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Assessing Predictive Power and Earnings Manipulations. Applied Study on Listed Consumer Goods and Service Companies in Ghana Using 3 Z-Score Models

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This study uses data from Ghana's public listed consumer goods and service companies for the period of 2014-2018 to test the predictive power of Altman's (2000), Taffler's (1983), and Beneish's (1999) models in detecting bankruptcy and Earnings Manipulation. Prediction power (accuracy) was tested for two Z-Score models: Altman's (2000) revised model and Taffler's (1983) model. All two models were found to have significant predictive power. Altman's revised model was found to be accurate for listed consumer firms in Ghana at a predictive power rate of 66%. Taffler's (1983) Z-Score model was equally found to be accurate for prediction at a higher predictive power of 88%. The Taffler (1983) model has a higher predictive power compared with Altman's (2000) revised model. The Beneish (1999) model also revealed that the financial statements of the industry were manipulated at a different degree. The study recommends that stakeholders would be better protected when the three models are deployed simultaneously as an important part of an Audit engagement. Also, Altman's (2000), Taffler (1983), and Beneish's (1999) model should be applied in predicting bankruptcy and financial statement fraud evaluation in the banking and mining sectors in Ghana taking into account the frequent collapse, mergers, and acquisitions that do occur.

Keywords: *Altman Model, Taffler Z-score, Beneish M-score, predictive power, earnings manipulations, Ghana, Z-score model*

JEL Classification: *G32, G33*

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1. Introduction

Corporate bankruptcy prediction is essential because the consequences of corporate bankruptcy result in heavy losses and affect the economy of a country. Enron's case is considered around the globe as one of the most famous bankruptcies. It is a major corporate accounting scandal that paved way to lots of regulations in the United States and other countries (Sulub, S. A. 2014). Financial bankruptcy is a term used in corporate finance to indicate that a firm cannot meet scheduled payments or cash flow expectations indicate that a firm will soon be unable to meet agreed payments plan (Brigham and Daves, 2004). The financial failure of any business may take the form of insolvency or bankruptcy. Insolvency means the company cannot meet its current obligations when it is due, which happens when the current liabilities exceed the current assets. On the other hand, bankruptcy may happen when the firm's current liabilities exceed the fair value of its assets (Mohammed and Soon, 2012). According to Elloumis and Gueyie, (2001), financial bankruptcy is a situation whereby a company's business worsens to the point where it unable to meet its financial obligations. Again, section 128 of South African's Companies Act (2008), defines financial bankruptcy as a state of the firm that appears to be reasonably unlikely to offset all of its obligations as they become due and payable within the immediately ensuing six months, or that it is likely the company will become insolvent within the immediately ensuing six months. Also, Khaliq, *et al,* (2014) added that financial bankruptcy can be term as financial distress.

Corporate organizations consist of manufacturing and non-manufacturing companies that play an important role in the economic and social development of every country including Ghana. Managers, shareholders, employees, investors, and financial institutions are concerned about organizational financial health. The ability to predict company financial bankruptcy is particularly significant for stakeholders to take the necessary preventive measures. In addition, corporate ethics and governance although have provided a podium to avoid financial bankruptcy, however, an early prediction is essential for especially investors that intend to safeguard their financial investments (Mahama, 2015).

Several business failures have occurred; thus a failure prediction model is crucial to serve as a benchmark for organizations. The prediction of organizational failure can enable companies to reduce bankruptcy costs, avoid failure, and help improve their financial stability. Therefore, financial health of any firm can be measured by its financial performance. Also, the ability to predict company bankruptcy is very important from both the social viewpoint and the investor's viewpoint as it stands as the indicator that measures the misallocation of company resources (Glautier and Underdown, 2001).

Current studies have shown several corporate failures across the globe. The annual flow of corporate bankruptcy from the past decades had not stop growing and this drifts had become more obvious during the period of world financial crisis in 2008 (Sami, 2013). Specific reference to some eminent corporate failure can be made of General Motors (GM), Chrysler, American International Group Inc., Delta Airline Limited Xerox, AIG, Freddie, WorldCom, Lehman Brothers, and Enron Corp (Mclntyre and Ogg, 2008). Also, the Ghanaian banking sector had been experiencing financial distress which leads to poor performance and failure of banks in 2019. Evidence of corporate failures includes the Ghana Co-operative Bank, Gateway Broadcasting Services, UT Bank, DKM financial, Bank for Housing and Construction, National Savings and Credit Bank and MensGold Ghana LTD (Appiah, 2011). An incident of corporate failure that is still renewed in the minds of Ghanaians is the collapse of UniBank Ghana Limited, Royal Bank Limited, Beige Bank Limited, Sovereign Bank Limited, and Construction Bank Limited due to liquidity and solvency challenges.

Deloitte (2008) indicated that there is a relationship between bankruptcy and fraud and there is a high probability that a firm at the brink of collapse would engage in financial statements fraud. This means that at the brink of bankruptcy; managers may be motivated to manipulate their financial statements to show the best financial performance to their capital providers. This creates a connection between the bankrupt firm and a fraudulent firm.

