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An Assessment of the Contribution of the Factors Included in Altman's Z Formula to the Discriminant Functions Associated with Corporate Efficiency

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Abstract

The objective of this research was to conduct an assessment of the contribution of the factors included in Altman's Z- factor formula to the discriminant functions associated with corporate efficiency in a sample of firms from insurance industry in Jordan. Sampled firms were grouped into two groups based on ROI to allow for the use of Multiple Discriminant Analysis (MDA) as s statistical tool for data analysis. Results indicated that, X1 (WorkingCapital/Total Assets) dominated both functions and ranked number one with massive contribution (Two third of total contribution) followed by X3 (Operating Expenses/ Total Assets) as number two and therefore, according to the results of this study both factors can be considered as having the highest contribution to corporate efficiency. Other remaining three factors showed moderate to weak but not significant contribution.

Keywords: Z-Factor, Corporate Efficiency, Discriminant function

*1.0 Introduction*and Overview

The Altman's Z-Score (enunciated in 1967 and published in 1968), was named after Edward Altman, (the New York University finance professor). It is a statistical technique or tool used by investors, asset managers, and rating agencies among others to predict the likelihood that a company may fail and/or go bankrupt. The Altman Z-score family of models significance comes from their application to the financial markets and their use in managerial strategies and the fields of banking, finance, and credit risk (Altman, 1968; Altman, 1983).

Altman's (1968) sample was composed of 66 corporations, with 33 in each of the two groups-bankrupt and successful businesses. Using financial statements, Altman compiled a list of 22 potentially important financial ratios for evaluation. He classified these variables into five standard ratio categories: liquidity, profitability, leverage, solvency, and activity. These ratios were chosen based on their popularity in the literature and their potential relevance to the subject studied. Altman then came up with the following formula known as Z score model, which is used often for companies listed at the capital market.

Z = 1.2X1+1.4X2+3.3X3+0.6X4+1.0X5 (1) Where: X1 - working capital / total assets, X2 - retained earnings /total assets, X3 – earnings before interest and tax / total assets, X4 - market value of owner´s equity /book value of total liabilities, X5 - sales / total assets. If the score is above 2.99, the firm is healthy. If the company scores below 1.81, the firm is viewed as failing business. When values ranging from 1.81 to 2.99, it represent the so-called grey area, which means there is no clear prediction about financial failure (Altman et. al., 2014).
The Altman's Z-Score was the first multivariate technique to predict company failure. However, it was not the first technique to predict company's bankruptcy. FitzPatrick (1932) compared 13 ratios of failed and successful firms and found that the two significant individual ratios were essential in predicting failure: Net Worth to Debt ratio and Net Profits to Net Worth ratio. So, FitzPatrick was one of the earliest univariate analysts to predict financial troubles or companies in financial distress (Fitzpatrck, 1932; Altman, 1968).

Smith and Winakor (1935) concluded that the ratio of Working Capital to Total Assets was the best predictor of the likelihood of company failure/bankruptcy. They analyzed 183 failed companies from different industries. About a decade later and in 1942, Merwin analyzed a sample of 79 failed and 79 operating companies to conclude that his predecessors Smith and Winakor's ratio to be the best indicator in addition to the Current Ratio and Net Worth to Total Debt. Two decades after that, Beaver (1966) concluded that Net Income to Total Debt was the strongest predictor of bankruptcy followed by Net Income to Sales. Beaver had taken Smith and Winakor's earlier study a step further and presented empirical evidence that certain financial ratios can discriminate between matched samples of failed and non-failed firms.

In all of these studies which took place prior to Altman's Z-score research about financial distress were conducted using single variable. Ratios were considered independent of each other, and will not express the whole situation in a single measure. Therefore, it is essential to have a multidimensional perspective where the important ratios are combined together to have a comprehensive look at the big financial picture of the company. Altman, in 1967 and 1968, came up with a multivariate model based on multivariate discriminate analysis. More specifically, he developed his five predicted factors and set the base for other researchers to examine the validity of such a model (El Khoury and Al Beaino, 2014).

