Explanatory and predictive values of the drivers of corporate bankruptcy.

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Abstract

Purpose: Most bankruptcy prediction models such as Altman, Beaver, and Zmijewski, only focuses on discriminant scores from which a determination is made about the financial health of firms. The most important indicators of financial distress and their order of importance as bankruptcy becomes imminent are not contained in literature. This paper aims to expand the domain of corporate bankruptcy by bringing to the fore the most important financial indicators in times of bankruptcy.

Design: This paper employs the Altman Z score as a proxy for financial distress. The independent variables are the discrete Altman variables. The Altman Z score of 105 firms for the last two years before bankruptcy were computed. A structured coefficient index was used to determine the most critical indicators of corporate distress.

Findings: A number of factors predicates financial distress. This paper focussed on indices in the Altman algorithm model. The paper provides empirical insights into how financial performance, relative to the Altman indices, deteriorates as bankruptcy approached. It suggests that profitability is the most significant predictor of bankruptcy.

Originality: This paper's foundation is the Altman algorithm model. However, the model does not explain how the discrete variables behave in the last two years before bankruptcy. This study is the first to examine the behavior of distressed firms relative to the Altman indices in the previous two years preceding bankruptcy.

Keywords: Corporate bankruptcy, Financial distress, Financial performance, Chapter 11, Chapter 7, Altman Z score

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Introduction

Determinant theories of financial distress mainly use techniques such as univariate, multivariate, conditional probability and neural networks to form bankruptcy prediction models [1]. Beaver [2] used a univariate technique to develop his pioneering bankruptcy predictive model. According to Beaver [2], cash flow to debt ratio is the most significant predictor of financial distress. Altman [3] used a multivariate technique to form a multi-discriminant function which is one of the most used bankruptcy prediction models in theory and practice [4].

Financial distress is defined by many researchers, including Foster [5] and Steyn-Bruwer and Hamman [6] as a precursor to bankruptcy. When a firm goes bankrupt, creditors will not be able to retrieve their debt [7]. Foster [5] argued that financial distress is a situation in which firms go through critical liquidity problems that cannot be solved by restructuring. Financial distress may lead to bankruptcy. According to Foster [5], bankruptcy is a legal event which is predicated by the inability to meet lender and investor demands.

The purpose of this quantitative explanatory study is to identify the variable in the Altman [3] algorithm model that is the most significant predictor of bankruptcy among mining and oil and gas firms in the United States. The study examines the relationship between the distinct variables in the Altman [3] algorithm model and the Altman Z score. According to Saunders, Lewis and Thornhill [8], studies that ascertain causal relationships among variables are termed explanatory.

The study dwells on extractive firms as they constituted the industries that initiated the most bankruptcy filings in the United States. According to the New Generation Report [9], 17 of the 25 largest public firm Chapter 11 bankruptcy filings in the United States in 2016 were initiated by companies in the oil and gas and mining industries. In the first half of 2016 alone, energy-related companies made up 10 of the 15 largest bankruptcies in the United States. Furthermore, $68 billion in assets entering bankruptcy were from the energy sub-sector of the United States economy [9]. Data on the bankrupt firms were collected from the bankruptcy yearbook and almanac which stores data on all bankruptcies in the United States. Financial statement information was retrieved from the Securities and Exchange Commission.

According to Altman, Haldeman and Narayanan [10], profitability is the most significant variable in the Altman [3] discriminant function. Liquidity and solvency are also significant indicators of financial distress, but their order of importance has not been explicitly stated in literature [11].

Altman's [3] initial sample consisted of 66 manufacturers that went bankrupt between 1946 and 1965. In contrast to the original Altman [3] study that was only composed of manufacturers, this study consists of 105 firms from two different industries.

Altman Bankruptcy Prediction Model

Altman [3] published the first bankruptcy prediction model based on multiple discriminant analysis. The study involved a sample of 66 firms that were equally divided into two groups. Group one included 33 firms in the manufacturing industry that had filed for bankruptcy between 1946 and 1965. Group two comprised of 33 healthy firms that Altman [3] chose on a stratified random basis based on industry and size.

Data was retrieved from Moody's industrial manuals [3]. Twenty-two variables were initially selected based on significant indicators of corporate failure in previous studies. According to Altman [3], the variables were categorized into liquidity, profitability, leverage, solvency and activity. Altman [3] chose the variables based on their popularity in literature and their prospective relevance to the study.

The Altman [3] algorithm model was mathematically formulated as follows:

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

Where Z= Altman's overall index

X_1 = Working capital/ total assets

X_2= Retained earnings/total assets

X_3 = Earnings before interest and taxes/ total assets

X_4 = Market value of equity/book value of total liabilities

X_5= Sales/total assets

According to Altman [3], working capital /total assets measures the net liquid assets of the firm compared to the total capitalization of the firm. It is a measure of liquidity. Altman [3] explained that this metric was chosen as a measure of liquidity because a firm in financial distress will experience dwindling current assets relative to total assets.

Altman [3] referred to the retained earnings/total assets variable as earned surplus. It is a measure of cumulative profitability and Altman [3] noted that age was a factor in this metric. A younger firm will record a low retained earnings/ total assets ratio as it takes time to build cumulative profits [3]. Consequently, young firms stand a higher chance of falling into financial distress and subsequently declaring bankruptcy. According to Dun and Bradstreet [12], half of all firms that went bankrupt did so in their first five years. According to Altman [3] retained earnings/total assets is also a measure of leverage. A high ratio indicates that the firm is financing their operations by reinvesting profits.

