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# PREDICTING CORPORATE DEFAULT – AN ASSESSMENT OF THE Z-SCORE MODEL ON THE U.S. MARKET 2007-2010

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# Abstract

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| **Title:** | Predicting Corporate Default – An Assessment of the Z-score Model on the U.S. Market 2007-2010 |
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| **Course:** | BUSM36, Degree Project Master level in Corporate and Financial Management, Business Administration Master level, 15 University Credit Points (15 ECTS) |
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| **Five key words:** | Bankruptcy, Default Prediction, Financial Distress, Z-score, Multiple Discriminant Analysis |
| **Purpose:** | The purpose of this paper is to investigate the performance of a purely numerical bankruptcy predicting formula during the economic downturn of 2007-2010. The investigation is concentrated around American manufacturing and non-manufacturing publicly traded firms that were put under pressure and filed for bankruptcy during this period. |
| **Methodology:** | Performing multiple discriminant analysis on a sample of firms by applying the Z-score and Z''-score models. |
| **Theoretical Perspectives:** | The model applied is based on empirical research of financial ratios. Moreover the results are discussed in relation to a number of concepts concerning default risk, financial distress costs and capital structure. |
| **Empirical foundation:** | A sample of 45 American firms filing for bankruptcy 2007-2010 and 45 corresponding peers. |
| **Conclusions:** | The models are between 70%-85% accurate in identifying bankrupt firms both one and two reporting periods prior to bankruptcy when applying a cut off of 2,99 and 2,60 which indicates good discriminant ability. However, the model should be complemented by soft factor evaluation and the user must be aware of potential consequences related to misclassifications/errors made by the models. |

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## Contents

# 1. Introduction

*This section introduces the reader to the subject. Furthermore the authors present the purpose of the study and also the relevant research question followed by delimitations, target audience and thesis outline.*

## 1.1 Background

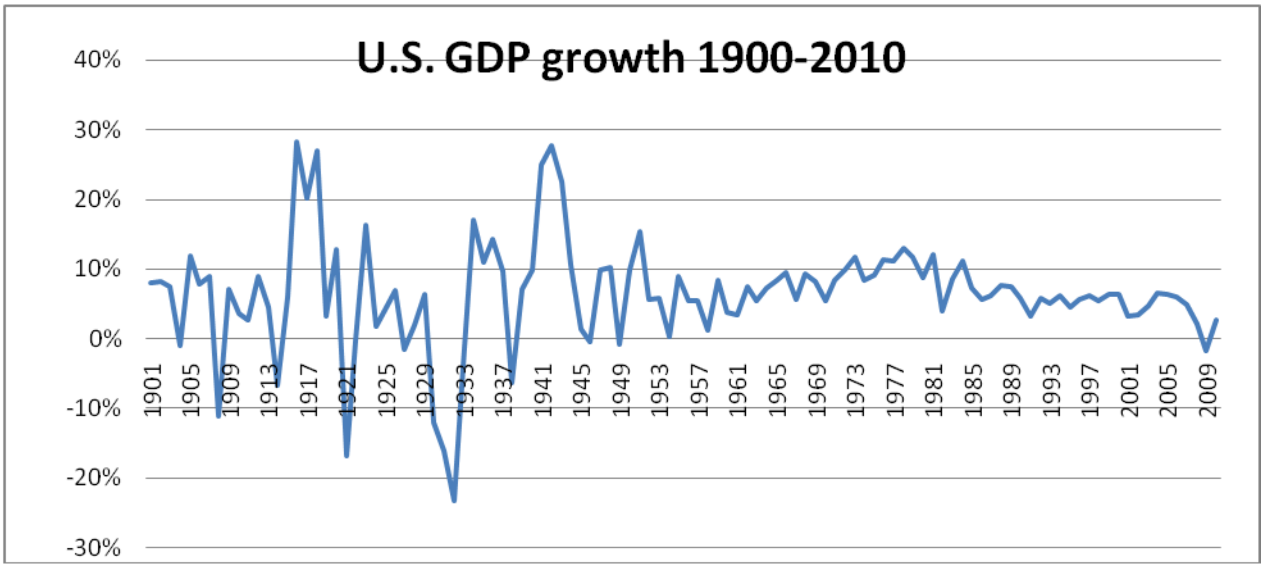
As long as there have been companies in need of external financing to further develop their operations and investors willingly to supply these firms with resources, there surely also have been efforts from the investors to assess whether the entities will continue to exist and produce a substantial return. Investments in various businesses will always result in taking on some risk and there are certainly as many techniques in assessing risk, as there are investors. However, as markets have developed and the availability of information has increased, numerous attempts have been made to find patterns and generic methods to evaluate the potential risk. Credit rating firms such as Standard and Poors, Moody's and Fitch have created large organizations concentrating on assessing and grading the creditworthiness of companies (Borrus, McNamee & Timmons 2002). Their services have been welcomed by investors around the world trying to navigate through the endless numbers of investment opportunities. Meanwhile there has also been extensive academic research on the subject, some more recognized than others. Both the commercial and academic approaches to different assessment methods indicate that there is a great need of attempted generic approaches in predicting corporate default. A selected number of methods will be presented later in this paper. 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.

## 1.2 Problem Discussion

The Z-score was originally developed in 1968 for default predictions of manufacturing companies and is based on discriminant analysis. The method proved to be significant in its discriminating ability at least two reporting periods prior to default (Altman 1968). During the past 40 years further development of the model has been made by both the originator and other researchers. Still, the original model is constantly referred to and taught in business schools. Simultaneously the external and internal conditions surrounding a corporation have changed in multiple ways and this evolution alone would have been a good reason for putting the model at test. However, in recent years the world has been shocked by what many said to be the worst financial crisis and recession in a very long time. During 2009, United States alone experienced negative GDP growth for the first time since 1949 and the highest negative GDP growth number since 1938 (See figure 1.1[1]).

*Figure 1.1Gross Domestic Product growth in United States 1900-2000*




[1] Information is retrieved from http://www.usgovernmentspending.com. Detailed information on number and years can be found in Exhibit 1.

If a model with the purpose of predicting bankruptcy does not perform well[2] in a rather extreme situation where corporations are highly pressured in a number of ways, what purpose does the model have? Does the model incorporate a generic functionality still viable? For that reason, it seems to be relevant to put the model at stress once again by testing its discriminant ability in the recent economic downturn of 2007-2010. In order to give the investigation additional significance, the later developed Z''-score created for non-manufacturing firms will be applied as well.

## 1.3 Purpose

The purpose of this paper is to investigate the performance of a purely numerical bankruptcy predicting formula during the economic downturn of 2007-2010. The investigation is concentrated around American manufacturing and non-manufacturing publicly traded firms that were put under pressure and filed for bankruptcy during this period.

## 1.4 Research question

How well do the Z-score and Z''-score models discriminate between firms that filed for bankruptcy or survived the economic downturn 2007-2010?

## 1.5 Delimitations

This paper is limited to testing the accuracy of the Z-score and the Z''-score models. No attempts will be made in trying to modify the formulas. Since the

[2] A comparison is made with the accuracy of the original findings and results in Altman 1968 and Altman 2000.

original model was developed and tested using American firms this paper will solely be concentrating on the U.S. market. Due to the need of information retrieved from stock markets and financial reports, the population tested is manufacturing and non-manufacturing firms traded on the American stock market. Excluded are financial institutions since this type of companies possesses other essential financial indicators not being captured by the models.

## 1.6 Target Audience

The intended target groups for this research paper are primarily finance students and researchers. Furthermore, it may also have some commercial value by spurring the interest of those who work professionally with credit rating and credit analysis. The reader should have some knowledge in credit assessment and basic statistical methods in order to fully understand the purpose and scope of the investigation. However, in order to increase the digestibility of the content and make it more available to a greater number of readers, attempts have been made to make the structure as pedagogical and easy to follow as possible.

## 1.7 Thesis Outline

The upcoming section will deal with the previous research on the subject followed by section 3 where a number of important concepts related to default prediction will be discussed. Section 4 will guide the reader through the methodology to be applied when approaching the testing of the models. The results of the testing will be presented and analyzed in section 5 and concluded in section 6. The paper will be finalized by the authors' view on further research approaches.

# 2. Previous Research

*During this part the authors present some of the vast research made within the field of default prediction. It starts off by explaining the concept of credit rating and is followed by a presentation of the research on common default prediction techniques.*

## 2.1 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 approaches.

### 2.1.1 Credit Rating Agencies

Credit rating agencies[3] 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 firms. 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

[3] The approach to each credit rating agency's methodology can be viewed on each firms website; www.standardandpoors.com, www.moodys.com, www.fitchratings.com

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 firms. 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 (Mählmann 2008).

### 2.1.2 Quantitative Default Prediction Models

#### *Univariate Financial Ratio Models*

Beaver (1966) tested the performance of single financial ratios as a measure of default prediction. The reason for using financial ratios was that they at that time had reached an increasing importance for security holders in assessing the financial health of a firm. The research is recognized as one of the first attempts to find some financial ratios that better could predict corporate default and contained the evaluation of a large number of ratios. Beaver (1968) further explores the usage of financial ratios as prediction of failure and concludes that investors seem to look at other information except for ratio analysis when making investment decisions.

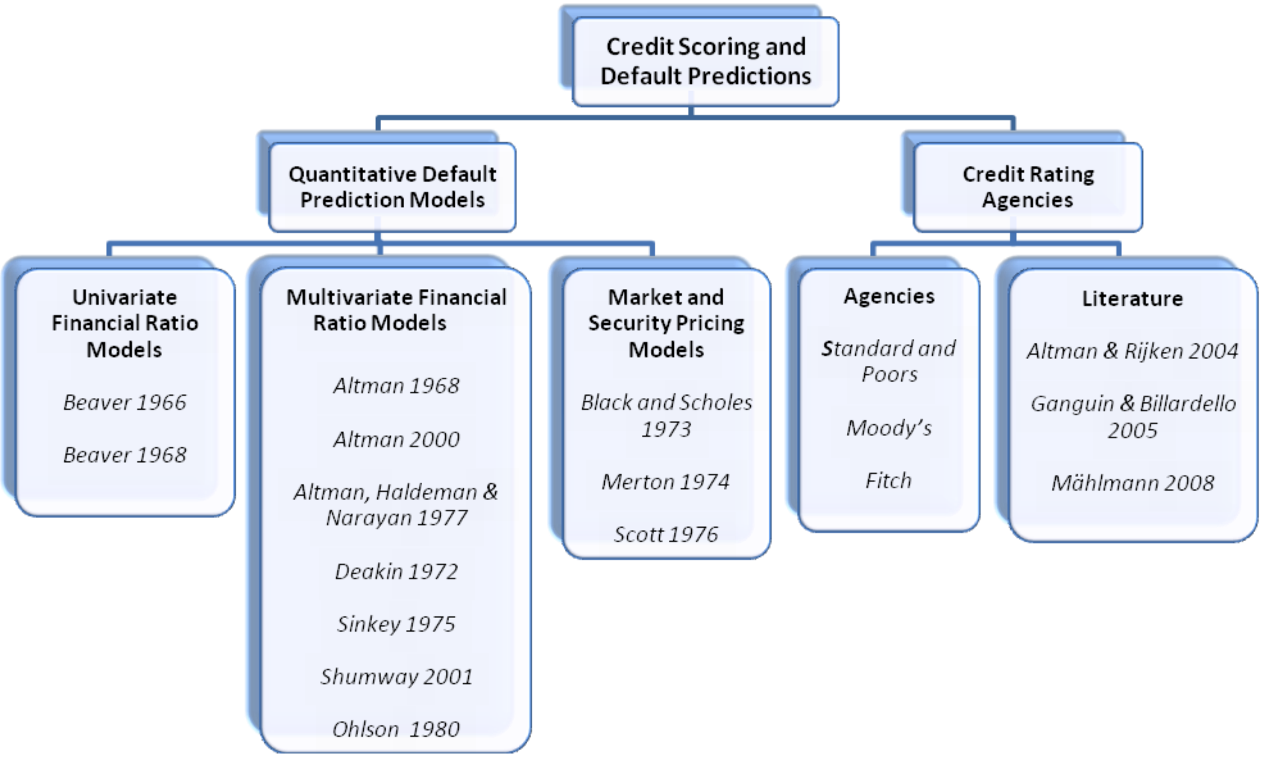
#### *Multivariate Financial Ratio Models*

