.159
TXCO Resources Inc.	12/31/2011	0.324	-0.088	0.115	2.411	1.082
In Phonic, Inc.	12/31/2011	0.501	0.840	0.212	0.399	1.415
Frontier Airlines Holdings, Inc.	12/31/2011	0.456	0.619	0.351	0.889	1.732

Citadel Broadcasting Corporation	12/31/2011	1.030	0.519	0.224	1.321	1.489
Primus Telecommunications Group, Inc.	12/31/2011	0.732	0.618	0.287	1.411	0.964
Tweeter Home Entertainment Group	12/31/2011	0.538	0.745	0.454	2.225	1.142
Circuit City Stores, Inc.	12/31/2011	1.069	0.402	0.001	3.237	0.180
Eddie Bauer Holdings, Inc.	12/31/2011	0.274	0.283	0.304	2.852	1.210
Bally Total Fitness Holding Corporati	12/31/2011	0.383	0.202	0.210	0.950	1.608
Six Flags, Inc.	12/31/2011	0.554	0.979	0.275	1.333	1.266
Finlay Enterprises Inc	12/31/2011	0.009	-0.423	-0.161	4.448	1.446
Trico Marine Services Inc	12/31/2011	0.681	0.062	-0.059	0.988	0.865

Exhibit 5: Altman Z Score vs. Taffler T score results

	Y-1				Y-2				Y-3				Y-4			
Manufacturing companies	Altman Z Score	zone	Taffler T-Score	zone	Altman Z Score	zone	Taffler T-Score	zone	Altman Z Score	zone	Taffler T-Score	zone	Altman Z Score	zone	Taffler T-Score	zone
Constar International Inc.	1.151	bankrupt	-0.942	bankrupt	1.434	bankrupt	0.191	bankrupt	1.516	bankrupt	0.204	grey	2.186	grey	0.190	bankrupt
Lenox Group, Inc.	1.897	grey	0.242	grey	1.631	bankrupt	0.178	bankrupt	1.816	grey	0.191	bankrupt	1.899	grey	0.177	bankrupt
Accuride Corporation	-0.234	bankrupt	-0.036	bankrupt	1.399	bankrupt	0.168	bankrupt	1.443	bankrupt	0.181	bankrupt	1.769	bankrupt	0.167	bankrupt
Asyst Technologies, Inc.	-0.015	bankrupt	0.112	bankrupt	1.020	bankrupt	0.161	bankrupt	1.234	bankrupt	0.174	bankrupt	1.865	grey	0.160	bankrupt
Champion Enterprises, Inc.	1.019	bankrupt	0.231	grey	2.025	grey	0.219	grey	1.970	grey	0.232	grey	2.061	grey	0.218	grey
Dayton Superior Corporation	-0.369	bankrupt	-0.042	bankrupt	1.006	bankrupt	0.151	bankrupt	1.056	bankrupt	0.164	bankrupt	1.334	bankrupt	0.150	bankrupt
Lear Corporation	2.676	grey	0.281	grey	2.303	grey	0.243	grey	2.217	grey	0.256	grey	2.377	grey	0.242	grey
Chesapeake Corp.	1.247	bankrupt	0.189	bankrupt	1.330	bankrupt	0.169	bankrupt	1.233	bankrupt	0.182	bankrupt	1.796	bankrupt	0.168	bankrupt
MPC Corporation	0.577	bankrupt	0.292	grey	0.276	bankrupt	-0.118	bankrupt	0.507	bankrupt	-0.105	bankrupt	0.594	bankrupt	-0.119	bankrupt
VeraSun Energy	0.871	bankrupt	0.177	bankrupt	2.444	grey	0.271	grey	2.706	grey	0.284	grey	3.152	safe	0.270	grey
Fleetwood Enterprises	1.960	grey	0.247	grey	2.154	grey	0.199	bankrupt	2.323	grey	0.212	grey	3.030	safe	0.232	grey