Earnings before interest and taxes/total assets (EBIT/TA) measures the asset productivity of a firm's assets minus tax or cost of debt. According to Altman [3], this metric is significant because a firm's survival is a function of earnings and cost of debt. Insolvency will occur when the productivity of assets is lower than liabilities.

The market value of equity/book value of total liabilities indicates the extent to which a firm's assets can decline in value before debt surpasses assets of the company to become insolvent [3]. The variable adds a market value aspect to the model and as indicated by Altman [3], its reciprocal, debt/ equity indicates financial leverage.

Sales/Total assets is a variable that measures the revenue-generating ability of a company's assets [3]. According to Altman [3], on a univariate basis, this metric is the least significant, although, in the multivariate function, it is the second most significant. The sales/total assets ratio varies from one industry to another and Altman [11] explained that it is a measure of management's capacity to react to competitive situations.

Altman and Hotchkiss [13] stated that the original Z score is primarily for manufacturers and it is based on publicly traded equity. Kumar and Rao [14] however conducted a study on a new methodology for estimating bankruptcy prediction and revealed that the original Z score model could accurately predict bankruptcy risk for firms in different industries.

Unegbu and Adefila [15] also examined the classification accuracy of Altman Z score and operating cash flow insolvency predictive models in firms from developing economies. Their study revealed that the original Altman Z score model had a high bankruptcy predictive accuracy not only for manufacturing firms but oil service firms as well. Li and Rahgozar [16] studied the application of the Altman Z score model in predicting corporate bankruptcy in the United States from 2000-2010. They concluded that the original Z score model could predict financial distress for both manufacturing and non-manufacturing companies.

The original Z score model had an initial bankruptcy prediction accuracy rate of 95%. Type I error was six percent, while type II error was three percent [3]. Altman concluded that firms that have a Z score higher than 2.99 falls outside the bankruptcy zone. Z score between 1.81 and 2.99 is defined as the gray zone where there is a high possibility of error classification. Firms that have a Z score less than 1.81 are classified to be in the distressed zone [3].

Altman [11] subsequently tested the model on three groups of financially distressed firms between 1969-1975, 1976-1995 and 1997-1999 with sizes of 86, 110 and 120 respectively. The accuracy classification rate was between 82% and 94% [11]. According to Altman [11], the Z score model accurately predicts bankruptcy up to two years before bankruptcy and its accuracy declines as the lead time ascends. Altman [11] further conducted a trend analysis of the individual variables in the original Z score model and concluded that all the variables exhibit a deteriorating trend as the possibility of bankruptcy became higher. Altman [11-16] also suggested that adverse deterioration of the variables occurred in the third and second years before bankruptcy.

The original Z score model is a function of the value of the organization, and it is only applicable to publicly traded firms. Altman [3] re-estimated the original model to apply to private firms. The market value of equity was replaced with the book value of equity in X_4. The resulting Z' score model for private firms is represented as follows:

$$Z' = 0.717X_1+0.847X_2+ 3.107X_3+ 0.420 X_4 + 0.998 X_5$$

Where X_1 = Working capital/total assets

X_2 = Retained earnings/total assets

X_3 = Earnings before interest and taxes/ total assets

X_4 = Book value of equity /book value of total liabilities

X_5 = Sales/ total assets

Z' = Overall score.

According to Altman, the cutoff scores are thus: Less than 1.23 indicates the possibility of bankruptcy, greater than 2.90 indicates non-bankrupt firms. Firms that have a Z score between 1.23 and 2.90 are determined to be in the gray area. According to Altman [11], the revised Z score model for private firms has not been widely tested on secondary sample as a result of a lack of data on private firms.

Altman further revised the Z score model to adapt to non-manufacturers and emerging markets. The new model excluded the sales/total assets variable (X_5) as a result of industry effect which arises from variation among industries. The resulting model is as follows:

$$Z= 6.56 (X_1) +3.26 (X_2) + 6.72 (X_3) +1.05 (X_4)$$

Altman added a constant term of +3.23 in the emerging market model. According to Altman (1983), this model is useful in industries where asset financing differs among firms. To test whether variation among industries affected the robustness of the predictive accuracy of the original Z score model, Ho, McCarthy and Yang [17] used a sample of 120 public firms from North America. The study also investigated investors' reactions to bankruptcy filing. Ho [17] concluded that even though the re-estimated Altman [3] model had a reduction of type II errors, variation among industries did not markedly affect the robustness of either model.

Since Altman [3], several researchers have applied multiple discriminant analysis on varying samples and industries to predict bankruptcy. Avenhuis [4] posited that Altman [3], Deakin [18], Ohlson [19] and Zmijewski [20] are the most cited accounting based bankruptcy prediction models in literature.

Research Design

The research design for this study is quantitative. The study will analyze the relative importance of the discrete Altman variables on the financial distress of 105 public firms in the mining and oil and gas industries that went bankrupt between 2006 and 2016 in the United States. The analyses thereafter will involve the immediate two years preceding the bankruptcy declaration of the distressed firms.