The multivariate approach of use of financial ratios is differentiated from univariate line as it is exploiting the combination of a number of financial ratios. The groundbreaking research of Altman (1968) and the introduction of the Z-score model set the start for numerous similar assessments. The Z-score model set a new standard for bankruptcy prediction by incorporating both traditional ratio analysis and statistical techniques such as Multiple Discriminant Analysis, MDA. The selection and combination of the ratios was the one best predicting which firms were to be experiencing corporate bankruptcy. Except for further development and performance testing by the originator such as Altman, Haldeman and Narayan (1977), Altman, Marco and Varetto (1993) and Altman (2000) there are several other researchers who both followed and criticized his approach. Deakin (1972) followed Altman (1968) and used multiple discriminant analysis by applying the same financial ratios as Beaver (1966). Sinkey (1975) further developed an MDA model which applied to banks in troubled conditions. As a response to Altman (1968) and various other publications of methods based on multiple discriminant analysis, Ohlson (1980) presents a logit model for bankruptcy prediction. The model incorporates some variables similar to that of the original Z-score model but it is argued that the logit analysis mitigate some of the most notable disadvantages of the discriminant analysis. Shumway (2001) is another proponent of multivariate financial ratio models. In his study he finds that half of the accounting ratios used in previous models are not statistically significant. Instead he developed a model that uses both accounting ratios and market-driven variables.

### *Market and Security Pricing Models*

Market and Security pricing models seem to have gained a lot of attention during the 1970's as many notable research articles were published during that time. To a large extent they have some reference to the assumptions of Modigliani and Miller (1958) and the weakening of these assumptions. Scott (1976) explored the optimal levels of debt and equity in relation to bankrupt and non-bankrupt firms. Maybe the most well-known attempt is the Merton model (Merton 1974), which is a further development of the even more famous option-pricing model presented in Black & Scholes (1973). The main variable of the model is the distance to default, which basically implies that if the market value of assets lies below the face value of debt in one year's time the firm enters default mode. A further development of the Merton model is the KVM Credit Monitor which uses implicit stock prices to calculate the value of a company (Ganguin and Billardello 2005).

## 2.2 Review of the Default Prediction Techniques



# 3. Literature

*This section presents important concepts with reference to the default subject such as default risk, capital structure and distress costs.*

## 3.1 Default Risk

The default risk of a firm is simply the risk that the firm will default within some predetermined time period. Tied to the risk is the probability that the risk is realized into the actual default. The assessment of default risk is important because if the firm is to default there is a danger for the security holder of not receiving its interest or principal claims on time or at all. Therefore firms generally are obliged to pay a spread over the default-free rate of interest that is proportional to their default probability. This is done in order to compensate lenders for the uncertainty. In the event of default, the loss suffered by a security lender is usually determined in the contract or obligation. The loss in the event of default can vary depending on the nature of different security holders (e g subordinated, senior debt). It may not be sufficient for the security holder to only be informed about the default risk, but also how the various borrowers and other security holders are related to each other (Crosbie & Bohn 2003).

## 3.2 Risk Management and Default Prediction

The economic downturn that took place between 2007 and 2010, showed more than ever how exposed an investor or lender can be without being able to locate profitable and non-profitable firms. It is therefore of great importance for investors to realize the value of the investment portfolio but also its risk (Crosbie & Bohn 2003). Additionally, many financial institutions are restricted by the Basel Capital Accords, which states how much regulatory capital the bank must allocate in relationship to the risk exposure of its loan portfolio. The regulatory capital will act as protection in case of default of some loan assets. With the emergence of Basel II, the Internal Rating-Based Approach was introduced which gave banks with sophisticated risk management systems the opportunity to make own risk assessments of their portfolio. This put some pressure upon the banks to apply a reliable and robust risk assessment system. By being able to apply their own risk assessment banks can make risk predictions for companies that are too small for being rated by credit rating agencies (Culp 2001) (Ganguin & Bilardello 2005). There is also a number of evidence that the internal credit rating system of banks tends to be faster in the migration of ratings than in traditional rating agencies (Carey & Hrycay 2001).

## 3.3 Financial Distress

According to the Modigliani-Miller Theorem the decision on which capital structure a company chooses to adapt should not have any effect on the total cash flows a firm can distribute to its debt and equity holders. It permits bankruptcy but no distress costs, which indicates that the ownership and control of the firm's assets move without any costs from equity holders to the debt holders. However, when observing the real world one may find several indicators that suggest that the Modigliani-Miller depiction is not very veracious. Taxes and distress costs indicate that debt potentially can be cheaper than equity (Hillier, Grinblatt & Titman 2008).

Financial distress costs may appear in case of insolvency and can be divided into direct and indirect expenses. As the management gets pressured to cover substantial losses of a firm there is a great risk of selling assets at a discount, which leads to investors not being paid back properly. Even if the assets of the firm can be sold so that the whole amount of debt can be repaid to debt holders, other distress costs may extensively lower that amount. Direct costs associated with this are primarily those of legal fees, which are to be paid by the firm as a result of the insolvency process. Other issues that may even appear prior to insolvency are costs related to impaired relationships with suppliers, customers and other external stakeholders in troubled times. These can be categorized as indirect distress costs together with the debt holder-equity holder conflict of interest and debt overhang-underinvestment problem. The latter implies that as the firm is in a highly leveraged state it may not have the possibility to obtain sufficient funding to support positive net present value investments. One important question is who bears the bankruptcy costs. According to the absolute priority rules, most of the value of a firm is transferred to its debt holders and since direct bankruptcy costs moderate the value of a firm, most direct bankrupt costs are of great interest to debt holders of the firm (Culp 2006) (Hillier, Grinblatt & Titman 2008).

## 3.4 The Asset Substitution Problem

An equity holder can receive an unlimited return if the firm performs better than expected but on the other hand they will have the lowest priority in the case of bankruptcy since the holders of debt must be paid before any equity holder can receive any proceeds. As the firm gets more leveraged the risk for equity holders losing their entire investments in favor of repaying debt holders in case of default increases. This gives the firm an incentive to take on extensively risky projects that in case of a successful outcome will mean great benefit for the shareholders. However, in case of failure of the project the debt holders will be the once to suffer (Hillier, Grinblatt & Titman, 2008).

## 3.5 Positive Net Present Value Investments

An investor may be able to identify a good investment opportunity by analyzing the net present value of the investment. Projects that are predicted to create value are those whose present value exceed their costs and therefore indicate that future cash flows can be produced more cheaply internally than by investing in financial assets. These are called *positive net present value investments* and indicate that an arbitrage profit associated with the investment project can be made. The project evaluation will result in one of two alternatives. If the net present value is negative the project will be rejected and if the net present value is positive it will be accepted (Hillier, Grinblatt & Titman, 2008).

### 3.6 Comments on Previous Research and Literature

In order to fulfill and also understand the importance and depth in predicting default it is important to be aware of the previous research within the field of default prediction.  However the focus of this paper relies only on testing the Z-score model and therefore no evaluation in comparison to other types of models is attempted. The Z-score model is developed out of a base of previous empirical studies and therefore does not have an extensive theoretical foundation in comparison to for example the Merton model (Scott 1981). Nevertheless, the literature section covers a number of concepts related to risk, financial distress, capital structure and investment theory. It is important to have some knowledge of these concepts in order to understand the importance of a high performing default predicting model and what consequences errors of the model may have on investors. This will be further discussed in the analysis section.

# 4. Methodology

*In this section a thorough explanation of the Z-score and Z''-score model will be given. Furthermore, the chapter will focus on the sample and data collection. The modeling of the test will be presented and the chapter will be finalized with a discussion on the methodology.*

## 4.1 Research Approach

The aim of this thesis is to test if the Z-score and Z''-score methods of predicting bankruptcy were valid in the 2007-2010 economic downturn. Furthermore, the functionality aspect of the model is evaluated. In order to accomplish this, the method developed by Edward Altman in 1968 (Altman 1968) and the revised version, the Z"-score, adjusted for use on non-manufacturing firms (Altman 2000) are applied. This can be done since the Z-score models are meant to have a generic functionality and it is this characteristic that will be tested. As usual in financial research, when evaluating different concepts and theories, a deductive quantitative approach will be applied. The data retrieved from each research object are analyzed in comparison to findings in Altman 1968 and Altman 2000. Hence, the empirical results will be related to previous statements on the predictive ability of the models (Ryans, Scapens & Theobald 2002). An important distinction between the methodology in this essay and the original one by Edward Altman, is that this method is designed to test the performance of the Z-score and Z''-score models while Altman's approach was to develop the actual models[4].

## 4.2 The Z-score and Z''-score models

The Z-score and Z''-score models are constructed as a type of discriminant analysis called Multiple Discriminant Analysis (MDA). The purpose of

[4] Altman 1968 evaluated e.g. the relevance of each component in the Z-score model. It is found not to be important in this study since it does not have the purpose of evaluating the model, only to evaluate the performance of the model. Excluded is a secondary sample of firms for the same reason. Implicitly, this research is a type of secondary sample testing the validity of the model, but of course under other conditions.

discriminant analysis is to linearly combine two or more input variables in order to produce an output which classifies the object into one of two groups. Each input variable is attached to a weight depending on its influence on the output variable. The components selected for use in the model are the variables that better than any other combination of variables discriminate between the two groups (Krishnaswamy, Sivakumar & Mathirajan 2009). The classification is then determined by a cut off value, which tackles the problem of defining a range where all possible values are situated in between (Doumpos & Zopounidis 2002).

The discriminant purpose of the Z-score and Z''-score models is to classify whether a firm will go bankrupt or not. The Z-score was initially developed as a reaction to the weakness of traditional ratio analysis used in evaluating companies performance at that time[5]. The findings from this study indicate that the model is able to discriminate between bankrupt and non-bankrupt firms, one and two reporting periods prior to bankruptcy filing of the defaulted companies. Although Altman (1968) recognized some succesful research on predicting bankruptcy through financial ratios he questioned their ability to actually be effectively applyable in practice. The reason for this was because each finding emphasized on individual signals of indicators rather than taking the aspects of all ratios in mind. This makes the method very vulnerable to subjective interpretation of the person performing the analysis. When revising the Z-score in 2000, Altman continues to stress the weakness of ratio analysis and points to the fact that more meticulous statistical approaches have increased in popularity among academic researchers. However, he also emphasizes that financial ratios gain some value if they are selected and combined to analyze the whole selection of variables. Moreover, multiple discriminant analysis seem to be a relevant in predicting bankruptcy since:

a) It has been proven to perform well on tests many years following the development of the model and has been widely used by analysts and researchers.

b) Even if there are statistical methods more appropriate for default assessment, only the fact that multiple discriminant analysis through the Z-

[5] 1968, the year of the publication of the Z-score

score model have been as recognized, tested and used during the past 40 years makes it worth testing.

c) The model brings simplicity to default assessment which makes it attractive to use for practioners.

The original Z-score for manufacturing firms was structured as folllows (Altman 1968):

$$Z= 0,012X_1+0.014X_2+0,33X_3+0,006X_4+0,999X_5$$

Altman ( 2000), presents a modification of this model for more practical use and to mitigate confusion:

$$Z= 1,2X_1+1,4X_2+3,3X_3+0,6X_4+1X_5$$

In the modified model, for variable $X_1$- $X_5$, percentages are turned into commonly written percentage, e.g. 10% →0,1. This is a deviation from the original model where $X_1$-$X_4$, 10%=10% and where $X_5$, 10% →0,1. This study will apply the modified model.

