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Estimation and comparison of corporate financial distress models on performance of major crude oil companies listed in S & P BSE oil and gas index

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Abstract
Crude oil price has held the attraction of academicians as well as practitioners over the last few decades as it is the life line of the world economy. In this article we examine the outer performance of six major distinct companies listed in S&P BSE Oil and Gas Index with the help of Altman Z score and Springate S score and examine the precisions of the above two models. The model consists of different financial ratios to ascertain the likelihood of corporate financial distress. Two different binary logistic regressions were constructed with the help of selected financial ratios for determining the performance of the company into two categories "non-distress and distress" based on the above two models for each year. The classification result showed a high predictive accuracy of 100.00% correct classification rate for original grouped data as well as for Altman and Springate model. The study also showed that, binomial logistic regression can be used by Investment Companies, Financial Manager, Investors and Researchers for investment as well as policy implications.

Keywords: Distress, binary, logistic, regression, Altman and springate

1. Introduction

Crude oil or black gold gaining its importance as it is the most traded commodity in the world's economy. It is influenced by the economic activities and fundamentals of supply and demand of the country from medium to long run. Fluctuations in global crude oil affect the economy of the nations depending on whether the country is a net importer or an exporter of crude oil. Hence exchange rate, inflation and employment are affected by increase in crude oil prices and ultimately lead to economic slowdown, on the other hand the government can manage the financial sector better and the minimal fiscal deficit through lower subsidies on petroleum product to decline in crude oil prices, which ultimately helps the government to remain executed to fiscal unification road map without any adjustment on economic growth.

The international financial conditions are relatively unstable in recent years due to some conflicts in the Middle East and Eastern Europe that have exacerbated international world present financial conditions. The recent collapse in oil price in the global market was caused by a combination of demand and supply issues as well as uncertainty about the future arose from to COVID - 19 Pandemic.

As a developing country, India's oil and gas sector is one of the six core industries, which committed to shine its economy in the upcoming years and plays a predominantly pivotal role in taking decisions in all other spheres of the economy. India being a net importer, the decrease in crude oil prices is welcome bait and provides a chance to bushel the fiscal deficit. For more intense corporate competition, companies need to improve the effectiveness and efficiency of corporate management and perform better by evaluating the company's strategy and policy. The financial health and performance of the company for maintaining competition, increasing profits, cost efficiency, economic growth and creating the economic value of the company can be judged by the evaluation process (Triyono, 2017) [1]. The management of the company may perform some actions and take decisions to improve the company's financial condition, if the distress condition of the company can be detected earlier and to minimize or even to overcome the occurrence of distress. Therefore, the management must supervise the company's financial condition by analyzing the company's financial statements by time to time.

2. Review of literature

During the past few decades, oil prices have made the headlines of the newspaper almost every day. For policy makers to take financial decision, production strategies, short term price movements of traders and refinery companies in financial markets, accurately forecasting of crude oil and natural gas prices have a key role. As well as, changes in energy prices affects growth rates, inflation and unemployment rates via production cost channels and is an important cost ingredient for long term and value added "Strategic Investment" decisions (Regnier, 2007) [2].

Many studies and researches have examined factors affecting crude oil prices that have contributed to the fluctuation of oil prices. Moreover, Kaufmann and Shiers, (2008) [3] argued about the presence of empirical evidence that speculation and futures markets played a major role in past crises, as it also resulted from a crisis in the housing market and financial variables (Hamilton, 2008) [4]. Mandelbrot (1999) [5] observes many time-varying economic variables and discovers that the financial econometric model always assumes the yield of financial assets obeying the normal distribution, thus obtaining the feature of changes in speculative price and yield. Zhang Tingting (2012) [6] cites the partial least squares regression method to analyse the influencing factors of future price of crude oil. Zhang Hui (2012) [7] points out the correlation between the international future price of crude oil and US dollar index.

Impact of crude oil determinants is not large because most of the economists are concerned with diminished growth rates, monetary policy or business cycle costs levied on economies and industries, if oil prices soar (Rotemberg and Woodford, 1996) [8]. Mork (1989) [9] investigated the connection between the effect of changing of oil prices and the inflation rate and found a significant relationship. Gisser and Goodwin (1986) [10] and Basher and Sadorsky (2006) [11] have found the same evidence. El-Sharif *et al.* (2005) [12] founds a positive relationship between the crude oil price and equity values in the oil and gas sector, whereas, Ojebiyi and Wilson (2011) [13], found a negative relationship between crude prices and exchange rates.