1.1Development and Importance of the Z-Score Formula:

The formula for the Z-Score is to predict the likelihood that a company may fail and/or go bankrupt. This formula is the results of dividing/multiplying seven simple pieces of data (see below) which will conclude with the Z score. The lower this score is, the higher the chance of bankruptcy will be. A Z-Score of above 3.0 means or interpreted as financial soundness; while a score of below 1.8 means or interpreted as a high probability of bankruptcy (Altman, 1993; Altman, 1968).

Moreover, because of the widespread of non- manufacturing companies (like large, public service companies) led him to come up with a second Z-Score model for public service companies or non-manufacturing companies. The difference in this new formula is the exclusion of the last part or component (sales / total assets) since Altman aimed to minimize the effects of manufacturing-intensive asset turnover. The formula was as follow:
Z-Score = ([Working Capital / Total Assets] x 1.2) + ([Retained Earnings / Total Assets] x 1.4) + ([Operating Earnings / Total Assets] x 3.3) + ([Market Capitalization / Total Liabilities] x 0.6) (Altman, 2006).

As explained above,Altman developed his Z-Score formula by evaluating 66 companies, where 50% of those companies already filed for bankruptcy between 1946 and 1965. He began with 22 ratios classified into five categories (liquidity, profitability, leverage, solvency and activity). However, he had narrowed these categories down to only five ratios that could be calculate from data found on a company's annual 10-K report to predict whether a company has high probability of being insolvent (Altman, 1968; Altman 1993).

Altman research and evaluation of his formula/method was tested by examining 86 'in danger' companies between 1969 to 1975 and then 110 bankrupt companies between 1976 to 1995 and after that 120 bankrupt companies between 1996 to 1999. The accuracy of resulted Z-Score was between 82% and 94% accurate assuming that the company financials records were accurate too and were not misleading or incorrect.

1.2 Accuracy and Predictability of Z- Score Formula

The accuracy and predictability of Z score formula was tested or shown in the case of Enron's Company. The Z score gave the company the equivalent of a BBB bond rating in 1999 (year end) , but it had a score equal to a B rating by June 2001 -- unlike the other ratings agencies, which rated Enron as BBB until just before it filed for bankruptcy.

The Altman Z-Scores accuracy and predictability was tested further by the events before and after the world financial crisis. For example, in the year 2007, the credit ratings of specific asset-related securities was inflated and rated higher than they should be. The Altman Z-score predicted that the companies' risks were increasing and may lead to bankruptcy. Altman's score predicted a crisis would soon occur. In the year 2009, corporations defaulted at the second-highest rate in history.

Carton and Hofer (2006) investigated a variety of common performance metrics. The optimal metric for providing “the greatest relative information about the market-adjusted return to shareholders” was found to be Altman’s Z-Score. Altman’s formula appeared to rate higher than other performance metrics such as the widely used return ratios (i.e., ROE & ROA), economic profit, growth rate of sales, cash flow, and expenses. Carton and Hoffer’s primary message was that Altman’s Z-score is more than a financial distress predictor; it is also efficacious as a performance management tool. (Hays et al., 2010)

Altman had developed his Z-Score formula further in the year 2012. He developed and published an updated version he called the Altman Z-score Plus which can be used to evaluate public and private companies, manufacturing and non-manufacturing companies, and U.S. and non-U.S. companies (Altman at el., 2014; Hays at. el., 2010)

In conclusion, the old Altman Z-score was created in 1966. However, it is still the standard against which most other bankruptcy formulas or default prediction models are measured. Also, it is the mostly used score by financial market practitioners and academic scholars.

2.0 Survey of Previous Literature

Dimitras et al. (1996) provides a review of the literature and a framework for the construct prediction models. This paper reviewed 47 studies on business prediction models, summarizing the methods employed and the variety of ratios used. Discriminant analysis was the prevailing method, and the most important financial ratios came from the solvency category, with profitability ratios also being important. Overall, relationships and research trends in the prediction of business failure were discussed.

Balcaen and Ooghe (2006) directed their research towards a thorough understanding of the features of the classic statistical business failure prediction models and their related problems. Theirpaper reviewed 43 models of business failure prediction by discussing all problems related to the classical paradigm, and the application focus in failure prediction modelling. Also, this research elaborates on a number of other problems related to the use of a linear classification rule, the use of annual account information, and neglect the multidimensional nature of failure.