The Altman Z score, which is a measure of financial distress [11] is the dependent variable. The independent variables are liquidity, profitability, asset productivity, solvency and activity ratios in the Altman [3] algorithm model. Financial statement data will be derived from the form 10-K of the sampled firms that have been filed with the Securities and Exchange Commission in the United States of America.

For the period between 2006 and 2016, 144 public firms in the mining and oil and gas industries in the United States of America were listed on the Bankruptcy Yearbook and Almanac as having filed bankruptcy. A random sampling technique will be used to sample 105 firms for analysis. According to Krejcie and Morgan [21], with a population of 144, a sample size of 105 was appropriate at a margin of error of five percent.

Data

Data for this study is secondary. Names of firms that have declared bankruptcy was obtained from the Bankruptcy Yearbook and Almanac, which is a business bankruptcy filing database in the United States of America. The final population consisted of public mining and oil and gas firms in the United States that went bankrupt between 2006 and 2016 for which financial data (form 10-K) was filed with the United States Securities and Exchange Commission.

Research questions and hypothesis

The study seeks to understand the relative association between the discrete variables in the Altman [3] bankruptcy predictor model and the Z score, which is a measure of financial distress [3]. The variables are profitability, liquidity, asset productivity, solvency and activity ratio. Altman [3] noted that profitability is a statistically significant variable in the Altman [3] discriminant function that has the highest level of association with financial distress.

Following from Altman [3], this study expects to find a relationship between profitability and financial distress. The study also expects to find an association between financial distress and liquidity, asset productivity, solvency, and profitability. The following hypothesis has been formed to ascertain or reject Altman [3].

H_0: Profitability is not a statistically significant variable in the Altman [3] discriminant function that has the highest level of association with the Altman.

H_a: Profitability is a statistically significant variable in the Altman [3] discriminant function that has the highest level of association with the Altman Z score.

To show evidence of statistically significant relationship between the variables under study, there has to be a correlation coefficient of more than 0.196 and a 95% confidence level.

The bankruptcy classification accuracy rate for the Altman [3] discriminant function has been certified by many studies such as Dugan and Zavgren [22] to be very high. This study expects to affirm the position of Dugan and Zavgren [22] by ascertaining a high Altman Z score accuracy rate among bankrupt firms in the mining and oil and gas firms in the United States.

Data analyses

The analyses included two major tools: Altman [3] discriminant function and multiple regression analysis. The null hypothesis for the research question states that profitability is not a statistically significant variable in the Altman [3] discriminant function that has the highest level of association with financial distress. The measure of financial distress in this study is the Altman Z score that is derived from the Altman [3] discriminant function stated below:

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

Where Z= Altman's overall index

X_1 = Working capital/ total assets

X_2= Retained earnings/total assets

X_3 = Earnings before interest and taxes/ total assets

The X4 = Market value of equity/book value of total liabilities

X_5= Sales/total assets

To test whether profitability is the variable in the Altman [3] discriminant function that has the highest level of association with financial distress, multiple regression analysis was used. Multiple regression is used to assess the relative importance of each of the variables to the function [23]. Regression determines the varying level of influence that profitability, asset productivity, liquidity, solvency, and activity has on the Altman Z score.

In interpreting the extent to which independent variables account for variance in a dependent variable, beta weights were used [24,25]. In multiple regression analysis, independent variables may intercorrelate leading to multicollinearity [26]. This study used beta weights as a starting point to explain the relative contribution of each of the Altman [3] variables to financial distress as suggested by Nathans [26].

A structure coefficient, which is the bivariate correlation between the predictor variable and the dependent variable, was computed. Computing structure coefficient is essential and appropriate as it is a useful indicator of a variable direct effect [27]. Structure coefficients are not affected by correlation between predictor variables [28]. The structure coefficient is computed as follows $r_s= r_{X,Y}/ R$

Where $r_{X,Y}$ is the bivariate correlation between the predictor variable (X) and the predicted variable (Y), R is the multiple correlation of the regression involving all the variables [28].

Results

Liquidity, profitability, asset productivity, solvency, activity, and the Altman Z score one year before bankruptcy are illustrated in Table 1.

Table 1. *Liquidity, profitability, asset productivity, solvency, activity, and the Altman Z score one year before.*