In an investigation by Hidhayathulla and Rafee (2012) [14], continuous import of crude oil leads to increase in demand for dollar and in turn this leads to weaken Rupee value against dollar. Serletis (2010) [15] researches the relationship between influencing factors of the price of crude oil, but Song (2012) [16] analyses the crude oil futures and finds that the future price of crude oil and crude oil inventory has the same growth relationship. In a study conducted by Papapetrou (2001) [17] found the relationship between crude oil prices, debt instrument rates, employment condition and stock market prices.

According to Trichet (2008) [18] factors unrelated to energy demand and supply can play in oil markets. Cheng Weili (2014) [19] carries out quantitative analysis of influencing factors of the international oil price and finds out a positive correlation between the future price and spot price. Farzanegan and Markwardt (2009) [20] emphasizes on "Dutch Disease" syndrome through significant real effective exchange rate appreciation to be highly vulnerable to oil price fluctuations. Subarna and Ali, (2012) [21] examined the co-movements of macroeconomic variables such as stock and gold price, exchange rate and the crude price and reported that there is a co-integration association between the macroeconomic variables and crude prices. Bhunia (2013) [22], pointed out that crude oil price, domestic gold price, stock market index movements and countries exchange rates are integrated in long run in India.

3. Methodology

The sample considers for this study is composed of six major oil and gas industries/companies (BPCL, GAIL, HPCL, IOC, ONGC and Reliance) listed in S&P BSE Oil and Gas index. The index is an equity benchmarks for BSE traded securities in economic sectors is a part of the S&P BSE 500. It employs a non-market capitalization weighting scheme effective after the close on April 1, 2015. Prior to the effective date, the index employed a free float-adjusted market capitalization weighting scheme.

Initially 13 financial ratios are taken for analysis and a normality test was conducted on all these explanatory variables to find whether these variables are normal or not with the help of P-P plot technique. Balance sheet and income statement data of companies are collected after the initial groups are defined and firms selected for analysis.

Two logistic regressions (One for Altman Model and another for Springate Model) were constructed with help of the selected financial ratios as independent variables for determining the performance of the above listed crude oil companies for each year and financial performance was measure. The study showed that logistic regression can be used by investors, investment companies and researchers for academic interest as well as policy and financial implications.

4. Development of bankruptcy models

Over the past few decades, various bankruptcy models were developed based upon alternative approaches to corporate distress model. Financial ratios are used mainly in parametric models, which are univariate and multivariate in nature and focuses on the symptoms of bankruptcy (Andan and Dar, 2006) [23]. Sometimes these models use non-financial information (Ohlson, 1980) [24]. Assumptions on the dichotomous variable, the sampling method, stationarity assumptions, data instability, selection of independent variables, use of accounting information and the time dimension are related to Problems of parametric models (Balcaen and Ooghe, 2004) [25].

The ability of individual financial ratios to classify a firm as a bankrupt or non-bankrupt with highest classification power was analysed by Beaver (1966) [26] with his univariate default prediction model and suggested multiple ratios considered simultaneously may have higher predictive ability than single ratios which created a platform for multiple ratio models.

Before Altman's discriminant analysis many researchers making changes in financial ratios, study sample, and change in business culture (Deakin, 1972) [27]. Huo (2006) [28] examined the service sector using different bankruptcy models and compared with Altman Z score, Springate S score and Fulmer F score with each other and found that Altman Z score was more efficient. Gunathilaka (2014) [29] analysed the financial distress using the Altman Z-score models and Springate S score and demonstrated a higher degree of accuracy in Z-score in predicting the financial distress at least a year before the entity distress, whereas, Adnan and Arisudhana (2010) [30] concluded that Z-Score model gives a different conclusion with Springate model.

In the Indian market, Bandyopadhyay (2006) [31] develops a bankruptcy prediction model for the Indian corporate bond sector using MDA and logistic technique. Bhumia and Sarkar, (2011) [32] developed a corporate failure model for the Indian pharmaceutical company based upon MDA technique. Ramkrishnan (2005) used discriminant and logistic model to foretell bankruptcy for Indian companies (Singh and Mishra, 2016) [34].