Kumar and Ravi (2007) presented a comprehensive review for the work done between 1968–2005, in the application of statistical and intelligent techniques to solve the bankruptcy prediction problem faced by banks and firms. 128 statistical and artificial intelligence models were reviewed for banks and firms to predict bankruptcy , paying special attention to the techniques used in the different models.

Pindado et al. (2008) noted that, the *Z*-Score was also used for other purposes, such as the evaluation of the costs and benefits of covenants in bonds, and the choice of debt type (bank versus non-bank, private or public). Tinoco and Wilson (2013) used the original *Z*-Score as one of the benchmarks to assess the performance of their model developed for U.K. listed companies with combined accounting, market, and macroeconomic data. Altman's *Z*Score presented very good classification accuracy in the case of financially distressed firms (81 versus 87 per cent for the new model). However, it was less correct for non-distressed firm's prediction.

Lyandres and Zhdanov (2013), who posed the question of whether the inclusion of variables related to investment opportunities improved the predictive power of three models (Altman's *Z*-score model and Zmijewski's and Shumway's models). They used three proxies for investment opportunities (market- to-book, value-to-book, and R&D to assets). The measures of investment opportunities were linked to the likelihood of default. The inclusion of either of these measures improved the out-of-sample forecasting ability of all three.
Acosta, González and Fernández,Rodríguez (2014) used genetic algorithms with the Schwarz information criterion (GASIC) for variable selection combined with the logit model for bankruptcy prediction. Altman's *Z*-Score model was used as one of two benchmarks for the authors' model evaluation. For one-step-ahead forecasting, Altman's model was better at predicting failed firms, but the type II error was high. Soon et al. (2014) used Altman's financial distress model to predict the financial hardship of 28 companies listed on trading services sector at the stock exchange of Malaysia for the period between 2003 and 2009, and concluded that Altman's score can be used.

2.0 Methodology

The objective of this research was to evaluate the relative contribution of the factors included in Alman's Z-Factor formula to the discriminant functions associated with corporate efficiency using a sample from the Insurance sector in Jordan. Secondary datawas collected and utilized in the calculation of the Z-factors as well as the Return on Investment as a measure of corporate efficiency for the study sample. As a matter of fact all insurance companies in the insurance sector inJordan were included in the study sample.

Data was collected for the year 2016, therefore the study is a cross-sectional research aims at assessing the individual contribution of each factor in Altamn's equation to the corporate efficiency measured by Return on Investment.

At thisstage of theresearchprocess, a detailedpresentation of methods and proceduresbecomerelevant. Thissection of theresearch describes theresearch variables, selection of theresearchinstrumentation, selection of participants, data collection, and analysis and hypothesestesting.

2.1 Selection of instrumentation

Secondary data collectionsourceswereused to collect data related to thestudydependent as well as independent variables. All data forthisstudy are publicallyavailablefromsecondarysources, such as corporatewebsites and industrypublications, therefore no needforanypermission to be obtained to conductthisprocess. Since data are going to be obtainedfromsecondary data sources, reliability of such data isalsoguaranteed. Forthepurpose of thisstudy, ReturnonInvestmentwasused as thedependent variable.

2.2 Formulation of the Study Groups

As part of the research methodology, the researchers have divided the study sample into two groups based on ROI score for each firm in the study sample. The first group is called "highefficient group" (group one), and the second one is called "the low efficient group" (group two).

The classification rule is that, firms with ROI equal to or greater than 5 percent were grouped in the high efficiency group(group one) and firms with less than 5 percent ROI were grouped in the low efficiency group (group two). This group classification scheme yielded 9 firms in group one and 12 firms in group two.

This classification was done in order to make data applicable for the use of Multiple Discriminant Analysis as a statistical tool for data analysis in this study. An important necessary condition has to be met in order to be able to apply MDA as a statistical tool for data analysis and hypotheses testing. This necessary condition is maintained when the sample is divided into two or more pre-defined groups.