The variables selected for the model are:

*$X_1$= working capital/total assets*
This variable is classified as the liquidity measure and working capital is defined by current asset minus current liabilities. The argument for including the variable is that a firm which continuously is experiencing losses will also experience shrinking working capital.

*$X_2$= retained earnings/total assets*

This variable is classified as the profitability measure and also incorporates the factor of a firm’s age. The argument for this assumption is that younger firms do not tend to have had the possibility to collect a substantial amount of retained earnings compared to older firms. The variable is present in the Z-score formula due to the fact that younger firms tend to be more vulnerable to financial distress.

*$X_3$= earnings before interest and taxes (EBIT)/total assets*

This variable is defined as the productivity measure. It is argued for that the survival of a firm is ultimately based on its ability to utilize and extract value from its assets.

*$X_4$= market value of equity/book value of total debt (total liabilities)*

This variable is defined as the insolvency measure and shows how much more value a firm can lose before its liabilities exceeds its equity value. A benefit of the measure is that it adds a market value aspect to the model.

*$X_5$= sales/total assets*

This variable is defined as the competitive measure since it is showing how well a firm can generate sales from its assets under the current market conditions. It is included in the model due to its relationship to many of the other variables.

The specific composition of the model including these certain variables are a result of research and testing of relevance done by the originator (Altman 1968).

The Z’’-score presented in Altman 2000 is developed for non-manufacturing firms and has not been tested as extensively as the Z-score. Whereas the Z-score model is a market model, i.e. the share price is used to define the equity value, the non-manufacturing model uses the book value of equity. This indicates a potential use on private firms. Nevertheless, due to the lack of a model explicitly developed for public firms, the Z’’-score model will be applied here. Besides using the book value of equity instead of the market value of equity, the Z’’-score is excluding the fifth ratio ($X_5$= *sales/total assets*). This is done *"in order to minimize the potential industry effect which is more likely to take place when such an industry-sensitive variable as asset turnover is included"* according to Altman 2000. Further, new weights are attached to the variables.

$$Z'' = 6{,}56X_1 + 3{,}26X_2 + 6{,}72X_3 + 1{,}05X_4$$

## 4.3 Sample and Data Collection

In order for a firm to be considered for being an object in this investigation it must fulfil the requirements of supplying the independent variables needed for producing a Z-score. The firms studied are American since the model originally was developed by using American companies filing for bankruptcy. For comparison reasons, this is of importance since the definition of bankruptcy may vary depending on which country the firms studied are situated. Clearly, no other country will apply the exact bankruptcy rules that are present in the United States.

The firms are collected from the UCLA-Lo Pucki Bankruptcy Research Database[6] and include both manufacturing and non-manufacturing companies[7]. The definition of bankrupt firms assembled in the UCLA-Lo Pucki Bankruptcy Research Database is cases filed for Chapter 7 or Chapter 11 under the U.S. bankruptcy code. Furthermore, the firms filed an annual report (Form 10-K) at the Securities and Exchange Commission, at least three years prior to the filing of the bankruptcy case (LoPucki, 2011). The population chosen for the tests possesses the following characteristics:

a) American public company

b) Listed on an American stock exchange

c) Filed for bankruptcy during 2007-2010

[6] The database can be found on the following website: http://lopucki.law.ucla.edu/

[7] The classification of firms as manufacturing and non-manufacturing was made by viewing each firm's SIC, Standard Industrial Classification (http://www.osha.gov/pls/imis/sic_manual.html)

d) Held at least $100 million of assets prior to bankruptcy filing.

Financial institutions are excluded from the study since they possess essential characteristics that is not captured by the components present in the Z-score and Z''-score models[8]. For each firm that filed for bankruptcy an additional firm is chosen at stratified random basis[9]. The selection is stratified according to the following characteristics[10]:

a) Industry belongingness (SIC-codes relevant at two first digits)

b) Size (Total Assets)

The mean asset size of the bankrupt manufacturing firms is $2,103 billion and $2,113 billion for surviving manufacturing firms[11]. The corresponding numbers for the non-manufacturing firms is $1,517 billion for bankrupt companies and $1,664 billion for survivors. This difference can be seen as a weakness of the sample. However, since the real world is not perfect this small deviation must be accepted in order to perform the testing. Table 4.1 presents the number of firms in each group. Excluded from the sample were firms that were not able to file a 10-K report one or two reporting periods prior to the bankruptcy and firms where no appropriate peer could be found.

Financial data and bankruptcy dates are collected from 10-K filings made by the firms to the U.S. Securities and Exchange Commission (www.sec.gov) and Bankruptcydata.com (www.bankruptcydata.com). Historical share prices are retrieved from Thomson Datastream.

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[8] There have been attempts on modifying the Z-score in order to use it on financial institutions. One of these studies is http://www.northernfinance.org/2010/NFAPapers2010/papers/51.pdf

[9] For complete list of firms and corresponding peers, see Exhibit 2

[10] Altman 1968 applied the same characteristics.

[11] Excluded from this calculation are General Motors Co and Ford Motor Company since they are very large companies and hence their deviations bring injustice to the numbers of the smaller firms.

*Table 4.1: Sample statistics*[12]

| Group | Manufacturing firms | Non-manufacturing firms |
|---|---|---|
| Bankrupt | 20 | 25 |
| Non-bankrupt | 20 | 25 |
| **Total** | **40** | **50** |

## 4.4 Modelling the test

By using the discriminant models, each firm gets assigned a value, a Z-score or Z''-score. This value indexes the firm into one of the two groups, bankrupt or non-bankrupt. The Z-score range consists of a grey area or *zone of ignorance* which refers to the range where the incorrectly classified firms from the original sample were located (Altman 1968). See table 4.2 for the grey area ranges. The lower and upper boundaries of the grey area are used as implications for cut off scores when indexing the firms. If significant differences are observed between the lower and upper cut off scores it implies that the grey area may still incorporates firms whose future is not as distinctive as firms located outside of the grey area. Diagnostic analysis is used to analyze the results. These types of tests are commonly used in predicting if a patient has a certain condition or not and this makes the method very appropriate for bankruptcy prediction since an increased default risk can be seen as a sickness of the firm. If a firm is predicted as bankrupt it is receiving a positive test result and if it is predicted as non-bankrupt it is receiving a negative test result (MacDonald 2007). See Figure 4.3 for explanation on the concepts of diagnostic analysis. Lastly an attempt is made to find the optimal cut off scores which is resulting in least errors for this particular sample of firms. This is done by analyzing Receiver Operating Characteristic (ROC) curves and applying the Youden Index (Le 2010) using MedCalc.

[12] For complete list of sample firms, see Exhibit 2

*Table 4.2 Area Ranges and Cut off scores[13]*

| | Bankruptcy Area | | Grey Area | | Non-Bankrupt Area |
|---|---|---|---|---|---|
| Z-score | <1.80 | Lower Cut Off | 1,8-2,99 | Upper Cut Off | >2,99 |
| Z''-score | <1.10 | | 1,10-2,60 | | >2,60 |

*Table 4.3 Concepts of Diagnostic Analysis[14]*

| Concept | Explanation |
|---|---|
| **Sensitivity** | The proportion of the sample which is predicted as bankrupt and also filed for bankruptcy. |
| **Specificity** | The proportion of the sample which is predicted as non-bankrupt and did survive. |
| **Positive** | For any particular test result, the probability that it will be predicted as bankrupt. |
| **Negative** | For any particular test result, the probability that it will be predicted as non-bankrupt. |
| **True Positive** | For any particular test result that is predicted bankrupt, the probability that it actually will be bankrupt. |
| **False positive** | For any particular test result that is predicted bankrupt, the probability that it actually will be non-bankrupt. |
| **True Negative** | For any particular test result that is predicted non-bankrupt, the probability that it actually will be non-bankrupt. |
| **False Negative** | For any particular test result that is predicted non-bankrupt, the probability that it actually will be bankrupt. |

[13] The ranges and boundaries have emerged from tests of the Z-score and Z''-score models and can be viewed on http://pages.stern.nyu.edu/~ealtman/3-%20CopCrScoringModels.pdf

[14] The concepts and calculations are retrieved from http://faculty.vassar.edu/lowry/clin1.html

### 4.5 Methodology Discussion

The underlying focus of this paper is the functionality of the actual models. By this is meant that the performance of the models might not be important if they cannot later be applied for their purpose of predicting bankruptcy by people with practical needs of their performance. Hence, they will not be applied under perfect information and under perfect conditions since there is no such condition. If one is to believe Modigliani and Miller, default prediction models would not even be needed in a perfect world with perfect capital markets. This being said the imperfections are needed to be taken for what they are and exploited when possible, for example in situations as this study. Still, one would like some reflection upon what has been presented in the methodology and this is done here. This section presents various statements that may result in the tests performed in this investigation of failing, containing errors or showing irrelevant results. Presented are also the authors' approaches to these issues. Some of the potential problems have already been mentioned in previous sections. However, a summary of these may fulfil the purpose of clarification and explanation.

*The Z-score model is outdated or no longer relevant*

Since the development of the original Z-score model, approaches to update the method or develop better options to the method have been made. Various updates are done by the originator himself such as Altman 2000, Altman 2002, Altman (ed) 2010. As the business and economic environment is evolving so is the research concerning its nature and impact. Despite of this argument, there are several reasons to test the Z-score and Z''-score models. One is that, at least the first model, is widely recognized, taught and used by researchers, analysts and business schools as a complement to credit analysis. A second reason is that the models have shown to be sufficiently accurate in recent research. One may state the question of whether it would not be more appropriate to test a more updated version of the model. The authors are aware of the immense recent research on trying to adjust the model to perform better in more recent conditions. However, the dynamic of this paper is built upon the action of putting a 40 year old method at test under recent conditions. Ultimately, this is a test on whether business logics have changed or not.

During the development of this research paper suggestions have been made that the model may produce more accurate results if the ratios are adjusted for e.g. off balance sheet items. However, the aim of this thesis is not to improve the results produced by the model but to test the models accuracy. Moreover, by not adjusting the financial data, the results will mirror the performance of the model in its simplest and most user friendly form.

### *The selection of test objects and data availability are not adequate or satisfactory*

Recognized as the greatest uncertainty of this investigation is the companies selected to be tested by the Z-score and Z''-score model. When defining the population the primary limitation is that the objects chosen are not necessary the objects that give access to most available or preferred data. This makes it difficult to achieve appropriate statistical evidence related to the models. The primary selection simply needs to be firms that have filed for bankruptcy during the period. Additionally, the firms need to have been traded on a stock market (manufacturing firms) and filed complete 10-K reports one and two reporting periods prior to bankruptcy. The objects are retrieved from a database created primarily for bankruptcy research and is considered to be adequate for this type of investigation. A factor in favour of this research however, is that test objects are collected from the U.S. which generally is regarded as a sovereign state with well-developed capital markets and controlled reporting systems. Another strength of this research in comparison to the original article from 1968 which retrieved data from "Moody's Manual" and only some information from actual financial reports, is that financial figures are collected from filings made to the Securities and Exchange Commission. Furthermore, the firms in this sample have a higher asset size than the firms in the original sample. This is not surprising when taking in account the time value of money. What today is considered a rather small firm was at that time considered at least substantially larger. Furthermore, substantial size can be seen as a fascinating aspect since larger firms usually have a greater possibility of attracting new financing and would then have a greater possibility of getting through during bad times. This brings an interesting twist to the paper since the business world is clearly under great pressure if a greater number of large firms are defaulting during a shorter period of time. An additional concern is the time aspect. Each Z-score is produced one or two reporting period prior to the bankruptcy filing which for example would mean 20XX-06-30 or 20XX-12-31. Consequently, this indicates that hypothetically the time period to default could be between 1 day and 12 months. A further issue of time is related to the above mentioned usage of 10-K reports in the case a practioner has the intention of forecasting a possible bankruptcy. As there is a gap between the end of the financial reporting period and the release of the 10-K report to the public there is a chance that the firm might go bankrupt within the time gap period and therefore there will be no chance of actually predicting the bankruptcy. This is of course unless one can actually rely on the prediction two reporting periods prior to bankruptcy. However, it will not affect this investigation since it is done post bankruptcy filing. The results from the study on predicting default two reporting periods prior to bankruptcy in this study, may indicate to what extent this will be a problem or not.