Liquidity, Profitability, Asset productivity, Solvency, Activity and Altman Z Score 1 Year before Bankruptcy (T-1)						
	X1	X2	X3	X4	X5	Z
STW Resource Holding Corp.	-2.92	-5.83	-1.9	0.85	2.78	-14.7
Atlas Resource Partners LP.	0.06	0	-0.41	0.06	0.43	-0.825
Halcon Resources Corp.	0.08	-0.93	-0.55	0.05	0.16	-2.83
C & J Energy Services Ltd.	0.09	-0.16	-0.52	0.36	0.78	-0.846
Triangle Petroleum Corp.	-0.03	-1.09	-1.16	0.03	0.48	-4.89
Seventy Seven Energy Inc.	0.09	-0.12	-0.11	0.04	0.59	0.191
Hercules Offshore Inc.	0.28	-0.02	0	0.08	0	0.356
Warren Resources Inc.	-1.98	-3.59	-2.51	0.03	0.38	-15.3
Sandridge Energy Inc.	0.09	-2.34	-1.34	0.03	0.26	-7.31
Breitburn Energy Inc.	0.06	0	-0.49	0.04	0.23	-1.29
Penn Virginia Corp.	-2.25	-4.11	-2.89	0.02	0.59	-17.4
Linn Co. LLC.	-0.25	-104	-31.7	4.31	0	-248
Midstates Petroleum Co. Inc.	-2.71	-3.26	-2.42	0	0.54	-15.3
Ultra Petroleum	-3.67	-3.6	-3.13	0.1	0.86	-18.9
Goodrich Petroleum Corp.	-4.85	-15.1	-4.29	0.03	0.78	-40.3
Energy XXI Ltd.	0.13	-0.55	-0.58	0.05	0.3	-2.2
Aztec Oil & Gas Inc.	-0.47	-2.33	0.03	0.71	0.14	-3.16
Hydrocarb Energy Corp.	-0.55	-2.66	-0.41	0.89	0.13	-5.07
Post Rock Energy Corp.	0.03	-2.35	0.02	0.13	0.43	-2.68
Emerald Oil Inc.	-0.11	-0.19	-0.07	0.25	0.16	-0.319
Quantum Fuel Systems Tech Inc.	0.07	-6.84	-0.2	1.01	0.48	-9.07
New Source Energy Partners LP.	0.01	0	-0.09	0.72	0.44	0.587
Red Mountain Resources Inc.	-0.43	-2.22	-1.21	0.33	0.38	-7.04
Paragon Offshore Plc.	0.36	-0.79	-0.4	0	0.63	-1.36
Osage Exploration & Dev't. Inc.	-1.04	-1.11	-0.86	0.39	0.36	-5.05
Swift Energy Co.	-0.52	-3.1	-3.3	0	0.47	-15.4
Magnum Hunter Resources	-0.06	-1.51	-0.65	0	0.15	-4.18
Cubic Energy Inc.	-0.58	-0.62	0.23	0.11	0.13	-0.609
Transcoastal Corp.	-0.63	-1.75	-0.04	0.44	0.18	-2.89
Far East Energy Corp.	-0.87	-1.46	-0.18	0.36	0	-3.46
Escalera Resources Co.	-0.34	-0.19	-0.07	0.07	0.34	-0.523
American Natural Energy Corp.	-0.71	-1.38	-0.05	0.01	0.17	-2.77
Miller Energy Resources Inc.	-0.04	0.21	-0.05	0	0.09	0.171
Hii Tech Inc.	-0.38	-0.75	-0.2	0.97	0.92	-0.664
Armada Oil Inc.	-0.29	-0.11	0.21	0.55	0.21	0.731
Stone Energy Corporation	0.17	-2.02	-0.46	0.02	0.33	-3.8
American Standard Energy Corp.	-0.3	-0.84	-0.5	0	0.15	-3.04
Sabine Oil & Gas Corp.	0.19	-4.87	-2.58	0	0.42	-14.7
Sino Clean Energy Inc.	0.71	0.37	0.3	4.45	0.82	5.85
Saratoga Resources Inc. (SARAQ)	-1.66	-1.65	-1.07	0.03	0.49	-7.32
American Eagle Energy Corp.	-0.69	-0.37	-0.3	0.08	0.22	-2.07
Quick Silver Resources Inc.	-1.41	-1.6	0.05	0.02	0.47	-3.29
USA Synthetic Fuel Corp.	-0.22	-1.3	-0.62	2.63	0	-2.55