2.3 Data Collection Sources

For the purpose of this study. all Jordanian insurance companies were included in the study sample provided that reliable data on the study variableswere available for the period of time covered by this study.

2.4 Measurement of variables

The dependent variableis going to be measured as follows:
Return on investment (ROI)
ROI= Net Profit/Total assets ……………………………………………………………………………Formula 1
Independent Variables
Z- Factor score components
Z= x1(1.2)+ X2(1.4) + X3(3.3)+ X4(0.6)+ X5(1.0)-------------------------------------Formula 2

Where,
Z is Altman's Z-Factor
X1is THE RATIO OF WORKING CAPITAL / TOTAL ASSETS
X2is THE RATIO OF RETAINED EARNINGS / TOTAL ASSETS
X3is THE RATIO OF OPERATING EARNINGS / TOTAL ASSETS
X4is THE RATIO OF MARKET CAPITALIZATION / TOTAL LIABILITIES
X5is THE RATIO OF SALES / TOTAL ASSETS

2.5 Statistical method for data analysis

To calculate discriminant functions associated with each group in the study, the Multiple Discriminant Analysis (MDA) statistical method was used.

MDA is a multivariate statistical method which was first introduced by Fisher. Applications of MDA were limited to behavioural sciences particularly to psychological testing. However, by the end of 1960s, MDA was applied to other disciplines as well. Management was among those disciplines using MDA. By late 1970s, MDAhad wide range of applications in marketing, finance and strategic management. MDA has to do with classifying objects into exactly one or more pre-determined groups.

Let us assume that we have two distinct groups, as the case in this study. Let X1 and X2 be the sample means vectors for the groups, and S be the pooled estimate of the population covariance matrix. Let "a" be a coefficient vector of the index a’x, then MDA computes the linear index of several measurements which best discriminate between groups. It therefore seeks to develop a linear combination that distinguishes between groups by maximal separation. What actually MDA does is that it maximizes the absolute difference [a” (x1-x2)] subject to the constraint a’sa=1. Then the critical ratio for the two group case will be:

T2 (a)= [a’ (x1-x2)[2 n2n2/(n1+n2) /a’sa

Where,
N1 is group 1 sample size
N2 is group 2 sample size
s. t. a’sa=1

Since MDA has proven to be a powerful tool to provide the most significant distinction between groups, itseems rather an appropriate tool for testing the analysis ofdata in this research. Its primary advantage as applied to thisresearch is its powerful ability to check the entire profile of corporate efficiency rather than sequentially examining individualmeasurement (Morrison, 1982).

Since the ultimate objective of this research is to calculate the discriminant functions associated with each group, this will allow the researchers to investigate if the five factors in Altman's z-formula are able to distinguish between firms with high efficient status and firms with low efficient status based on their ROI, therefore Multiple Discriminant Analysis (MDA) seems to be useful to achieve this end.

The linear two groups’ discriminant analysis can be defined as:

Yi= a1 X1i + … + am Xmi

Where:
Y1 is a binary variable used to indicate two alternatives option.
X1, X2, …, are independent variables
The objectives of using (MDA) are:

1- To test for the mean group differences and to describe the overlaps among groups.
2- To construct a classification system based upon a set of variables in order to be able to assign previously unclassified observations to its appropriate groups.
3- Based on (1) and (2) above, the multiple discriminant functions associated with each group can be calculated. (Morrison, 2005). In calculating the discriminant functions, MDA computes a linear combinations that maximally distinguish between the two groups.

As mentioned earlier, the objective of using MDA is to test the ability of the study independent variables to distinguish between high efficient firms and low efficient ones in the study sample. MDA Statistical analysis will be conducted using the SPSS statistical software, to obtain the following:

First, to use the stepwise discriminant analysis which can select variables to be included in the model based on their abilities to distinguish high efficient group from low efficient one. Therefore a set of independent variables were identified and used in the analysis.

Second, Walk's lambda was calculated which shows the overall discriminatory power of the independent variables in the model. Walk's lambda is the multivariate extension of R-squared in regression analysis, but interpreted backward from R-squared. It varies between 1 and 0, where values near 1 imply low discriminatory power and values close to 0 imply high discriminatory power (Statsoft, 2008).