Hayes lemmerz Inti Inc	0.506	bankrupt	0.198	bankrupt	0.634	bankrupt	-0.117	bankrupt	0.701	bankrupt	-0.104	bankrupt	0.847	bankrupt	-0.118	bankrupt
GMCo	0.013	bankrupt	-0.167	bankrupt	1.126	bankrupt	0.019	bankrupt	1.175	bankrupt	0.032	bankrupt	1.599	bankrupt	0.018	bankrupt
Schweitzer- Mauduit Inti Inc	1.867	grey	0.252	grey	2.091	grey	0.221	grey	2.28	grey	0.2685	grey	2.748	grey	0.255	grey
Domtar Corp.	3.247	safe	0.421	safe	3.751	safe	0.267	grey	3.7677	safe	0.4375	safe	3.8179	safe	0.442	safe
Federal Signal	2.309	grey	0.281	grey	1.944	grey	0.231	grey	2.174	grey	0.2975	grey	2.6685	grey	0.302	safe
Apogee Enterprises	3.291	safe	0.291	grey	4.423	safe	0.489	safe	4.501	safe	0.3075	safe	4.746	safe	0.312	safe
Alamo Group	3.958	safe	0.341	safe	3.936	safe	0.437	safe	3.955	safe	0.3575	safe	4.0128	safe	0.362	safe
Northwest Pipe Co	3.592	safe	0.332	safe	3.276	safe	0.394	safe	3.325	safe	0.3485	safe	3.4752	safe	0.353	safe
Cooper Inds.	4.473	safe	0.356	safe	4.169	safe	0.388	safe	4.208	safe	0.3725	safe	4.331	safe	0.377	safe
Temple-Inland	3.453	safe	0.312	safe	3.410	safe	0.311	safe	3.498	safe	0.3285	safe	3.675	safe	0.333	safe
Oshkosh Corp.	4.593	safe	0.361	safe	4.639	safe	0.368	safe	4.656	safe	0.3775	safe	4.7089	safe	0.382	safe
Georgia Gulf	2.649	grey	0.261	grey	2.721	grey	0.231	grey	2.807	grey	0.2775	grey	3.0669	safe	0.282	grey
FMC Corp.	3.725	safe	0.331	safe	2.954	grey	0.3187	safe	3.087	safe	0.3475	safe	3.495	safe	0.352	safe
International Textile Group	3.813	safe	0.298	grey	4.973	safe	0.2857	grey	4.992	safe	0.3145	safe	5.05	safe	0.319	safe
Ford Motor Co	2.017	grey	0.278	grey	2.396	grey	0.2657	grey	2.479	grey	0.2945	grey	2.734	grey	0.299	grey

	Y-1				Y-2				Y-3				Y-4			
Non-Manufacturing Companies	Altman Z" Score	zone	Taffler T-Score	zone	Altman Z" Score	zone	Taffler T-Score	zone	Altman Z" Score	zone	Taffler T-Score	zone	Altman Z" Score	zone	Taffler T-Score	zone
Edge Petroleum Corporation	-3.12	bankrupt	-0.129	bankrupt	1.602	grey	-0.1413	bankrupt	2.061	grey	-0.1125	bankrupt	2.285	safe	-0.108	bankrupt
TXCO Resources Inc.	-2.677	bankrupt	-0.213	bankrupt	0.808	bankrupt	-0.2253	bankrupt	0.8751	bankrupt	-0.1965	bankrupt	1.7128	grey	-0.192	bankrupt
In Phonic, Inc.	-2.518	bankrupt	-0.167	bankrupt	-1.102	bankrupt	-0.1793	bankrupt	-0.7685	bankrupt	-0.1505	bankrupt	-0.1824	bankrupt	-0.146	bankrupt
Frontier Airlines Holdings, Inc.	-0.906	bankrupt	0.210	grey	0.136	bankrupt	0.1977	bankrupt	0.481	bankrupt	0.2265	grey	0.988	bankrupt	0.231	grey
Citadel Broadcasting Corporation	-0.209	bankrupt	0.010	bankrupt	2.026	grey	-0.0023	bankrupt	2.1044	grey	0.0265	bankrupt	2.1358	grey	0.031	bankrupt