BPZ Resources Inc.	-0.57	-1.85	-0.2	0.13	0.29	-3.57
Dune Energy Inc.	-0.04	-0.22	-0.15	0.74	0.22	-0.187
Cal Dive International Inc.	0.1	-0.29	-0.08	0.46	0.79	0.516
Buccaneer Energy Ltd.	0.07	-0.44	-0.1	0	0.15	-0.712
Global Geophysical Services Inc.	-0.85	-0.53	-0.4	0	0.73	-2.35
Tuscany International Drilling Inc.	-0.44	-0.87	-0.36	0.09	0.46	-2.42
Samson Oil & Gas Ltd.	0.06	-2.19	-0.89	0.56	0.41	-5.19
Endeavour International Corp.	0.5	-1.81	-1.07	0	0.43	-5.04
China Natural Gas Inc.	-0.19	0.3	0.05	0	0.5	0.857
South Texas Oil Co.	-0.5	-0.41	-0.23	0.16	0.14	-1.69
Aurora Oil & Gas Ltd.	-0.06	0.11	0.15	0	0.35	0.927
Midcoast Energy Partners	0	0	-0.05	0.12	0.54	0.447
Nova Biosource Fuels	-0.02	-0.75	0.05	0.22	0.56	-0.217
GMX Resources Inc.	0.04	-2.52	-0.44	0.09	0.17	-4.71
Geokinetics Inc.	-0.78	-1.31	-0.04	0	1.52	-1.38
ATP Oil & Gas Corp.	-0.1	-0.16	0.05	0.11	0.2	0.082
Tri-Valley Corp.	-0.36	-3.9	0.01	0.67	0.14	-5.32
SMF Energy Corp.	0.18	-1.59	-0.02	0.09	0.01	-2.01
Sulphco, Inc.	-0.36	-99.3	0.02	0	0	-139
Reostar Energy Corp.	-0.43	-0.26	-0.19	0	0.16	-1.39
Kentucky USA Energy	-0.94	-0.55	-0.16	0	0	-2.43
Environmental Power Corp.	-1.13	-2.46	-0.77	0.05	0.11	-7.2
Sonoran Energy Inc.	-0.06	0.11	0.15	1.18	0.35	1.64
Aurora Gas Ltd.	-0.32	-1.14	0.01	0	0.24	-1.71
Knight Energy Corp.	-0.44	-1.19	0.05	0	0.05	-1.98
Saratoga Resources Inc.	-0.06	0.08	0.21	0.32	0.4	1.33
BPI Energy Holdings	-0.44	-2.31	0.05	0	0.07	-3.53
Cygnus Oil & Gas Corp.	-0.1	-1.95	-0.73	0	0.03	-5.23
Peabody Energy Corp.	-0.55	-0.05	-0.14	0.01	0.51	-0.679
Arch Coal Inc.	-0.85	-0.83	-0.57	0	0.5	-3.56
Legend International Holdings	-0.11	-22.8	-1.21	6.83	0.04	-31.9
Nord Resources Corp.	-1.14	-2.77	-0.12	0.03	0.16	-5.46
Santa Fe Gold Corp.	-1.14	-4	-0.48	0.26	0.1	-8.3
Alpha Natural Resources	0.08	-0.43	-0.06	0.05	0.4	-0.274
Walter Energy Inc.	0.1	-0.22	-0.05	0.02	0.26	-0.081
Molycorp Inc.	0.13	-0.56	-0.18	0	0.18	-1.04
Midway Gold Corp.	0.05	-0.51	-0.08	1.33	0	-0.12
Patriot Coal Corp.	0	-0.19	-0.16	0	0.5	-0.29
Xinergy Ltd	0.08	-1.17	-0.13	0.06	0.14	-1.8
Allied Nevada Gold Corp.	-0.31	-0.52	-0.51	0.16	0.33	-2.36
James River Coal Co.	0.12	-0.2	-0.07	0.12	0.91	0.615
Centrus Energy Corp.	0.37	-0.28	-0.2	0.01	0.51	-0.092
Chesapeake Corporation	-0.12	-1.35	-0.32	0.43	0.6	-2.232
Iron Mining Group Inc.	-0.35	-3.3	-0.3	0	0	-6.03
Copper King Mining	-1.33	-8.49	0	0	0.74	-12.74
America West Resources Inc.	-0.89	-1.98	0.42	0.48	0.44	-1.73
Gryphon Gold Corp.	0.03	-1.43	0.03	1.54	0.09	-0.853
Consol Energy Inc.	-0.08	0.24	-0.03	0.29	0.28	0.595
Core Resource Management	-0.01	0.81	-0.51	0.53	0.03	-0.213
Evergreen Energy Incorporated	0.12	-18.62	0.08	0.3	0.13	-25.4
Cano Petroleum	-0.27	-0.21	-0.07	0	0.09	-0.759
Extera Energy Resources	-0.83	-8.22	-2.11	0	0.18	-19.3
T Rex Oil Inc.	-0.39	-9.61	-5.61	10.7	0.2	-25.8
Forbes Energy Services Ltd.	-0.85	-0.76	-0.26	0	0.37	-2.57
Memorial Production Partners LP.	0.8	0	-0.2	0.01	0.14	0.446
Key Energy Services	0.2	-0.6	-0.78	0.06	0.6	-2.54
Berry Petroleum Co.	-0.04	0.2	0.1	0.79	0.29	1.33
Chancellor Group Inc.	0.43	-14.2	-5.45	0	0.52	-36.9
High Velocity Alternative	-7.18	-35.06	0.21	0	3.58	-53.4
Bonanza Creek Energy, Inc.	-0.84	-0.7	-0.12	0.05	0.17	-2.18
Best Energy Services Inc.	0.02	-0.17	-0.05	0	0.4	0.021
Vantage Drilling Company	-0.02	-0.1	0.08	0.05	0.24	0.37

Liquidity, profitability, asset productivity, solvency, activity, and the Altman Z score two years before bankruptcy are illustrated in Table 2.

Table 2. *Liquidity, profitability, asset productivity, solvency, activity, and the Altman Z score two years before bankruptcy are illustrated.*