On the topic of finding an appropriate peer, the aim is to locate non-bankrupt firms that are as similar as possible in terms of size and industry to the ones who filed for bankruptcy. It is nearly impossible to find duplicates fitting the exact requirements. This is also a matter brought to attention during the development of the models. However, the next best thing is to try to find firms as closely related as possible. To find appropriate peers is a delicate task but is of high importance to the end result. The mean asset sizes from the sample in this study are more than satisfactory which is seen as a great strength.

Another concern is the usage of the SIC system when classifying companies into manufacturing or non-manufacturing entities. The Z-score and Z''-score models are created for firms incorporating the specific characteristics of manufacturing and non-manufacturing business models. However, due to the continuous development of the business world and the possible errors of secondary sources[15] there might be a risk of a company classified as manufacturing having some characteristics of a non-manufacturing firm and vice versa. Nevertheless, due to the inefficiency of investigating each and every object for its specific characteristic and classification accordingly, the SIC system is used. Further, the SIC system is generally recognized and thereby viewed as sufficiently reliable.

[15] The SIC of the firms tested is retrieved from the Security and Exchange Commission

### *Using legal bankruptcy filings as a definition of default may give misleading results*

The definition of bankruptcy in this study is related to the filing under chapter 7 and chapter 11 of the U.S. bankruptcy code. The reason is that during the development of the Z-score model legal corporate default was similarly applied. This can be argued as a great weakness since firms can experience trouble in paying off debt earlier than in the event of the actual legal bankruptcy filing which may further affect the time aspect discussed earlier. Correspondingly, surviving firms may experience trouble fulfilling all their financial obligations without ever actually filing for bankruptcy. This being said, the event of legal bankruptcy filing can still be useful as a proxy for default in these kinds of studies when default prediction models are tested. It is an easy, accessible indication of trouble in a particular firm.

### *Using a book value of equity-model can be considered problematic*

As mentioned previously the Z-score model is using share price when defining the equity value and the Z''-score model is using the book value of equity. Since the two models are not tested in the same test a direct comparison in the relation between firms are not affected by the various compositions. However, the actual accuracy of each model in predicting bankruptcy or survival is compared. When evaluating the accuracy it should be kept in mind those different definitions that are used in stating the value of equity. One may argue that the market is the most suitable in predicting the performance of a firm and because of this the book value of equity is not a very reliable figure compared to the market value. Ultimately, since this essay is simply testing models and not attempting to modify or develop new ones, this criticism should rather be considered as a reason why the model itself would fail and should be discussed in the analysis. Simply it should not be thought of as weakness in this particular research methodology.

# 5. Empirical Results and Analysis

*The results and analysis will be presented during this section in relation to different cut off values. Moreover the author's will also evaluate the perfect cut off for this sample.*

## 5.1 Empirical Results

Table 5.1 presents the classification of the firms depending on the score given by either the Z-score or Z''-score.

*Table 5.1 Test Results of Z-score and Z''-score*

| | **Z-score one reporting period prior to bankruptcy** (20 bankrupt/20 non-bankrupt) | **Z-score two reporting periods prior to bankruptcy** (20 bankrupt/20 non-bankrupt) | **Z''-score one reporting period prior to bankruptcy** (25 bankrupt/25 non-bankrupt) | **Z''-score two reporting periods prior to bankruptcy** (25 bankrupt/25 non-bankrupt) |
|---|---|---|---|---|
| Bankrupt Firms Classified Bankrupt, | **13** | **11** | **19** | **13** |
| Bankrupt firms Classified within Grey Area | 4 | 4 | 2 | 5 |
| Bankrupt Firms Classified as Non-Bankrupts | 3 | 5 | 4 | 7 |
| Total number Bankrupt Firms not Classified as Bankrupt | *7* | *9* | *6* | *12* |
| Non-Bankrupt firms Classified as Non-Bankrupt | **14** | **13** | **11** | **15** |
| Non-Bankrupt firms Classified within Grey Area | 4 | 4 | 5 | 3 |
| Non-Bankrupt firms Classified as Bankrupt | 2 | 3 | 9 | 7 |
| Total number Non-Bankrupt Firms not Classified as Non-Bankrupt | *6* | *7* | *14* | *10* |

## 5.2 Analysis and Implications of Results

### 5.2.1 The application of the grey area boundary cut off scores

Table 5.2 presents the diagnostic test results on the Z-score model and the Z''-score model. Two cut off scores are tested, the upper and the lower limit of the grey area which means that in some tests the bankrupt firms within grey area are indexed as incorrectly classified and in some tests they are indexed as correctly classified.

*Table 5.2 Z-score and Z"-score test analysis*

| | Z-score One reporting period – lower limit cut off score | Z-score One reporting period – upper limit cut off score | Z-score Two reporting period – lower limit cut off score | Z-score Two reporting period – upper limit cut off score |
|---|---|---|---|---|
| Sensitivity | 0,65 | 0,85 | 0,55 | 0,75 |
| Specificity | 0,9 | 0,7 | 0,85 | 0,65 |
| | | | | |
| Positive | 0,375 | 0,575 | 0,35 | 0,55 |
| Negative | 0,625 | 0,425 | 0,65 | 0,45 |
| | | | | |
| True Positive | 0,866667 | 0,73913 | 0,785714 | 0,681818 |
| False Positive | 0,133333 | 0,26087 | 0,214286 | 0,318182 |
| | | | | |
| True Negative | 0,72 | 0,823529 | 0,653846 | 0,722222 |
| False Negative | 0,28 | 0,176471 | 0,346154 | 0,277778 |

| | *Z''-score One reporting period – lower limit cut off score* | *Z''-score One reporting period – upper limit cut off score* | *Z''-score Two reporting period – lower limit cut off score* | *Z''-score Two reporting period – upper limit cut off score* |
|---|---|---|---|---|
| **Sensitivity** | 0,76 | 0,84 | 0,52 | 0,72 |
| **Specificity** | 0,64 | 0,44 | 0,72 | 0,6 |
| | | | | |
| **Positive** | 0,56 | 0,7 | 0,4 | 0,56 |
| **Negative** | 0,44 | 0,3 | 0,6 | 0,44 |
| | | | | |
| **True Positive** | 0,678571 | 0,6 | 0,65 | 0,642857 |
| **False Positive** | 0,321429 | 0,4 | 0,35 | 0,357143 |
| | | | | |
| **True Negative** | 0,727273 | 0,733333 | 0,6 | 0,681818 |
| **False Negative** | 0,272727 | 0,2666667 | 0,4 | 0,3118182 |

When observing the results one can spot a significant difference between the two cut off scores in being able to identify which firms will go bankrupt and which will survive. The lower cut off score is much better in identifying surviving firms and the upper cut off score is much better in identifying bankrupt firms. This supplies some proof that there is a relatively large number of firms situated within the grey area boundary which supports the notion that the optimal cut off score is situated within this range. For example, Altman (1968) suggested using an optimal cut off score situated within the grey area of 2,675 when applying the Z-score model. Whether this value performs better results than both the lower and the upper cut off is analyzed later on.

When testing the performance of a model designed to predict bankruptcy it is particularly interesting to review its ability to identify bankrupt firms. Both models present attractive numbers when applying the upper cut off scores, over

80% accuracy[16] one reporting period prior to bankruptcy and over 70% accuracy two reporting periods prior to bankruptcy. In agreement with the findings in Altman (1968) it is not very remarkable that the result from two reporting periods prior to bankruptcy is worse than the values retrieved closer to the date of bankruptcy filing. However, Altman (1968) concludes that a 72% accuracy or above is sufficient evidence that the model can predict bankruptcy two years prior to default. Altman (2000) mentions that for several studies performed from 1968 and onwards, an accuracy of the model between 80%-90% is observed one reporting period prior to bankruptcy, which is considered as good evidence of predictability. This study achieves equivalent or better results when applying the upper cut off in relation to these findings. Moreover, an even better performance can be spotted when viewing the results of the Z-score model in predicting which firms are to survive for this sample. When applying the lower cut off score it is between 85%-95% accurate in its identifying ability. This can potentially be good news for the person interested in finding out which firms will manage another two years.

So far the discussion has been concentrated around how well the models are in identifying which firms will go bankrupt and which will survive. However, when applying the model on a group where the outcome is unknown since it has not yet been realized, it is of high importance to be aware of the potential rate of misclassifications. In this study they are represented by the false negative and false positive rates in relation to all negative or positive predictions. When once again reviewing the excellent results of bankruptcy identification of the upper cut off score, one can also spot a great weakness. Out of all the positive predictions the false positive rate is between 25%-40%. This can result in a security holder demanding a too high default premium by the firm or even rejecting an investment since it perceives it as too risky. Further, this may by mistake disrupt the possibility to take on all positive net present value projects due to overestimating prospective financial distress costs. What can be considered even worse than a large rate of false positives is a large rate of false negatives since it may result in real losses. False negatives are all firms assigned a non-bankrupt prediction but in reality they will go bankrupt. For example, for the 85%-90% accurate

[16] Note that accuracy is referred to sensitivity in the diagnostic test tables.

identification of non-bankrupt firms applying the lower cut off, a false negative rate of 28%-35% is observed.

To sum up the misclassification discussion, an indication of delicacy when using a model with high false positive and false negative rates is recommended. By mistake rejecting a firm that will survive and perform well may result in losing a great investment but by mistake investing in a firm that will go bankrupt may result in severe real losses due to discount sales of assets and high direct and indirect bankruptcy costs. This calls for the aspiration to find a model that is performing great in identifying both bankrupt and non-bankrupt firms and hence this will result in fewer errors. Moreover, it is preferred that the sensitivity and specificity rates are not too dispersed. If they are more closely stuck together the bias of favoring positive predictions in relation to negative predictions and vice versa will be reduced. In the next section, the proposed optimal cut off of 2,675 will be tested in order to evaluate if it can achieve this.

### 5.2.2 The Altman 1968 optimal cut off score

The discussion above is based on the assumptions using the grey area cut offs in both the Z-score and Z''-score. However, Altman (1968) proposes an optimal cut off for the Z-score of 2,675. Using this cut off, the model was able to predict bankruptcy with the accuracy of 94% in the initial study. Table 5.3 shows the result of that cut off applied on the sample of firms in this investigation.