4.1 Altman Z model

MDA is a statistical technique that identifies some financial ratios which are influencing the value of an event and then it develops it into a model (Altman, 1968) [35]. In 1983, a revised Z-score model was developed by Altman for privately held firms for credit analysis, private placement dealers, accounting auditors and firms themselves by substituting the book value of equity for the market value (Altman, 1983) [36]. In 1993, Altman produced a further revised model, one that eliminates variables "sales/total assets: to minimize "the potential industry effect which is more likely to take place when such an industry sensitive variable as asset turnover is included (Altman, 1993) [37]. Altman, (2002) [38] defines the market value of equity, or market capitalization, as a summation of both preferred and common stock or market value of equity/book value of total debt. This ratio is a more effective financial distress predictor than net worth/total debt (book values). His model correctly predicts financial failure for 95% of the firms, one year prior to their demise (Anjum, 2012) [39].

4.2 Springate model

Springate model was introduced by Gordon LV Springate (1978) [40] and is a revolution of the Altman model developed on Multiple Discriminant Analysis (MDA). Springate model initially used 19 financial ratios and after testing four financial ratios to be used to determine whether the company is said to be either a healthy company or potentially insolvent. Terzi (2011) [41] reported to have obtained quite successful results in Springate model while determining the financial failure risks of the food companies. According to Adriana (2011) [42], Springate method can be used as a means of evaluating the condition and performance of a company for the parties concerned. Springate model that can be used as an early warning system of bankruptcy and more reliable as compared to other model (Imanzadeh *et al.* 2011) [43].

Models under study, their ratios and cut-off values are details provided in Table - 1.

Table 1: Models under study, respective ratios and their cut-off values

Sl. No.	Model	Variables	Cut-off values
1	Altman Z score For manufacturing firms (1968) $Z = 0.012x_1 + 0.014x_2 + 0.033x_3 + 0.006x_4 + 0.999x_5$	X^1 = WC/TA, X^2 = RE/TA, X^3 = EBIT/TA, X^4 = MVE/BVD, X^5 = S/TA	Z < 1.8 – Bankrupt zone Z > 1.8 – Non-bankrupt zone
2	Springate model (1978) $S = 1.03\,A + 3.07\,B + 0.66\,C + 0.40\,D$	A = WC/TA B = EBIT/TA C = PBT/CL D = S/TA	S < 0.862 – Bankrupt zone S > 0.862 – Non-bankrupt zone

5. Analysis of the model

Binary logistic regression deals with situations in which the observed outcome for a dependent variable can have only two possible types (Peel and Peel, 1988) [44]. It is helpful for prediction of the presence or absence of a characteristic or outcome based on values of a set of predictive variables is a multivariate analysis model (Lee, 2004) [45]. Anggraini and Mulya (2017) [46] used Binary logistic regression method to find the influence of financial distress prediction on several financial ratios. Jones (1987) [47] found that there were some inadequacies in MDA with respect to the assumptions of normality and group dispersion. This may bias the test of significance and estimated error rates. Lee, Ryu and Kim, (2007) [48] emphasized that logistic regression can come to handy in conditions where prediction of the existence or feature is dependent on values of a set of predictor variables. It also yields coefficients for each independent variable based on a sample of data (Dutta *et al*. 2012) [49]. Logistic regression model with two or more explanatory variables are widely used in practice and parameters are commonly estimated by maximum likelihood (Pardo *et al*. 2005) [50].

5.1 Dependent variable encoding

For performing logistic regression analysis, it is necessary to classifying a company as a "Distress" or "Non Distress" bases upon Altman and Springate models for a given year. Since there is no such method for defining a company as a "Distress" or "Non Distress", in this study we use Altman and Springate models to classify the company as a distress or non-distress. If the Z score and S score of the Altman and Springate model are less than 1.8 and 0.862, it is classified as distress otherwise non distress.

Table 2: Dependent variables and their encoding

Status of company (Based on Z score and S score)	Classification	Internal value
Distress	Z score and S score of the Altman and Springate model are less than 1.8 and 0.862	0
Non Distress	Z score and S score of the Altman and Springate model are greater than 1.8 and 0.862	1

5.2 Binary classification

From the table it is seen that, the non-distress companies have a 100.00% correct classification rate for Altman and Springate model and overall percentage 55.60% for Altman model, which is little better than tossing of a coin.