Liquidity, Profitability, Asset productivity, Solvency, Activity, and Altman Z Score 2 Years before Bankruptcy (T-2)						
	X1	X2	X3	X4	X5	Z
STW Resource Holding Corp.	-7.5	-16.1	-3.88	0.77	1.28	-42.5
Atlas Resource Partners LP	0	0	-0.19	0.49	0.25	-0.083
Halcon Resources Corp.	-0.01	-0.19	0.05	0.17	0.18	0.169
C & J Energy Services Ltd.	0.11	0.32	0.07	0.88	1	2.34
Triangle Petroleum Corp.	0.03	0	0.1	0.36	0.35	0.932
Seventy Seven Energy Inc.	0.11	0.32	0.07	0.88	1	2.34
Hercules Offshore Inc.	0.09	0	0.03	0.13	0.91	1.2
Warren Resources Inc.	0.12	-0.75	-0.05	0.12	0.45	-0.55
Sandridge Energy Inc.	-0.04	-0.27	0.04	0.25	0.18	0.036
Breitburn Energy Inc.	0.01	-0.45	0.08	0.17	0.21	-0.042
Penn Virginia Corp.	0.03	0	0.07	0.38	0.19	0.685
Linn Co. LLC.	0.01	-0.24	-0.21	0.31	0.29	-0.541
Midstates Petroleum Co. Inc.	0.05	-1.91	-1.43	19.2	0	4.18
Ultra Petroleum	0.01	-0.17	0.11	0.05	0.32	0.487
Goodrich Petroleum Corp.	-0.04	-0.07	0.16	0.5	0.29	0.972
Energy Xxi Ltd.	-0.03	-0.01	0.03	0.4	0.16	0.449
Aztec Oil & Gas Inc.	-0.14	-2.32	0.01	0.45	0.05	-3.06
Hydrocarb Energy Corp.	-0.14	-2.72	-0.25	5.09	0.2	-1.55
Post Rock Energy Corp.	0.04	-2.54	-0.11	0.16	0.39	-3.39
Emerald Oil Inc.	0.28	-0.19	-0.02	5.3	0.12	3.3
Quantum Fuel Systems Tech Inc.	0.04	-7.2	-0.3	3	0.48	-8.74
New Source Energy Partners LP.	0.01	0	0.07	2.27	0.2	1.81
Red Mountain Resources Inc.	-0.02	-0.35	-0.06	1.16	0.23	0.214
Paragon Offshore Plc.	0	-0.28	-0.16	0.09	0.61	-0.256
Osage Exploration & Dev't. Inc.	-0.39	-0.13	0.03	2.35	0.24	1.1
Swift Energy Co.	-0.04	0.01	-0.2	0.13	0.25	-0.366
Magnum Hunter Resources	-0.03	-0.47	-0.03	0.51	0.23	-0.257
Cubic Energy Inc.	-1.67	-4.76	-0.19	0.74	0.21	-8.64
Transcoastal Corp.	-0.72	-1.65	-0.13	1.28	0.14	-2.7
Far East Energy Corp.	-0.6	-1.98	-0.3	0.39	0.02	-4.23
Escalera Resources Co.	0.01	-0.12	-0.14	0.25	0.27	-0.198
American Natural Energy Corp.	-0.47	-1.15	-0.1	0	0.1	-2.4
Miller Energy Resources Inc.	0	0.35	-0.05	0	0.06	0.385
Hi Tech Inc.	-0.25	-2.67	-0.07	2.72	1.42	-1.22
Armada Oil Inc.	-0.06	-0.11	-0.34	0.49	0.34	-0.714
Stone Energy Corporation	-0.01	-1.21	-0.97	0.16	0.39	-4.42
American Standard Energy Corp.	-0.11	-0.16	-0.15	3.41	0.1	1.3
Sabine Oil & Gas Corp.	-0.86	-0.69	-0.07	0.19	0.19	-1.93
Sino Clean Energy Inc.	0.56	0.14	0.63	7.88	1.03	8.71