Primus Telecommunications Group, Inc.	-2.093	bankrupt	-0.154	bankrupt	-7.969	bankrupt	-0.1663	bankrupt	-7.7634	bankrupt	-0.1375	bankrupt	-6.0024	bankrupt	-0.133	bankrupt
Tweeter Home Entertainment Group	4.05	safe	0.421	safe	2.754	safe	0.4087	safe	2.237	grey	0.4375	safe	2.255	grey	0.442	safe
Circuit City Stores, Inc.	2.354	grey	0.301	safe	3.841	safe	0.2887	grey	3.932	safe	0.3175	safe	4.008	safe	0.322	safe
Eddie Bauer Holdings, Inc.	-3.368	bankrupt	-0.342	bankrupt	-0.522	bankrupt	-0.3543	bankrupt	-0.4483	bankrupt	-0.3255	bankrupt	0.093	bankrupt	-0.321	bankrupt
Bally Total Fitness Holding Corporati	-2.048	bankrupt	0.234	grey	8.650	safe	0.2217	grey	7.5587	safe	0.2505	grey	8.0859	safe	0.289	grey
Six Flags, Inc.	-2.096	bankrupt	-0.237	bankrupt	-2.071	bankrupt	-0.2493	bankrupt	-1.512	bankrupt	-0.2205	bankrupt	-1.2673	bankrupt	-0.216	bankrupt
Finlay Enterprises Inc	0.314	bankrupt	-0.165	bankrupt	2.423	grey	-0.1773	bankrupt	2.502	grey	-0.1485	bankrupt	2.984	safe	-0.144	bankrupt
Trico Marine Services Inc	-0.37	bankrupt	-0.123	bankrupt	-0.37	bankrupt	-0.1353	bankrupt	-0.02	bankrupt	-0.1065	bankrupt	0.156	bankrupt	-0.102	bankrupt
StillWater Mining	1.511	grey	0.211	grey	3.456	safe	0.1987	bankrupt	3.915	safe	0.2275	grey	4.473	safe	0.232	grey
USA Mobility Inc	5.778	safe	0.367	safe	6.092	safe	0.3547	safe	6.1591	safe	0.3835	safe	6.2261	safe	0.388	safe
Atlantic Tele-Network	4.779	safe	0.321	safe	5.48	safe	0.3087	safe	5.8135	safe	0.3375	safe	6.3425	safe	0.342	safe
Pinnacle Airlines Corp	1.269	grey	0.243	grey	6.149	safe	0.3220	safe	6.494	safe	0.2595	grey	6.828	safe	0.264	grey
Otelco Inc	1.137	grey	0.213	grey	2.839	safe	0.2007	grey	2.9174	safe	0.2295	grey	2.995	safe	0.234	grey
Bombay Co.	0.128	bankrupt	0.321	safe	5.031	safe	0.3087	safe	5.2366	safe	0.3375	safe	5.439	safe	0.342	safe
Duckwall-ALCO Stores	5.584	safe	0.243	grey	6.495	safe	0.3013	safe	6.669	safe	0.2595	grey	6.837	safe	0.264	grey
BioScrip Inc	0.879	bankrupt	0.211	grey	2.483	grey	0.2340	grey	2.574	grey	0.2275	grey	2.752	safe	0.232	grey
PharMerica Corp.	3.128	safe	0.389	safe	7.125	safe	0.3767	safe	7.1987	safe	0.4055	safe	7.2705	safe	0.410	safe
Cedar Fair	9.586	safe	0.261	grey	0.364	bankrupt	0.2487	grey	0.7137	bankrupt	0.2775	grey	1.0615	bankrupt	0.282	grey
FTI Consulting	0.643	bankrupt	0.210	grey	3.156	safe	0.3100	safe	3.715	safe	0.2265	grey	4.265	safe	0.231	grey
Gaylord Entertainment	2.093	grey	0.312	safe	0.804	bankrupt	0.2997	grey	0.883	bankrupt	0.3285	safe	0.961	bankrupt	0.333	safe
Hunt J B Transport Service Inc	3.529	safe	0.421	safe	4.085	safe	0.4087	safe	4.435	safe	0.4375	safe	4.779	safe	0.442	safe