*Table 5.3 Z-score test analysis with cut off 2,675*

| | Z-score predictability one reporting period | Z-score predictability two reporting periods |
|---|---|---|
| **Sensitivity** | 0,8 | 0,75 |
| **Specificity** | 0,7 | 0,7 |

| | | |
|---|---|---|
| **Positive** | 0,55 | 0,525 |
| **Negative** | 0,45 | 0,475 |
| | | |
| **True Positive** | 0,73333 | 0,714286 |
| **False Positive** | 0,26667 | 0,28574 |
| | | |
| **True Negative** | 0,777778 | 0,736842 |
| **False Negative** | 0,222222 | 0,263158 |

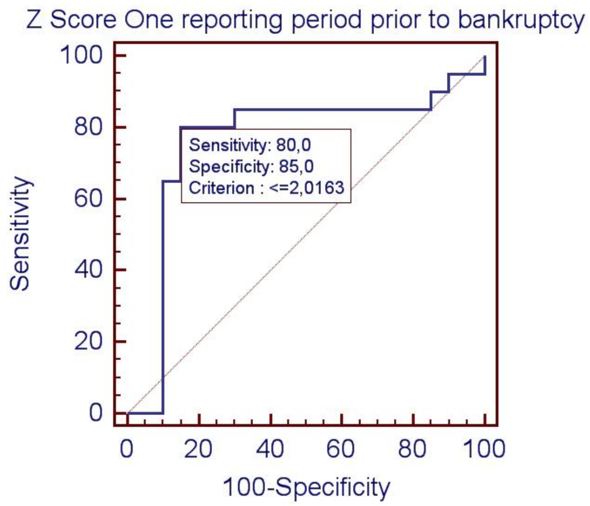
The reason for testing the 2,675 cut off value was to evaluate if it gives the model better discriminant ability than the lower and upper cut off score. This was true when comparing the result with the ones for the lower cut off. However, for the sample in this study the upper cut off 2,99 was more accurate in identifying the bankrupt firms whereas the specificity level was the same. Nevertheless, it seems like the 2,675 cut off brings less bias to the tests since the dispersion of the sensitivity and specificity is smaller. Furthermore, the cut off achieves in line or better in comparison to the results presented as sufficient in Altman (2000). Altman (2000) further suggests that the lower cut off may give a more realistic result due to the increased rate of false positives in recent studies and the lower cut off mitigating this. As discussed earlier this is also true for this sample since the lower cut off shows very impressive results in identifying non-bankrupt firms. However, the amount of false negatives in relation to all negative predictions is so high that for this sample the use of the lower cut off should be questioned, at least if the false negatives are valued as worse than the false positives.

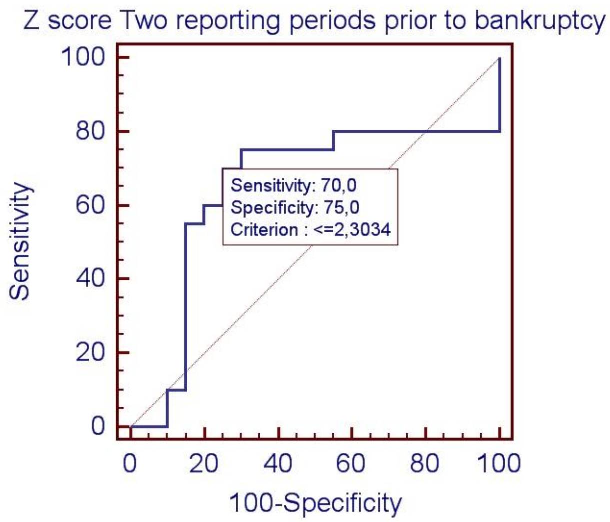
There can be several reasons for the model not favoring the 2,675 or the lower cut off scores as it did in the previous research presented in Altman (1968) and Altman (2000). The sample in this study is somewhat smaller than the samples tested on previously which may not be as representative as a larger sample. Moreover, Altman (2000) comments on his findings of an increased average Z-score as a result of increasing stock prices. This tendency could be a factor in the upper cut off value resulting in better figures than the lower cut off which was proposed by Altman. However, more can be said on this issue when the optimal cut off scores for this particular sample has been analyzed.

### 5.2.3 Optimal Cut Off Scores For This Particular Sample

By analyzing the ROC curves for each test group the optimal cut off score that implies the least number of incorrectly classified firms, both false positive and false negative, can be found. The ROC curve illustrates the plot of sensitivity as a function of the false positive rate and every dot on the curve is assigned a cut off value. The diagonal line through the graph represents how the curve would have looked like if the test had no predictive ability and is called the *by chance*-line. A perfect test would have been assigned a curve following the upper horizontal boundary and the left vertical boundary of the graph and holding an optimal cut off value of x=0 and y=100 (Zhou, Obuchowski & McClish 2002). The optimal cut off scores for the tests in this study is found using the Youden Index (Le 2010). These cut off scores are presented together with their corresponding

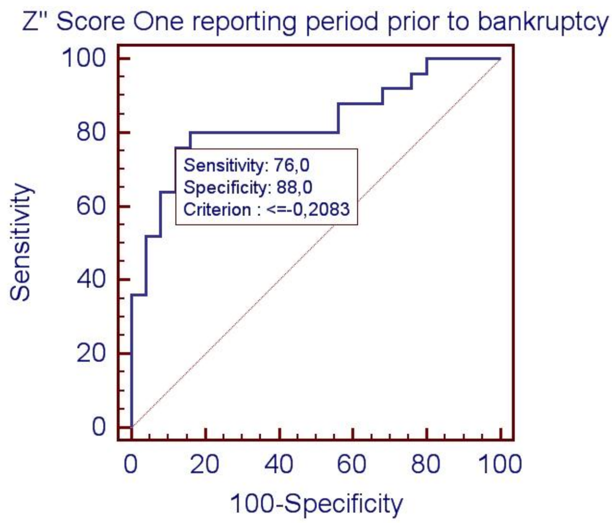
*Figure 5.4 Optimal cut off – Z-score*

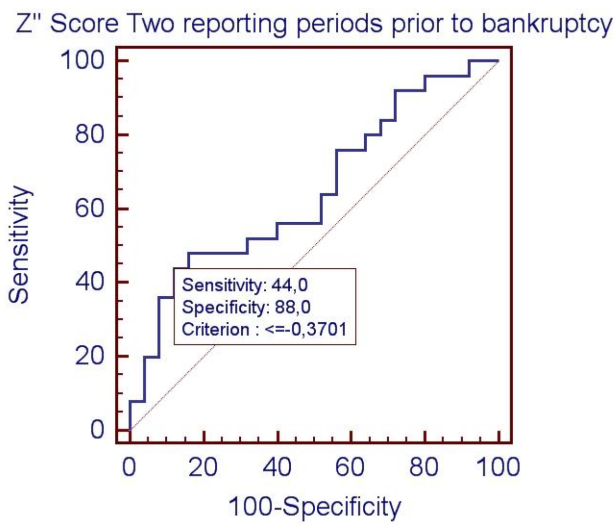


sensitivity and specificity level in Figure 5.4 and 5.5.

*Figure 5.5 Optimal cut off – Z''-score*




As mentioned above, the Youden Index analysis values both the false positive and false negative classification as equally bad and therefore it is only interested in the total number of incorrect classifications. This can be problematic in a bankruptcy prediction model since the user of the model may feel that a larger percentage of false negatives may incur larger losses to him or her, than a large percentage of false positives. Therefore, the optimal cut off values presented in the graph are not by any means recommended for usage when applying the model. They have an illustrative purpose and are only viable for this particular sample. Nevertheless, they together with the ROC curves are still able to supply some valuable information about the tests performed and potential strength and weaknesses of the models applied.

The optimal cut off values for the Z-score model is situated between the lower cut off and the 2,675 cut off. However, the ability to identify the bankrupt firms is not more accurate compared to the upper limit or 2,675 values, but what has been improved is the identification of non-bankrupt firms. This supports the idea that the inflation in stock prices may have been pushing the cut off presenting the least amount of false positives upwards in this case. This would further weaken the argument of Altman (2000) that a cut off representing the lower limit would be most appropriate when wanting to achieve a lower false positive rate.

The ROC curves and corresponding cut off values for the Z''-score results may seem somewhat confusing since they are suggesting a negative cut off for both one and two reporting periods prior to bankruptcy. Once again a very high ability of identifying non-bankrupt firms is improved but what is different from the Z-score is the much worsened ability to identify bankrupt firms. Moreover, in this case the grey area does not seem to be enough to cover most misclassifications. This shows some evidence that a large number of non-bankrupt firms are situated below the grey area. The reason for this could be that some of the surviving firms are having a very low or even a negative book value of equity. This proves how weak the Z''-score model is due to the fact that it is using the book value instead of the market value and a strong indication that it probably would have performed better if the actual market values of the traded companies would have been used. An additional weakness which is particularly clear in the results from the Z''-score two reporting periods prior to bankruptcy is how small the area under the graph is and how close the curve is to the *by chance*-line. This implies that the predictability of the model for this sample is substantially low and this mitigates the reliability even more.

The analysis of the ROC curves indicates some difficulties when predicting default using a model developed through empirical research. The largest weakness supported by this analysis is what is an optimal model varies by sample. Additionally, the prediction process is very complex due to its vast dependency on the situation surrounding the firm. These situations demand more than just relying on numbers and call for a soft factor analysis complementing the assessment where the investor can evaluate the risk of, for example, the occurrence of the asset substitution problem. However, a well performing and uncomplicated bankruptcy predicting model can be of great use and indications for both more simplistic evaluations and more advanced assessments where banks have the possibility to develop their own default probability methods for risk management purposes on firms lacking a public rating.

# 6. Conclusions

*During this part the authors will sum up the findings from the analysis and also discuss the models' functionality. The part will be concluded by propositions on further research.*

## 6.1 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 firms 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 85% accuracy for the Z-score and a 75% accuracy for the Z''-score in identifying bankrupt firms is good news. Furthermore, when applying the optimal cut off value suggested by Altman (1968) more than 40 years ago and getting an accuracy of 80% and 75% for one and two 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 trade off 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 practioner to understand the potential outcomes resulting from errors, bias and weaknesses of the models, many of them discussed in this paper.

## 6.2 Further Research

After having examined this paper it is obvious to many that the model incorporates a substantial number of flaws that would encourage further research on continuing the quest for a more refined Z-score model or even a completely new method. Rejecting the attempt to make an extensive list of possible improvements the section below covers some requests from Swedish practioners on future testing of the Z-score model.

During the thesis process, the authors have received a great amount of appreciation upon the chosen subject from people with a background in business and finance. Some of them would though have been even more interested in the results from a study assessing the application of the model on the Swedish market and analyzing whether the Z-score could have predicted the default of Swedish firms. However, applying a similar methodology requires a significant peer for every bankrupt firm, which can be difficult to find in a country like Sweden where the market is relatively small. Furthermore, the model is originally developed on empirical data from the American market where certain factors apply which may not be present or similar in other markets. Despite of these considerations, it calls for more extensive testing of the accuracy of the model on the Swedish market.