Saratoga Resources Inc. (SARAQ)	0.08	-0.16	0.01	1.67	0.27	1.18
American Eagle Energy Corp.	0.23	-0.04	0.04	0.92	0.2	1.1
Quick Silver Resources Inc.	0.19	-1.34	0.31	0.23	0.41	-0.077
USA Synthetic Fuel Corp.	0.08	-0.44	-0.1	0.74	0	-0.416
BPZ Resources Inc.	0.18	-1.06	-0.12	0.8	0.12	-1.06
Dune Energy Inc.	0.05	-0.03	0.01	0.77	0.2	0.713
Cal Dive International Inc.	0.11	-0.24	-0.13	0.47	0.74	0.389
Buccaneer Energy Ltd.	-0.16	-0.71	-0.23	0	0.05	-1.9
Global Geophysical Services Inc.	0.01	-0.1	0.07	0	0.62	0.723
Tuscany International Drilling Inc.	0.02	-0.13	-0.03	0	0.37	0.113
Samson Oil & Gas Ltd.	0.14	-0.76	-0.22	4.11	0.2	1.04
Endeavour International Corp.	-0.04	-0.32	0.01	0.16	0.22	-0.147
China Natural Gas Inc.	-0.03	0.28	0.08	0	0.45	1.07
South Texas Oil Co.	0	-0.14	-0.06	4.35	0.09	2.31
Aurora Oil & Gas Ltd.	-0.02	0.05	0.11	0	0.27	0.679
Midcoast Energy Partners	0.01	0	0.03	0.16	1.02	1.23
Nova Biosource Fuels	0.13	-0.38	0	3.81	0.2	2.11
GMX Resources Inc.	0.16	-1.2	-0.32	0.16	0.22	-2.23
Geokinetics Inc.	0.04	-0.84	-0.33	0.06	1.49	-0.691
ATP Oil & Gas Corp.	-0.03	-0.11	-0.04	0.28	0.13	-0.024
Tri-Valley Corp.	-0.17	-4.07	0.02	2.88	0.12	-3.99
SMF Energy Corp.	0.29	-0.85	0.07	0.46	7.05	6.72
Sulphco, Inc.	0.24	-43.5	0.27	0	0	-59.7
Reostar Energy Corp.	0.06	-0.1	-0.1	0	0.3	-0.098
Kentucky USA Energy	-16	-49	0	0	0	-87.8
Environmental Power Corp.	0.64	-0.44	-0.14	0.07	0.02	-0.248
Sonoran Energy Inc.	-0.32	-1.41	0.04	0	0.07	-2.16
Aurora Gas Ltd.	0.02	0.05	0.11	2.61	0.27	2.29
Knight Energy Corp.	-0.14	-1.46	0.24	0	0.27	-1.15
Saratoga Resources Inc.	-1.99	-6.17	0.09	35.2	0.05	10.5
Bpi Energy Holdings	0.44	-1.22	-0.53	3.97	0.03	-0.517
Cygnus Oil & Gas Corp.	-0.07	-0.78	-0.4	0	0.01	-2.49
Peabody Energy Corp.	-0.01	0.12	-0.01	0.2	0.51	0.753
Arch Coal Inc.	0.21	-0.16	-0.02	0.06	0.35	0.348
Legend International Holdings	-0.43	-4.86	-0.3	0.34	0	-8.11
Nord Resources Corp.	-0.92	-2.34	-0.12	0.12	0.26	-4.44
Santa Fe Gold Corp.	-0.67	-2.86	-0.3	0.72	0.56	-4.81
Alpha Natural Resources	0.06	-0.32	-0.09	0.2	0.42	-0.133
Walter Energy Inc.	0.08	-0.13	-0.03	0.22	0.33	0.277
Molycorp Inc.	0.14	-0.28	-0.12	0	0.18	-0.44
Midway Gold Corp.	0.37	-0.68	0.06	1.83	0	0.788
Patriot Coal Corp.	0.01	0	-0.02	0	0.62	0.566
Xinergy Ltd.	0.16	-0.66	-0.27	0.15	0.43	-1.1
Allied Nevada Gold Corp.	0.16	-0.22	0	0.5	0.18	0.364
James River Coal Co.	0.16	-0.07	0.02	0.24	0.83	1.13
Centrus Energy Corp.	0.34	-0.04	0.27	0.03	0.44	1.7
Chesapeake Corporation	-0.07	-0.76	-1.08	0.17	0.74	-3.87
Iron Mining Group Inc.	-0.31	-16.8	-0.48	50	0	4.52
Copper King Mining	-7.78	-20.1	0	0	1.74	-35.7
America West Resources Inc.	-1.28	-1.67	0.23	2	0.42	-1.5
Gryphon Gold Corp.	0.21	-8.91	-0.79	33.7	0	5.43
Consol Energy Inc.	0	0.26	0.04	1.23	0.32	1.55
Core Resource Management	-0.17	-1.08	0.66	0.51	0.03	0.798
Evergreen Energy Incorporated	0.1	-7.11	0.06	0.63	0.01	-9.25
Cano Petroleum	-1.62	-3.71	-2.88	0	0.4	-16.2
Extera Energy Resources	-1.24	-9	-1.29	0	0.12	-18.2
T Rex Oil Inc.	-0.12	-0.67	-0.67	13	0	4.52
Forbes Energy Services Ltd.	0.16	-0.31	-0.08	0.02	0.6	0.106
Memorial Production Partners LP.	0.08	0	-0.1	0.1	0.12	-0.054
Key Energy Services	0.08	0.05	-0.09	0.2	0.61	0.599
Berry Petroleum Co.	-0.03	0.18	-0.11	1.2	0.34	0.913
Chancellor Group Inc.	0.2	-4.39	-1.63	0	0.18	-11.1
High Velocity Alternative	-1.9	-14.9	0.11	0	1.45	-21.3
Bonanza Creek Energy, Inc.	-0.01	-0.47	-0.68	0.25	0.23	-2.53
Best Energy Services Inc.	-0.27	-1.05	-0.43	0	0.19	-3.02
Vantage Drilling Company	-0.02	0.11	0.04	0.18	0.2	0.57

Multiple regression analysis was used to test the null hypothesis (H_0) which states that profitability is not a statistically significant variable in the Altman [3] discriminant function that has the highest level of association with the Altman Z. The regression equation was of the form:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon$$

Where Z= the dependent variable, Altman Z score

X_1 through X_5 are the independent Altman [3] variables

β_1 is the slope coefficient for X_1 and so forth

β_0 is the intercept

ε depicts the sample error

Table 3 presents the summary of the multiple regression analysis one year before bankruptcy. The Durbin-Watson statistic for the regression analysis was 2.29 indicating independence of residuals. Tolerance values were greater than 0.1 indicating evidence of no multicollinearity [23]. The adjusted R^2 is 1.00, and it illustrates how well the regression equation fits the data. This indicates that the independent Altman [3] variables could explain 100% of the variation in the Altman Z score. The multiple regression equation for the Altman Z score, one year before bankruptcy is as follows: Z score = 1.201 X_1 + 1.4 X_2 + 3.3 X_3 + 0.6 X_4 + 1.001X_5. The constant was 0.00.