Table 3: Model summary - observed classification table a, b

	Observed	Altman			Springate		
		Distress (0.00)	Non Dist. (1.00)	Percentage (%)	Distress 0.00	Non Dist. 1.00	Percentage (%)
Step 0	Distress (0.000)	0	16	0.00	0	5	0.00
	Non Dist. (1.00)	0	20	100.00	0	31	100.00
	Overall Percentage			55.60	Overall Percentage		86.10

Note: a. Constant is included in the model b. The cut value is 500.

Similarly, for Springate model the overall percentage 86.10 signifies that, a better prediction as compared to Altman model.

5.3 Variables in the equation (Without explanatory variables)

The coefficient for the constant (B_o) is shown in the "Variables in the Equation" table and highlighted the level of significance to adorn a cautionary tale. From the table, the Altman model with the constant is a statistically non-significant predictor of the outcome ($p > 0.001$). However, it is only over all accurate 55.60% of the time. Similarly, Springate model with the constant is a statistically significant predictor of the outcome ($p < 0.001$) and indicate over all accurate 86.10% of the time.

Table 4: Variables in the equation

Model		B	S.E.	Wald	df	Sig.	Exp (B)
Altman	Step 0 constant	0.223	0.335	0.443	1	0.506	1.250
Springate		1.825	0.482	14.333	1	0.000	6.200

5.4 The Omnibus test

The Omnibus Tests of Model Coefficients is used to check that the new model (with explanatory variables included) is an improvement over the baseline model. It uses chi-square test to see if there is a significant difference between the Log-likelihoods (specifically the -2LLs) of the baseline model and the new model. If the new model has a significantly reduced -2LL compared to the baseline then it suggests that the new model is explaining more of the variance in the outcome and is an improvement. In this case we have added all five explanatory variables for Altman model and four explanatory variables for Springate model in one block and therefore have only one step. This means that the chi-square values are the same for step, block and model (49.461 on 5 df and 29.012 on 4 df for Altman and Springate model respectively). The Sig. values are p <.001, which indicates the accuracy of the model improves when we add our explanatory variables.

Table 5: Omnibus tests of model coefficients

		Altman			Springate		
		Chi-square	df	Sig.	Chi-square	df	Sig.
Step 1	Step	49.461	5	0.000	29.012	4	0.000
	Block	49.461	5	0.000	29.012	4	0.000
	Model	49.461	5	0.000	29.012	4	0.000

Note: There are three different versions; Step, Block and Model. The Model row always compares the new model to the baseline. The Step and Block rows are only important if explanatory variables are adding to the model in a stepwise or hierarchical manner.

5.5 The model summary

The model summary provides the -2LL and pseudo-R square values for the full model. The -2LL value for Altman and Springate model is 0.000 what was compared to the -2LL for the previous null model in the Omnibus test of model coefficients and was significant decrease in the -2LL, i.e. that our new model (with explanatory variables) is significantly better fit than the null model.

The R square values tell us approximately how much variation in the outcome is explained by the model. The Nagelkerke's R square, which suggests that the model explains 100% of the variation in the outcome for both the Altman and Springate model.

Table 6: Model summary - Cox & Snell R square, Nagelkerke's R square and -2 log likelihood

	Models	-2 Log likelihood	Cox & Snell R square	Nagelkerke's R square
Step 1	Altman	.000a	.747	1.000
	Springate	.000a	.553	1.000

Note: a. Estimation terminated at iteration number 20 because maximum iterations have been reached. Final solution cannot be found.

5.6 Variables in the equation (With explanatory variables)

we can be so confident that our models has some predictive power, which is better than just guessing, if the sample size is large - even though it only marginally improves the prediction (the effect size) we have enough cases to provide strong evidence that this improvement is unlikely to be due to sampling.