Finally, the discriminant functions associated with each group were calculated and used to classify firms into their respective group. Depending on this test the study results were obtained.

3.0 Goodness of fit Model

To guarantee the adequacy of the testing procedures, results of the testing model goodness of fit is presented in the following section, followed by the presentation of the findings.

3.1 Testing the model goodness of fit

In order to assure that the model used to analyze the research is actually fit for this type of testing, two important values must be assessed. These two values are the f-value and the probability associated with it and the value of Wilk's Lambda.

The results indicated the following values:
F-value = 16.89
Probability = 0.03
Wilk's Lambda = 0.761
F-value and probability level 5.2

For the model to be suitable for hypotheses testing and can yield reliable results, the f-value must be more than 2 in an absolute value and the probability level associated with it must equal to 0.05 or less.

As shown in the results, the f-value is equal to 2.95 and associated probability equal to 0.03, this permits the researchers to conclude that, the model is good to guarantee its use for the data analysis.

3.2 Wilk's Lambda

Table 1 Shows results pertaining to Wilk's lambda. As shown in the table, Wilk's Lambda value is 0.761 which indicates an acceptable level of discriminatory power of the model used in this research.

Table 1: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.761	4.516	5	.478

The value of Wilk's lambda is used to assess the overall discriminatory power of the model. In other words, it measures the model ability to distinguish between the groups based on the study independent variables. The value of Wilk's lambda ranges between zero and one, where values too close to one indicates low discriminatory power (McLachlan, 2004). The value of Wilk's lambda for this research is 0.601which provides an evidence to support reasonable significance for the model.

Therefore, the values of f and Wilk's lambda allow the researcher to conclude that the model used to test the research hypotheses is reasonably fit to guarantee reliable results

3.3 Classification Results

Table 2 shows the classification results which indicates that the discriminant function associated with group one was able to distinguish between groups 66.7 percent of the time.

Table 2: Classification Results[a]

		Y2	Predicted Group Membership		Total
			1	2	
Original	Count	1	6	3	9
		2	1	11	12
	%	1	66.7	33.3	100.0
		2	8.3	91.7	100.0

a. 81.0% of original grouped cases correctly classified.

This means that three firms out of nine in group one were reclassified in the same group while three firms misclassified in group two. On the other hand, one firm misclassified from group two into group one and eleven firms were correctly classified in their respective group.

4.0 The Research findings

Table 2 contains the linear discriminant functions coefficients which represent the contribution of each of the factor in Altman formula in each of the study groups. As shown in the table 2 , X1 is dominating the high efficient group function with a coefficient of 66.410, followed by X3 with a coefficient value of 25.889. X2 came third with a coefficient value of 21.242 followed by x5 andX4 with coefficients values of 17.142 and -12.122 respectively.

Table 2: Linear Discriminant functions

Independent Variables	Functions	
	1	2
X1	66.410	35.456
X2	21.242	19.797
X3	25.889	27.980
X4	12.122	10.887
X5	17.142	19.241
(Constant)	-12.691	-11.046

Fisher's linear discriminant functions

The low efficient group coefficients are almost exhibiting the same pattern noticed in the high efficient group classification function with smaller coefficients values.

X1 has the highest coefficient value of 35.456 followed by x3 with a coefficient value of 27.980. X2 came third with a coefficient value of 19.797, followed by x5 with a coefficient value of 19.241 followed lastly by x4 with a coefficient value of 10.887.

5.0 Conclusions and Discussions

Results presented above yielded the following conclusions:

1- X1(working Capital/Total assets) has the most contribution in both functions to corporate efficiency in the study sample, (66.410 in the function associated with group one and 35.456 in the function associated with group two).
2- X3 (operating earnings/Total Assets) has the next value of contribution in both functions where the value was 25.889 in group one function and 27.980 in group two function.
3- X2 (Retained Earnings/Total assets) came third with a coefficients of 21.242 and 19.797 in each group respectively.
4- X5 (Sales/ Total Assets) ranked fourth with coefficients 17.142 in group one and 19.241 in group two.
5- Lastly, X4 (Market Capitalization/ Total Assets) showed the lowest contribution with 12.122 and 10.887 for each group respectively.