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## Exhibit 1: GDP growth in United States

| US GDP growth 1900-2010 | | | |
|---|---|---|---|
| *Year 1900-1954* | % -change in GDP | *Year 1955-2010* | % -change in GDP |
| 1900 | 8% | 1955 | 5% |
| 1901 | 8% | 1956 | 5% |
| 1902 | 8% | 1957 | 1% |
| 1903 | -1% | 1958 | 8% |
| 1904 | 12% | 1959 | 4% |
| 1905 | 8% | 1960 | 3% |
| 1906 | 9% | 1961 | 8% |
| 1907 | -11% | 1962 | 5% |
| 1908 | 7% | 1963 | 7% |
| 1909 | 4% | 1964 | 8% |
| 1910 | 3% | 1965 | 10% |
| 1911 | 9% | 1966 | 6% |
| 1912 | 5% | 1967 | 9% |
| 1913 | -7% | 1968 | 8% |
| 1914 | 6% | 1969 | 5% |
| 1915 | 28% | 1970 | 9% |
| 1916 | 20% | 1971 | 10% |
| 1917 | 27% | 1972 | 12% |
| 1918 | 3% | 1973 | 8% |
| 1919 | 13% | 1974 | 9% |
| 1920 | -17% | 1975 | 11% |
| 1921 | 0% | 1976 | 11% |
| 1922 | 16% | 1977 | 13% |
| 1923 | 2% | 1978 | 12% |
| 1924 | 4% | 1979 | 9% |
| 1925 | 7% | 1980 | 12% |
| 1926 | -1% | 1981 | 4% |
| 1927 | 2% | 1982 | 9% |
| 1928 | 6% | 1983 | 11% |
| 1929 | -12% | 1984 | 7% |
| 1930 | -16% | 1985 | 6% |
| 1931 | -23% | 1986 | 6% |
| 1932 | -4% | 1987 | 8% |
| 1933 | 17% | 1988 | 7% |
| 1934 | 11% | 1989 | 6% |
| 1935 | 14% | 1990 | 3% |
| 1936 | 10% | 1991 | 6% |
| 1937 | -6% | 1992 | 5% |
| 1938 | 7% | 1993 | 6% |
| 1939 | 10% | 1994 | 5% |
| 1940 | 25% | 1995 | 6% |
| 1941 | 28% | 1996 | 6% |
| 1942 | 23% | 1997 | 6% |
| 1943 | 11% | 1998 | 6% |
| 1944 | 1% | 1999 | 6% |
| 1945 | 0% | 2000 | 3% |
| 1946 | 10% | 2001 | 3% |
| 1947 | 10% | 2002 | 5% |
| 1948 | -1% | 2003 | 7% |
| 1949 | 10% | 2004 | 6% |
| 1950 | 16% | 2005 | 6% |
| 1951 | 6% | 2006 | 5% |
| 1952 | 6% | 2007 | 2% |
| 1953 | 0% | 2008 | -2% |
| 1954 | 9% | 2009 | 3% |

# Exhibit 2: Sample Firms and Corresponding Peers

| ***Bankrupt*** | | | | | ***Non Bankrupt*** | | |
|---|---|---|---|---|---|---|---|
| | *Year filed* | *Corp. Name* | *SIC Code* | *BV Total Assets (mill)* | *Corp. Name* | *SIC Code* | *BV Total Assets (mill)* |
| Mining | | | | | | | |
| | 2009 | Apex Silver Mines Limited | 1040 | $606,30 | StillWater Mining | 1090 | $724,80 |
| | 2009 | Edge Petroleum Corp | 1311 | $357,60 | Approach Resources Inc | 1311 | $338,20 |
| | 2009 | Energy Partners, Ltd. | 1311 | $814,90 | GMX Resources INC | 1311 | $519,60 |
| | 2009 | TXCO Resources Inc. | 1311 | $486,90 | Brigham Exploration Inc | 1311 | $498,30 |
| | | | | | | | |
| Transportation | | | | | | | |
| Communications | 2007 | InPhonic, Inc. | 4833 | $264,40 | USA Mobility Inc | 4812 | $241,40 |
| Electric | 2008 | WorldSpace, Inc. | 4832 | $340,00 | Atlantic Tele-Network | 4813 | $344,60 |
| Gas | 2008 | Frontier Airlines Holdings, Inc. | 4512 | $1 250,00 | Pinnacle Airlines Corp | 4512 | $1 133,10 |
| | 2009 | Citadel Broadcasting Corp | 4832 | $2 433,00 | Cincinnati Bell | 4813 | $2 019,60 |
| | 2009 | Charter Communications, Inc | 4841 | $13 882,00 | DIRECTV | 4841 | $16 539,00 |
| | 2009 | FairPoint Communications, Inc. | 4813 | $3 334,50 | Clearwire Corp. | 4899 | $2 686,00 |
| | 2009 | Primus Telecommunications Group | 4813 | $460,40 | Otelco Inc | 4813 | $355,50 |
| | 2010 | Trico Marine Services, Inc. | 4400 | $1 202,60 | Eagle Bulk Shipping | 4412 | $1 136,00 |
| | 2010 | Mesa Air Group | 4510 | $959,20 | Air Transport Services Grp. | 4510 | $1 002,80 |
| | | | | | | | |
| Retail Trade | | | | | | | |
| | 2007 | Tweeter Home Entertainment Group | 5731 | $258,60 | Bombay Co. | 5712 | $238,10 |
| | 2008 | Circuit City Stores, Inc. | 5731 | $3 745,90 | Bed Bath & beyond | 5700 | $3 844,10 |
| | 2008 | Sharper Image Corp | 5940 | $264,00 | A C Moore Arts & Crafts | 5940 | $321,90 |
| | 2009 | Eddie Bauer Holdings, Inc. | 5600 | $596,90 | Aeropostale | 5600 | $657,90 |
| | 2009 | Gottschalks Inc. | 5311 | $332,00 | Duckwall-ALCO Stores | 5331 | $208,80 |
| | 2007 | Hancock Fabrics | 5940 | $242,00 | BioScrip Inc | 5910 | $305,50 |
| | 2009 | Finlay Enterprises Inc | 5944 | $567,60 | PharMerica Corp. | 5910 | $679,20 |
| | 2009 | Fairchild Corp. | 5600 | $357,40 | Buckle (The) Inc. | 5600 | $465,30 |
| | | | | | | | |
| Services | | | | | | | |
| | 2008 | Bally Total Fitness Holding Corp | 7997 | $396,80 | Cedar Fair L.P. | 7900 | $2 510,90 |
| | 2009 | BearingPoint, Inc. | 8742 | $1 654,90 | FTI Consulting | 8742 | $2 088,20 |
| | 2009 | Magna Entertainment Corp. | 7948 | $1 242,60 | Life Time Fitness Inc | 7900 | $1 647,70 |
| | 2009 | Six Flags, Inc. | 7990 | $2 945,30 | International Speedway Corp | 7900 | $2 180,80 |
| | 2009 | Young Broadcasting, Inc. | 7950 | $348,20 | Spanish Broadcasting System | 4833 | $478,79 |
| | 2009 | Trump Entertainment Resorts | 7011 | $2 231,20 | Gaylord Entertainment | 7011 | $2 560,40 |
| | 2010 | RHI Entertainment, Inc. | 7812 | $1 014,20 | Netflix Inc. | 7841 | $679,70 |
| | 2008 | SIRVA Inc | 4213 | $1 419,20 | Hunt (J.B.) | 4213 | $1 862,80 |
| | | | | | | | |
| Manufacturing | | | | | | | |
| | 2007 | Pope & Talbot, Inc. | 2611 | $662,00 | Schweitzer-Mauduit Intl Inc | 2621 | $696,60 |
| | 2008 | Constar International Inc. | 3080 | $472,30 | Axion International Holdings | 3086 | $669,00 |
| | 2008 | Syntax-Brillian Corp | 3663 | $514,70 | Harbin Electric Inc | 3621 | $235,50 |
| | 2008 | Lenox Group, Inc. | 3260 | $352,10 | Apogee Enterprises | 3231 | $527,70 |
| | 2009 | AbitibiBowater Inc. | 2621 | $8 072,00 | Domtar Corp. | 2621 | $7 748,00 |
| | 2009 | Accuride Corp | 3714 | $808,50 | Federal Signal | 3711 | $834,00 |
| | 2009 | Asyst Technologies, Inc. | 3559 | $445,70 | Alamo Group | 3500 | $384,40 |
| | 2009 | Champion Enterprises, Inc. | 2451 | $1 022,20 | Thor Inds. | 3761 | $996,60 |
| | 2009 | Chemtura Corp | 2820 | $3 064,00 | FMC Corp. | 2810 | $2 993,90 |
| | 2009 | Dayton Superior Corp | 3317 | $300,10 | Northwest Pipe Co | 3311 | $509,40 |
| | 2009 | Hartmarx Corp | 2300 | $459,90 | Under Armour | 2300 | $487,60 |
| | 2009 | Lear Corp | 3714 | $6 872,90 | Goodrich Corp. | 3760 | $7 482,90 |
| | 2009 | Milacron Inc. | 3559 | $602,90 | Astec Industries Inc | 3531 | $612,80 |
| | 2009 | Noble International, Ltd. | 3714 | $803,70 | Gentex Corp. | 3714 | $763,10 |
| | 2009 | Nortel Networks Corp. | 3661 | $8 837,00 | Cooper Inds. | 3600 | $6 164,90 |
| | 2009 | Silicon Graphics, Inc. | 3571 | $415,20 | Brooks Automation Inc | 3559 | $663,60 |
| | 2009 | Smurfit-Stone Container Corp | 2631 | $4 594,00 | Temple-Inland | 2600 | $5 869,00 |
| | 2009 | Visteon Corporation | 3714 | $5 248,00 | Oshkosh Corp. | 3711 | $6 081,50 |
| | 2008 | Chesapeake Corp. | 2650 | $1 114,80 | Buckeye Technologies | 2611 | $1 009,20 |
| | 2008 | MPC Corp | 7372 | $122,40 | ActivIdentity Corp | 7372 | $117,60 |
| | 2008 | VeraSun Energy | 2826 | $1 863,50 | Georgia Gulf | 2810 | $1 610,40 |
| | 2009 | Fleetwood Enterprises | 3716 | $625,60 | International Textile Group | 2220 | $761,30 |
| | 2009 | Hayes Lemmerz Intl Inc | 3714 | $1 096,20 | AAR Corp. | 3720 | $1 377,50 |
| | 2010 | General Motors | 3711 | $136 295,00 | Ford Motor Co | 3711 | $194 850,00 |