Table 7: Variables in the equation – Altman model

	Variables	B	S.E.	Wald	df	Sig.
Step 1A	WCTA	-219.004	76342.889	0.000	1	0.998
	RETA	1227.981	284194.398	0.000	1	0.997
	EBITA	-346.268	81972.831	0.000	1	0.997
	MVEBVD	-2.430	465.479	0.000	1	0.996
	STA	154.421	12329.977	0.000	1	0.990
	Constant	-291.114	26089.206	0.000	1	0.991

Note: a. Variable (s) entered on step 1: WCTA, RETA, EBITA, MVEBVD, STA

We also see that, the sample size will lead to high levels of statistical significance for relatively small effects in a number of cases in Springate model with compared to Altman model. The final logistic regression equation is estimated by using the maximum likelihood estimation for classifying a company:

ALTMAN (X) = -219.004 WCTA + 1227.981 RETA - 346.268 EBITA - 2.430 MVEBVD + 154.421 STA - 291.114

SPRINGATE (Y) = 115.773 WCTA + 955.233 EBITA + 41.215 PBTCL + 52.189 STA - 137.311

Table 8: Variables in the equation – Springate model

	Variables	B	S.E.	Wald	df	Sig.
Step 1A	WCTA	115.773	109098.747	.000	1	.999
	EBITA	955.233	1099073.192	.000	1	.999
	PBTCL	41.215	264594.816	.000	1	1.000
	STA	52.189	7890.332	.000	1	.995
	Constant	-137.311	25471.464	.000	1	.996

Note: a. Variable (s) entered on step 1: WCTA, EBITA, PBTCL, STA

From the above two equations, it is possible to classify a company by calculating the X and Y values. If the p value obtained from X is higher than 0.42, then the company was classified as distress; and if it is lower than 0.42, then the company was classified as non-distress for Altman model (Neter *et al*. 1996) [51]. Similar result also holds for Springate model.

5.7 Classification accuracy

The classification accuracy table helps to assess the performance of the model by cross-tabulating the observed response categories with the predicted response categories. For each case, the predicted response is the category treated as 1, if that category's predicted probability is greater than the user-specified cut off and the cut off value is taken at 0.5.

Table 9: Model summary - predicted classification table[a]

	Observed	Altman			Springate		
		Distress (0.00)	Non Dist. (1.00)	Percentage (%)	Distress 0.00	Non Dist. 1.00	Percentage (%)
Step 1	Distress (0.000)	16	0	100.00	5	0	100.00
	Non Dist. (1.00)	0	20	100.00	0	31	100.00
	Overall Percentage			100.00	Overall Percentage		100.00

Note: a. The cut value is .500

Table - 9 shows the comparison of the observed and the predicted performance of the companies and the degree of their prediction accuracy for future prediction. It also shows the degree of success of the classification for future. The number and percentage of cases correctly classified and misclassified are displayed. It is clear from this table that both the distress and non-distress companies have a 100.00% correct classification rate for Altman and Springate model and overall correct classification was observed in 100.00% of original grouped cases.

6. Conclusion

In ordinary parlance, the crude oil companies in India are mostly in good health despite a condition of ups and down. In this paper, we compare some traditional statistical methods for predicting financial distress to some more unconventional methods, such as decision tree classification and logistic regression techniques, using data collected from 2014 to 2019 financial year. Empirical experiments were conducted using a total of 13 financial ratios.

However, when using the Altman Z Score prediction model many companies come under bankrupt due to differences in scale calculations on each model. Z-Score approach to predict bankruptcy of crude oil companies showed that only 55.56% experienced non distress condition and 44.44% experienced distress condition over the past 6 years. Whereas, Springate approach stated that, 86.11% of crude oil companies are experiencing non distress condition (healthy), while the other 13.89% is declared potentially distress. The non-distress companies have a 100.00% correct classification rate for Altman and Springate model and overall percentage row tells us that this approach of prediction is correct up to 55.60% of the time for Altman model and a little better than tossing of a coin. Similarly, for Springate model the overall percentage 86.10 signifies that, a better prediction as compared to Altman model.

The comprehensive performance models used in the evaluation process may yield unreliable results, if both financial and non-financial measures are not taken place. Therefore, it is recommended to applying both evaluations

process to obtain accurate results and maintain objective from personal intervention to reach a more reliable result. The major finding of the study suggests that, the Altman and Springate models are careful to time periods and financial condition. When recent data are used in the estimation process and the sample size increases, the predictive accuracy of the models increases. The major limitation of the study is that it can be applied to only crude oil companies. The study can also use larger data set applying various other parametric and non-parametric models to check validity and robustness of the model as well as stability of the parameters.

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