Findings of this research as presented above showed that one specific factor has more than two thirds of the total contribution of factors in Altman's Z-factor formula, namely Working Capital/ Total assets.
This result validates what Smith and Winakor (1995) have found. They mentioned that, according to their findings Working capital/ Total assets was the best predictor of the likelihood of company failure/bankruptcy among Altman's Z-factor formula.

Results of this research has also indicted that the ratio of Operating expenses/ Total assets indicated strong contribution to Alatman's Z-Factor formula. This ratio ranked second in terms of its contribution which is consistent with many of the previous research studies findings.

5.0 References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance, 23, 589-609.

Altman, E. I. (1983). Corporate financial distress: A complete guide to predicting, avoiding, and dealing with bankruptcy. (1st ed.). New York: John Wiley & Sons.

Altman, E. I. (1993). Corporate financial distress and Bankrupcty: A complete guide to predicting & distress and profiting from bankruptcy. (2nd ed.). New York: John Wiley..

Altman, Edward I. ,Iwanicz-Drozdowska, Malgorzata , Laitinen, Erkki K. and Suvas, Arto (2014). Distressed Firm and Bankruptcy Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model (August 10, 2014). Available at SRN: https://ssrn.com/abstract=2536340 ; http://dx.doi.org/10.2139/ssrn.2536340 Access Date: March 2, 2019.

Altman, E.I., & Hotchkiss, E. (Eds.). (2006). Corporate financial distress and bankruptcy: predict and avoid bankruptcy, analyze and invest in distressed debt (3rd ed.)Hoboken, NJ: Wiley.

Balcaen, Sofia and Ooghe, Hubert (2006). 35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and Their Related Problems. The British Accounting Review, 38(1):63-93, March, 2006.

Beaver, W. H. (1966). Financial ratios as predictors of failure. Journal of Accounting Research, 4, 71-111.

Dimitras, A. I. &Zanakis, S. H. &Zopounidis, C., 1996. "A survey of business failures with an emphasis on prediction methods and industrial applications," European Journal of Operational Research, Elsevier, vol. 90(3), pages 487-513, May.

El Khouri, Rima, Al Beaïno, Roy.Classifying Manufacturing Firms in Lebanon: An Application of Altman’s Model, Social and Behavioral Sciences 109 (2014) 11 – 18.

Fitzpatrick, P. J. (1932). A comparison of ratios of successful industrial enterprises with those of failed companies. The Certified Public Accountant, 598-605.

Grice, J.S., & Ingram, R.W. (2001). Tests of the generalizability of Altman’s bankruptcy prediction model. Journal of Business Research, 54(1), 53-61.

Hayes, Suzanne, Hodge, Kay and Hughes, Larry W. (2010) A study of the efficacy of Altman’S Z to predict bankruptcy of specialty retail firms doing business in contemporary times, Economic & Business Journal: Inquires & Perspectives, Volume 3, No 1

Kumar P. Ravi and Ravi *V.* (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques - A review. *European Journal of Operational Research*, 2007, vol. 180, issue 1, 1-28 .

Lyandres, E., Zhdanov, A. (2013). "Investment Opportunities and Bankruptcy Prediction", Journal of Financial Markets, 3 (16), 439-476

Pindado et al. (2008) estimate the likelihood of financial distress by using. a panel data methodology and obtain a more stable model of the FDL ...https://www.researchgate.net/publication/272417735_Thedeterminants of the costs of financial distress, International Small Business Journal.1-20.

Smith, R. and A. Winakor. (1935). Changes in Financial Structure of Unsuccessful Industrial Corporations. Bureau of Business Research, Bulletin No. 51. Urbana: University of Illinois Press.

Soon, Ng Kim, Mohammed, A. Abusalah, and Mostafa, M. Rahil (2014) Using Altman's Z-Score Model to Predict the Financial Hardship of Companies Listed In the Trading Services Sector of Malaysian Stock Exchange. Aust. J. Basic & Appl. Sci., 8(6): 379-384

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