## Exhibit 3: Z-Scores and Z”-Scores for Sample Firms

| Bankrupt Manufacturing firms - Z-score- One reporting period prior to bankruptcy | | | | | | | |
|---|---|---|---|---|---|---|---|
| Company | Filing date 10-K | 1,2X | 1,4X | 3,3X | 0,6X | 1X | Z-score |
| Pope & Talbot, Inc. | 2006-12-31 | 0,282 | -0,057 | 0,416 | 0,104 | 1,271 | 2,016 |
| Constar International Inc. | 2007-12-31 | 0,098 | -0,976 | 0,105 | 0,057 | 1,867 | 1,151 |
| Lenox Group, Inc. | 2007-12-31 | 0,355 | 0,154 | -0,069 | 0,173 | 1,284 | 1,898 |
| AbitibiBowater Inc. | 2008-12-31 | 0,057 | -0,492 | -0,585 | 1,757 | 0,839 | 1,576 |
| Accuride Corporation | 2008-12-31 | 0,270 | -0,533 | -1,129 | 0,006 | 1,152 | -0,234 |
| Asyst Technologies, Inc. | 2008-03-31 | 0,142 | -1,258 | -0,099 | 0,174 | 1,026 | -0,015 |
| Champion Enterprises, Inc. | 2008-12-31 | -0,070 | -0,382 | -0,178 | 0,047 | 1,602 | 1,020 |
| Chemtura Corporation | 2008-12-31 | -0,219 | -1,000 | -1,001 | 5,725 | 1,157 | 4,663 |
| Dayton Superior Corporation | 2008-12-31 | -1,036 | -1,433 | 0,496 | 0,018 | 1,586 | -0,370 |
| Lear Corporation | 2008-12-31 | -0,163 | -0,037 | -0,144 | 1,046 | 1,974 | 2,677 |
| Nortel Networks Corp. | 2008-12-31 | 0,288 | 6,711 | -0,815 | 0,649 | 1,179 | 8,013 |
| Silicon Graphics, Inc. | 2008-12-29 | -0,043 | -0,866 | -1,011 | 0,040 | 0,853 | -1,027 |
| Smurfit-Stone Container Corporat | 2008-12-31 | -1,004 | -1,395 | -2,010 | 1,897 | 1,551 | -0,959 |
| Visteon Corporation | 2008-12-31 | -0,343 | -1,255 | 0,173 | 4,485 | 1,819 | 4,879 |
| Chesapeake Corp. | 2007-12-31 | 0,093 | 0,137 | 0,073 | 0,071 | 0,873 | 1,247 |
| MPC Corporation | 2007-12-31 | -0,172 | -0,494 | -0,177 | 0,050 | 1,370 | 0,577 |
| VeraSun Energy | 2007-12-31 | 0,147 | 0,087 | 0,095 | 0,089 | 0,453 | 0,871 |
| Fleetwood Enterprises | 2008-04-27 | 0,207 | -1,066 | 0,094 | 0,071 | 2,654 | 1,960 |
| Hayes Lemmerz Intl Inc | 2009-01-31 | -0,509 | -0,002 | -0,760 | 0,040 | 1,737 | 0,507 |
| GM Co | 2008-12-31 | -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 | 1,2X | 1,4X | 3,3X | 0,6X | 1X | Z-score |
| Pope & Talbot, Inc. | 2005-12-31 | 0,0930 | 0,0246 | -0,1527 | 0,1658 | 1,3460 | 1,4767 |
| Constar International Inc. | 2006-12-31 | 0,1575 | -0,8363 | 0,1768 | 0,0962 | 1,8394 | 1,4335 |
| Lenox Group, Inc. | 2006-12-31 | 0,0971 | 0,1063 | -0,3031 | 0,3868 | 1,3443 | 1,6315 |
| AbitibiBowater Inc. | 2007-12-31 | -0,0042 | -0,0814 | -0,1283 | 7,8725 | 0,3768 | 8,0354 |
| Accuride Corporation | 2007-12-31 | 0,1761 | 0,0260 | 0,0877 | 0,1986 | 0,9103 | 1,3986 |
| Asyst Technologies, Inc. | 2007-03-31 | -0,0697 | -0,3816 | -0,1776 | 0,0468 | 1,6018 | 1,0197 |
| Champion Enterprises, Inc. | 2007-12-21 | 0,0494 | 0,0324 | 0,0750 | 0,6224 | 1,2458 | 2,0249 |
| Chemtura Corporation | 2007-12-31 | 0,1902 | -0,3738 | 0,0441 | 3,2158 | 0,8485 | 3,9248 |
| Dayton Superior Corporation | 2007-12-31 | 0,2347 | -1,3032 | 0,4428 | 0,1096 | 1,5223 | 1,0063 |
| Lear Corporation | 2007-12-31 | 0,0176 | -0,0050 | 0,2382 | 0,0020 | 2,0505 | 2,3034 |
| Nortel Networks Corp. | 2007-12-31 | 0,1670 | 2,9965 | 0,0437 | 2,9380 | 0,6414 | 6,7866 |
| Silicon Graphics, Inc. | 2007-12-29 | 0,1534 | -0,3547 | -0,6914 | 0,3759 | 0,8338 | 0,3170 |
| Smurfit-Stone Container Corpora | 2007-12-31 | 0,0023 | -0,3214 | 1,3179 | 8,7399 | 1,0045 | 10,7430 |
| Visteon Corporation | 2007-12-31 | 0,2572 | 0,1375 | 0,0435 | 4,6939 | 1,5649 | 6,6969 |
| Chesapeake Corp. | 2006-12-31 | 0,0343 | 0,1720 | 0,0009 | 0,2295 | 0,8929 | 1,3297 |
| MPC Corporation | 2006-12-31 | -0,1030 | -0,9442 | -1,0523 | 0,0482 | 2,3277 | 0,2764 |
| VeraSun Energy | 2006-12-31 | 0,5801 | 0,1579 | 0,6298 | 0,3791 | 0,6973 | 2,4440 |
| Fleetwood Enterprises | 2007-04-29 | 0,2802 | -0,9461 | -0,2712 | 0,3615 | 2,7296 | 2,1540 |
| Hayes Lemmerz Intl Inc | 2008-01-31 | 0,1136 | -0,7200 | -0,0707 | 0,1331 | 1,1776 | 0,6336 |
| GM Co | 2007-12-31 | -0,0756 | -0,3704 | -0,0955 | 0,4585 | 1,2089 | 1,1259 |

| Surviving Manufacturing firms - Z-score - One reporting period prior to bankruptcy | | | | | | | |
|---|---|---|---|---|---|---|---|
| Company | Filing date 10-K | 1,2X | 1,4X | 3,3X | 0,6X | 1X | Z-score |
| Schweitzer-Mauduit Intl Inc | 2006-12-31 | 0,119 | 0,546 | 0,025 | 0,236 | 0,941 | 1,866 |
| Domtar Corp. | 2008-12-31 | 0,179 | -0,121 | -0,236 | 2,377 | 1,048 | 3,247 |
| Federal Signal | 2008-12-31 | 0,229 | 0,380 | 0,220 | 0,330 | 1,150 | 2,308 |
| Thor Inds. | 2009-07-31 | 0,529 | 0,997 | 0,058 | 1,507 | 1,600 | 4,692 |
| Under Armour | 2008-12-31 | 0,648 | 0,448 | 0,521 | 0,939 | 1,488 | 4,043 |
| Goodrich Corp. | 2008-12-31 | 0,293 | 1,830 | 0,486 | 0,661 | 0,944 | 4,213 |
| Axion International Holdings Inc | 2009-09-30 | 0,282 | -6,399 | -6,750 | 4,102 | 0,676 | -8,091 |
| Apogee Enterprises | 2008-03-01 | 0,174 | 0,452 | 0,389 | 0,711 | 1,565 | 3,291 |
| Alamo Group | 2008-12-31 | 0,563 | 0,481 | 0,183 | 1,281 | 1,450 | 3,958 |
| Northwest Pipe Co | 2008-12-31 | 0,526 | 0,517 | 0,379 | 1,307 | 0,863 | 3,593 |
| Cooper Inds. | 2008-12-31 | 0,143 | 0,667 | 0,470 | 2,135 | 1,058 | 4,472 |
| Temple-Inland | 2009-01-03 | 0,128 | 0,223 | 0,046 | 3,055 | 0,001 | 3,453 |
| Oshkosh Corp. | 2008-09-30 | 0,136 | 0,249 | 0,220 | 2,814 | 1,174 | 4,593 |
| Buckeye Technologies | 2008-06-30 | 0,190 | 0,491 | 0,328 | 3,478 | 0,818 | 5,305 |
| ActivIdentity Corp | 2008-09-30 | 0,736 | -3,846 | -1,585 | 1,677 | 0,502 | -2,516 |
| Georgia Gulf | 2007-12-31 | 0,109 | 0,028 | -0,125 | 1,203 | 1,434 | 2,649 |
| FMC Corp. | 2008-12-31 | 0,270 | 0,713 | 0,552 | 1,149 | 1,041 | 3,724 |
| International Textile Group | 2008-12-31 | -0,330 | -0,562 | -0,810 | 4,208 | 1,307 | 3,813 |
| AAR Corp. | 2009-05-31 | 0,520 | 0,417 | 0,246 | 2,797 | 1,034 | 5,014 |
| Ford Motor Co | 2008-12-31 | 0,301 | -0,104 | -0,179 | 1,407 | 0,592 | 2,017 |

| Surviving Manufacturing firms - Z-score - Two reporting periods prior to bankruptcy | | | | | | | |
|---|---|---|---|---|---|---|---|
| Company | Filing date 10-K | 1,2X | 1,4X | 3,3X | 0,6X | 1X | Z-score |
| Schweitzer-Mauduit Intl Inc | 2005-12-31 | 0,123 | 0,571 | 0,188 | 0,239 | 0,970 | 2,090 |
| Domtar Corp. | 2007-12-31 | 0,140 | 0,009 | 0,115 | 2,717 | 0,770 | 3,751 |
| Federal Signal | 2007-12-31 | 0,098 | 0,400 | 0,212 | 0,435 | 0,799 | 1,943 |
| Thor Inds. | 2008-07-31 | 0,337 | 0,950 | 0,446 | 1,781 | 2,650 | 6,163 |
| Goodrich Corp. | 2007-12-31 | 0,696 | 0,268 | 0,386 | 3,235 | 0,848 | 5,025 |
| Axion International Holdings Inc | 2008-09-30 | -0,629 | -7,412 | -8,483 | 0,798 | 0,010 | -15,718 |
| Apogee Enterprises | 2008-12-31 | 0,205 | 0,459 | 0,351 | 1,674 | 1,734 | 4,422 |
| Alamo Group | 2007-12-31 | 0,580 | 0,493 | 0,224 | 1,200 | 1,439 | 3,936 |
| Northwest Pipe Co | 2007-12-31 | 0,480 | 0,481 | 0,287 | 1,184 | 0,844 | 3,277 |
| Cooper Inds. | 2007-12-31 | 0,131 | 0,647 | 0,454 | 1,975 | 0,962 | 4,169 |
| Temple-Inland | 2008-01-03 | 0,078 | 0,233 | 0,001 | 3,097 | 0,001 | 3,410 |
| Oshkosh Corp. | 2007-09-30 | 0,121 | 0,227 | 0,304 | 3,001 | 0,986 | 4,639 |
| Buckeye Technologies | 2007-06-30 | 0,173 | 0,453 | 0,282 | 3,628 | 0,808 | 5,343 |
| ActivIdentity Corp | 2007-09-30 | 0,736 | -1,831 | -0,324 | 1,719 | 0,316 | 0,615 |
| Georgia Gulf | 2006-12-31 | 0,099 | 0,185 | 0,210 | 1,239 | 0,988 | 2,720 |
| FMC Corp. | 2007-12-31 | 0,194 | 0,643 | 0,275 | 0,879 | 0,963 | 2,955 |
| International Textile Group | 2007-12-31 | 0,296 | -0,094 | -0,161 | 3,883 | 1,049 | 4,972 |
| AAR Corp. | 2008-05-31 | 0,498 | 0,340 | 0,326 | 3,350 | 1,017 | 5,530 |
| Brooks automation | 2008-09-30 | 0,426 | -2,246 | -1,181 | 0,727 | 0,793 | -1,480 |
| Ford Motor Co | 2007-12-31 | 0,276 | -0,007 | -0,059 | 1,633 | 0,553 | 2,396 |