Table 3. *Multiple regression analysis, one year before bankruptcy.*

Multiple Regression Analysis, One Year before Bankruptcy					
Variable	**Beta**	**Spectrum Coefficient**	**Tolerance**	**Unstandardized Coefficient (B)**	**P-value**
X_1	0.045	0.192	0.582	1.2	0.025
X_2	0.713	0.962	0.536	1.4	0
X_3	0.373	0.844	0.509	3.3	0
X_4	0.029	-0.287	0.853	0.601	0.001
X_5	0.017	-0.034	0.602	1.001	0.364
p<0.05; Durbin Watson= 2.296; R square= 1.000					

The multiple regression analysis resulted in profitability having the highest beta weight and spectrum coefficient. Profitability was followed by asset productivity, liquidity, solvency and activity ratio as seen in Table 3. Consequently, the null hypothesis is rejected as there is evidence to support the alternative hypothesis which states that profitability is a statistically significant variable in the Altman [3] discriminant function that has the highest level of association with the Altman Z score.

The Multiple regression output in Table 4 indicates that two years before bankruptcy, profitability had the highest spectrum coefficient followed by liquidity, asset productivity, solvency and activity. The Durbin Watson statistic was 1.83 and the adjusted R^2 was 1.0. Tolerance values were greater than 0.1. The regression model had a p-value of < 0.05. There is therefore evidence to support the alternative hypothesis which states that profitability is a statistically significant variable in the Altman [3] discriminant function that has the highest level of association with the Altman Z score. The null hypothesis (H_0) is therefore rejected.

Table 4. *Multiple regression output.*

Multiple Regression Analysis, Two Years before Bankruptcy (T-2)					
Variable	Beta	Spectrum Coefficient	Tolerance	Unstandardized Coefficient (B)	P-value
X_1	0.187	0.816	0.425	1.2	0
X_2	0.814	0.911	0.435	1.4	0
X_3	0.153	0.274	0.916	3.301	0
X_4	0.346	0.182	0.906	0.6	0
X_5	0.061	0.016	0.983	1.001	0
p<0.05; Durbin Watson= 1.83; R square= 1.000					

Conclusion

The analyses began with a computation of the Altman Z score and the five individual ratios in the Altman [3] discriminant function. The data generated after that showed that the bankruptcy prediction accuracy rate for the Altman [3] discriminant function two years before liquidation or restructuring was 87.6%. Only 7.6 % and 4.8% bankrupt firms were misclassified to be in the safe and grey zones respectively as characterized by Altman [3]. The prediction accuracy rate improved to 99.05%, one year before bankruptcy.

Structural coefficients provided a basis to test the hypothesis that profitability has the highest level of association with the Altman Z score. The data analysis initially compiled beta weights to explain the relative importance of each of the Altman [3] variables, but unlike spectrum coefficients, they are affected by correlation between predictor variables.

The results for the analysis supported the alternative hypothesis (H_a) that profitability is a statistically significant variable in the Altman [3] discriminant function that has the highest level of association with the Altman Z score. The results from a spectrum coefficient index corroborated Altman, Haldeman, and Narayanan [10] as profitability has the highest spectrum coefficient compared to the rest of the variables in each of the last two years before bankruptcy.

With one year before bankruptcy, the spectrum coefficient was thus: Profitability ($r_{s=}$0.962); Asset productivity ($r_{s=}$0.844); Liquidity ($r_{s=}$ 0.192); Solvency ($r_{s=}$ -0.287) and Activity ($r_{s=}$ -0.340). This is illustrated in Figure 1.

With two years before bankruptcy, the spectrum coefficient was the following: Profitability ($r_{s=}$ 0.911); Liquidity ($r_{s=}$ 0.816); Asset productivity ($r_{s=}$ 0.274); Solvency ($r_{s=}$ 0.182) and Activity ($r_{s=}$0.016) as depicted in Figure 2.

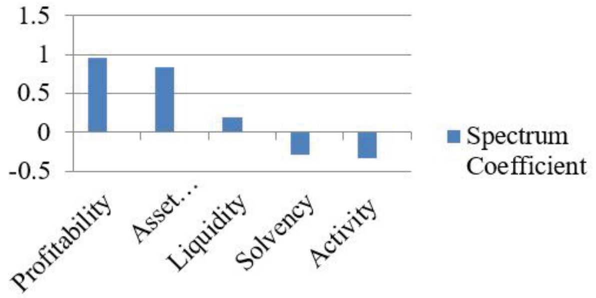

Figure 1. *The degree of association of variables in the Altman (1968) algorithm model with the Altman Z score, one year before bankruptcy.*

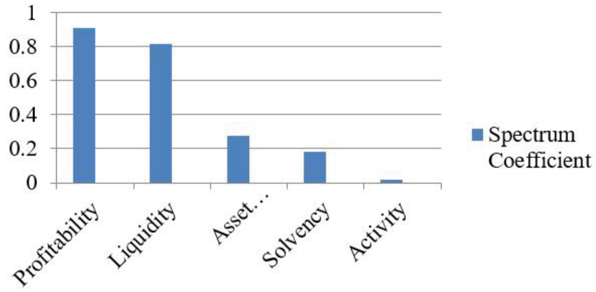

Figure 2. *Degree of association of variables in the Altman (1968) algorithm model with the Altman Z score, two years before bankruptcy.*

Except the activity ratio, which did not have a statistically significant relationship with the Altman Z score, the relationship between the independent Altman [3] variables and the Altman Z score was statistically significant in the last two years preceding bankruptcy.

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