| Bankrupt Non-Manufacturing firms - Z''-score - One reporting period prior to bankruptcy | | | | | | |
|---|---|---|---|---|---|---|
| Company | Filing date 10-K | 6,56X | 3,26X | 6,72X | 1,05X | Z''-score |
| Apex Silver Mines Limited | 2008-12-31 | -4,464 | -4,731 | -2,272 | -0,319 | -11,787 |
| Edge Petroleum Corporation | 2008-12-31 | -0,991 | -1,874 | -0,192 | -0,063 | -3,120 |
| Energy Partners, Ltd. | 2008-12-31 | -4,922 | -0,286 | -0,224 | 0,085 | -5,347 |
| TXCO Resources Inc. | 2008-12-31 | -3,462 | 0,021 | 0,270 | 0,494 | -2,677 |
| InPhonic, Inc. | 2006-12-31 | 1,500 | -2,816 | -1,607 | 0,405 | -2,517 |
| Frontier Airlines Holdings, Inc. | 2008-03-31 | -0,751 | -0,112 | -0,188 | 0,145 | -0,906 |
| WorldSpace, Inc. | 2007-12-31 | -1,343 | -2,392 | -2,959 | -0,880 | -7,573 |
| Citadel Broadcasting Corporation | 2008-12-31 | 0,286 | -3,208 | 2,828 | -0,115 | -0,208 |
| Primus Telecommunications Group, | 2008-12-31 | -1,185 | -1,085 | 0,789 | -0,612 | -2,092 |
| Tweeter Home Entertainment Grour | 2006-09-30 | 0,998 | 3,031 | -0,355 | 0,376 | 4,050 |
| Circuit City Stores, Inc. | 2008-02-29 | 1,461 | 0,854 | -0,665 | 0,704 | 2,353 |
| Eddie Bauer Holdings, Inc. | 2009-01-03 | 0,838 | -2,743 | -1,609 | 0,146 | -3,368 |
| Gottschalks Inc. | 2008-02-02 | 2,080 | 0,348 | -0,204 | 0,534 | 2,759 |
| Bally Total Fitness Holding Corporati | 2006-12-31 | -1,461 | -1,702 | 1,933 | -0,818 | -2,049 |
| BearingPoint, Inc. | 2008-12-31 | 0,405 | 4,359 | 0,522 | -0,261 | 5,025 |
| Six Flags, Inc. | 2008-12-31 | -0,316 | -1,930 | 0,319 | -0,169 | -2,096 |
| Hancock Fabrics | 2006-01-28 | 2,439 | 1,981 | -1,305 | 0,345 | 3,459 |
| Finlay Enterprises Inc | 2009-01-31 | 1,921 | -0,354 | -1,266 | 0,013 | 0,313 |
| SIRVA Inc | 2007-12-31 | -2,915 | -2,992 | -3,137 | -0,297 | -9,342 |
| Young Broadcasting, Inc. | 2008-12-31 | -1,545 | -9,195 | -0,614 | -0,659 | -12,013 |
| Trump Entertainment Resorts, Inc. | 2008-12-31 | -6,064 | -0,913 | -0,437 | 0,400 | -7,014 |
| RHI Entertainment, Inc. | 2009-12-31 | -1,724 | -1,593 | -4,253 | -0,298 | -7,868 |
| Charter Communications, Inc | 2008-03-31 | -0,117 | -3,651 | -0,297 | -0,452 | -4,517 |
| Fairpoint Communications Inc | 2008-12-31 | -0,034 | -0,565 | 0,118 | 0,008 | -0,474 |
| Trico Marine Services Inc | 2009-12-31 | 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 | 6,56X | 3,26X | 6,72X | 1,05X | Z''-score |
| Apex Silver Mines Limited | 2007-12-31 | -0,991 | -1,874 | -0,192 | -0,063 | -3,120 |
| Edge Petroleum Corporation | 2007-12-31 | 0,019 | 0,053 | 0,186 | 1,344 | 1,603 |
| Energy Partners, Ltd. | 2007-12-31 | -0,495 | -0,060 | -0,462 | 0,150 | -0,867 |
| TXCO Resources Inc. | 2007-12-31 | -0,442 | 0,033 | 0,197 | 1,020 | 0,807 |
| InPhonic, Inc. | 2005-12-31 | 1,881 | -2,737 | -1,335 | 1,089 | -1,102 |
| Frontier Airlines Holdings, Inc. | 2007-03-31 | -0,119 | 0,054 | -0,063 | 0,264 | 0,136 |
| WorldSpace, Inc. | 2006-12-31 | 1,233 | -1,331 | -2,154 | -0,775 | -3,027 |
| Charter Communications, Inc | 2007-03-31 | -0,446 | -2,911 | 0,251 | -0,367 | -3,473 |
| Citadel Broadcasting Corporation | 2007-12-31 | 0,554 | -1,208 | 2,475 | 0,205 | 2,026 |
| Fairpoint Communications Inc | 2007-12-31 | 0,088 | 1,067 | 0,414 | 0,686 | 2,255 |
| Primus Telecommunications Group, Inc. | 2007-12-31 | -0,304 | -7,610 | 0,463 | -0,518 | -7,969 |
| Tweeter Home Entertainment Grou| | 2005-09-30 | 0,904 | 2,531 | -1,114 | 0,433 | 2,753 |
| Circuit City Stores, Inc. | 2007-02-28 | 1,914 | 1,087 | -0,009 | 0,849 | 3,841 |
| Eddie Bauer Holdings, Inc. | 2008-12-29 | 0,581 | -1,353 | -0,235 | 0,485 | -0,523 |
| Gottschalks Inc. | 2007-02-03 | 2,198 | 0,446 | 0,264 | 0,580 | 3,488 |
| Bally Total Fitness Holding Corporati | 2005-12-31 | -5,565 | 13,919 | 1,081 | -0,785 | 8,650 |
| BearingPoint, Inc. | 2007-12-31 | 1,099 | 3,588 | -0,790 | -0,201 | 3,696 |
| Six Flags, Inc. | 2007-12-31 | -0,216 | -1,836 | 0,087 | -0,106 | -2,072 |
| Hancock Fabrics | 2005-01-28 | 2,885 | 2,356 | -0,710 | 0,524 | 5,054 |
| Finlay Enterprises Inc | 2008-02-02 | 1,983 | 0,202 | 0,047 | 0,191 | 2,422 |
| SIRVA Inc | 2006-12-31 | 0,161 | -0,938 | 0,002 | 0,045 | -0,729 |
| Young Broadcasting, Inc. | 2007-12-31 | 0,501 | -2,728 | -0,545 | -0,242 | -3,015 |
| Trump Entertainment Resorts, Inc. | 2007-12-31 | 5,106 | -1,923 | -0,078 | 0,119 | 3,224 |
| RHI Entertainment, Inc. | 2008-12-31 | 1,432 | -0,116 | -0,272 | 0,222 | 1,266 |
| Trico Marine Services Inc | 2008-12-31 | 0,064 | 0,068 | -0,713 | 0,211 | -0,370 |

| Surviving Non-Manufacturing firms - Z"-score - One reporting period prior to bankruptcy | | | | | | |
|---|---|---|---|---|---|---|
| Company | Filing date 10-K | 6,56X | 3,26X | 6,72X | 1,05X | Z"-score |
| StillWater Mining | 2008-12-31 | 2,087 | -0,985 | -1,061 | 1,470 | 1,512 |
| Approach Resources Inc | 2008-12-31 | 0,079 | 0,547 | 0,548 | 2,054 | 3,228 |
| GMX Resources INC | 2008-12-31 | -0,191 | -0,320 | -1,104 | 0,970 | -0,645 |
| Brigham Exploration Inc | 2008-12-31 | 0,406 | -0,603 | -2,816 | 0,346 | -2,666 |
| USA Mobility Inc | 2008-12-31 | 0,454 | 0,105 | 0,766 | 4,453 | 5,778 |
| Atlantic Tele-Network | 2006-12-31 | 1,399 | 1,026 | 0,330 | 2,024 | 4,779 |
| Pinnacle Airlines Corp | 2007-12-31 | 0,476 | 0,206 | 0,494 | 0,093 | 1,270 |
| Cincinnati Bell | 2008-12-31 | -0,008 | -5,244 | 0,983 | -0,266 | -4,536 |
| Otelco Inc | 2008-12-31 | 0,350 | -0,035 | 0,412 | 0,410 | 1,137 |
| Bombay Co. | 2007-02-03 | 1,314 | -0,399 | -1,361 | 0,574 | 0,128 |
| Bed Bath & Beyond Inc | 2008-03-01 | 1,818 | 3,163 | 1,465 | 2,098 | 8,544 |
| Aeropostale Inc | 2009-03-30 | 2,178 | 3,435 | 2,536 | 1,231 | 9,381 |
| Duckwall-ALCO Stores | 2009-02-01 | 3,755 | 0,990 | -0,165 | 1,004 | 5,585 |
| BioScrip Inc | 2006-12-31 | 0,795 | -0,742 | -0,357 | 1,183 | 0,879 |
| PharMerica Corp. | 2008-12-31 | 2,627 | -0,103 | -0,299 | 0,903 | 3,128 |
| Cedar Fair | 2008-01-31 | 2,684 | 2,105 | 1,635 | 3,162 | 9,586 |
| FTI Consulting | 2007-12-31 | -0,143 | -0,046 | 0,587 | 0,245 | 0,644 |
| International Speedway Corp | 2007-12-31 | -0,474 | 0,470 | 0,666 | 0,739 | 1,400 |
| Spanish Broadcasting System I | 2007-11-30 | -0,174 | 0,883 | 0,820 | 1,479 | 3,008 |
| Gaylord Entertainment | 2007-12-31 | 0,501 | 0,752 | 0,249 | 0,591 | 2,092 |
| Netflix Inc. | 2007-12-31 | -0,421 | 0,320 | 0,124 | 0,703 | 0,725 |
| Hunt JB Transport Service Inc | 2007-12-31 | -0,125 | 2,087 | 1,330 | 0,237 | 3,530 |
| Direct TV | 2008-12-31 | 0,398 | -0,686 | 0,304 | 0,341 | 0,357 |
| Clearwire corp | 2008-12-31 | 2,264 | -0,011 | 0,363 | 1,338 | 3,954 |
| Eagle Bulk Shipping | 2008-12-31 | -0,022 | -0,258 | 0,379 | 0,556 | 0,655 |

| Surviving Non-Manufacturing firms - Z"-score - Two reporting periods prior bankruptcy | | | | | | |
|---|---|---|---|---|---|---|
| Company | Filing date 10-K | 6,56X | 3,26X | 6,72X | 1,05X | Z"-score |
| StillWater Mining | 2007-12-31 | 1,665 | -0,467 | -0,147 | 2,405 | 3,456 |
| Approach Resources Inc | 2007-12-31 | -1,377 | 4,382 | 1,820 | 4,290 | 9,115 |
| GMX Resources INC | 2007-12-31 | -0,491 | 0,245 | 0,489 | 1,177 | 1,420 |
| Brigham Exploration Inc | 2007-12-31 | -0,110 | 0,427 | 0,208 | 1,088 | 1,612 |
| USA Mobility Inc | 2007-12-31 | 0,192 | 0,060 | 0,288 | 5,552 | 6,092 |
| Atlantic Tele-Network | 2005-12-31 | 1,216 | 0,858 | 1,489 | 1,917 | 5,480 |
| Pinnacle Airlines Corp | 2006-12-31 | 2,690 | 0,115 | 2,845 | 0,499 | 6,149 |
| Cincinnati Bell | 2007-12-31 | 0,000 | -5,584 | 0,940 | -0,261 | -4,904 |
| Otelco Inc | 2007-12-31 | 0,450 | -0,057 | 0,618 | 1,828 | 2,838 |
| Eagle bulk | 2008-12-31 | -0,022 | -0,258 | 0,379 | 0,556 | 0,655 |
| Bombay Co. | 2006-01-28 | 2,296 | 0,323 | 1,028 | 1,384 | 5,031 |
| Bed Bath & Beyond Inc | 2007-03-01 | 2,574 | 2,597 | 1,510 | 2,123 | 8,803 |
| Aeropostale Inc | 2008-02-02 | 1,114 | 3,449 | 2,646 | 0,654 | 7,862 |
| Duckwall-ALCO Stores | 2008-02-01 | 3,811 | 1,203 | 0,042 | 1,439 | 6,495 |
| Direct TV | 2007-12-31 | 0,000 | -5,584 | 0,940 | -0,261 | -4,904 |
| Clearwire corp | 2007-12-31 | 2,027 | -1,440 | -1,248 | 0,803 | 0,142 |
| BioScrip Inc | 2005-12-31 | 1,483 | -0,341 | -0,657 | 1,998 | 2,483 |
| PharMerica Corp. | 2007-12-31 | 3,787 | 1,883 | 0,305 | 1,150 | 7,124 |
| Cedar Fair | 2008-12-31 | -0,163 | -0,074 | 0,429 | 0,172 | 0,365 |
| FTI Consulting | 2008-12-31 | 0,404 | 0,760 | 0,768 | 1,224 | 3,155 |
| International Speedway Corp | 2008-11-30 | -0,084 | 0,995 | 0,727 | 1,153 | 2,791 |
| Spanish Broadcasting System Ir | 2008-12-31 | 0,571 | -3,693 | -5,606 | -0,091 | -8,820 |
| Gaylord Entertainment | 2008-12-31 | -0,165 | 0,299 | 0,098 | 0,572 | 0,804 |
| Netflix Inc. | 2009-12-31 | 1,782 | 0,954 | 1,898 | 0,435 | 5,068 |
| Hunt JB Transport Service Inc | 2006-12-31 | -0,028 | 1,908 | 1,415 | 0,790 | 4,084 |