It is therefore desirable to find a method for detecting deteriorating financial conditions of Ghanaian companies for prudent measures to be put in place to ensure sustenance, growth, and business expansion. Therefore, the study aimed at testing the effectiveness or applicability of Altman's (2000), Taffler's (1983), and Beneish (1999) model on listed consumer goods and service companies in Ghana. As Altman and Taffler's model (Z-score) can be used best on financial statements that are not manipulated, the Beneish model (M-score) is also used to determine whether the financial statement is manipulated. Therefore, for a firm's successful analysis, there is the need to deploy the Beneish M-score model prior to the deployment of the Altman and Taffler's Z-score model. To use Beneish M-score before Altman and Taffler's Z-score model, the Beneish M-score model was first adopted to detect whether the financial statements were manipulated. Then the Altman (2000) and Taffler's (1983) Z-score model was used to determine whether the sample firms are financially distressed.

The contribution of this study is to extend the application of Altmann (2000), Tattler (1983) and Beneish (1999) Model on listed consumer goods and service companies in Ghana which has not been previously carried out in the practice for companies' failure prediction. The results of this study will further contribute to the literature on the applicability of Altman's (2000) model and Taffler (1983) model on listed companies in Ghana, and help the general public and investors on the financial health of consumer goods and service companies listed on the Ghana Stock Exchange.

2. Theoretical Framework and Literature Review

The examination of corporate failure prediction can be categorized into three broad areas: First, developing a prediction models and it often provides general index which can be used to measure the possibility of failure, such as the study of Zeytunoglu and Akarim (2013); Altman (1968); Christidis and Gregory (2010); Beaver (1966). The Second field looks at the assessment of the validity and predictive accuracy of newly developed models such as the study of Wang and Campbell (2010); Kiyak and Labanauskaite (2012); Mamo (2011) and Soon *et al.*, (2014). The third category deals with an applied investigation or studies which aim to tell the bankruptcy status of particular firms in a given country like the study of Mohammed and Soon (2012); Kenneth and Adeniyi, (2014).

This paper follows the path of the 2nd category where the Altman revised model, Taffler (1983) and Beneish (1999) model is tested on listed non-failed consumer goods and service companies in Ghana to determine the predictive accuracy and state of financial statement fraud.

2.1. Empirical Review

A number of studies have materialized to explicate corporate bankruptcy and the ability of predictive models in successfully predicting their occurrence. This section offers insight into the pieces of literature and models for forecasting business insolvency and manipulation of annual financial accounts.

The study of Patrick in 1932 is considered the earliest study in this field. The study was later extended by Beaver in 1966 and provided the first statistical model for business bankruptcy prediction. In his study Patrick used a model called "a univariate model", and 30 financial ratios were tested on 79 failed companies and 79 similar successful companies between 1954 and 1964. The study of Beaver (1966) also used 30 financial ratios among 79 failed and non-failed companies from 1954 to 1964. Beaver revealed that the most important ratio which can be used to expect bankruptcy is (Cash flow to total debt ratio) with a 78% success rate for five years before failing and 13% of the sample for one year before insolvency. Altman (1968) extended Beaver's approach by using the Z-Score model. Altman (1968) study which used 66 failed and non-failed manufacturing companies among 22 ratios were classified into five groups namely; liquidity, activity, profitability, solvency ratios, and leverage. The Z-Score model overall correctly classified 95% of the total sample, one year prior to bankruptcy.

Moreover, Kidane (2004) surveyed the portability of Springate and Altman models in forecasting financial failure in IT and service firms of South Africa from 1999 to 2003, and the results showed that the two models were abortive in predicting failure and non-failure amongst South African service firms. Odipo, and Sitati, (2010), evaluated whether Altman's model could be suitable in forecasting corporate failure in Kenya using a sample of 10 listed and delisted firms in the Nairobi Stock Exchange spanned from 1989 to 2008.The study revealed that the model could correctly predict failure in Kenya. Further studies were done by Kpodoh, (2009) to test the applicability of Altman's Z score model using data set from the communication firms in Ghana. His results confirmed the ability of the Z score model in forecasting corporate failure. Alareeni and Branson (2013) conducted a study on 71 non failed and failed firms in Jordan to test the predictive accuracy of Altman's model for the time span from 1989-2008 and the result showed that the model is effective and could predict the failure of industrial firms. However, for service firms, they found that the Altman models could not distinguish between non failed and failed companies. Therefore, Soon and Mohammed, (2012), used Altman's financial bankruptcy prediction model and current ratio to evaluate the financial situation of 44 companies listed in the Malaysia Stock Exchange for 2008 and 2009. The study concluded that Altman's model and current ratio are useful tools for investor to expect the financial failure of companies.

Naidoo and du Toit, (2007) used a two-stage approach to analyze the financial bankruptcy of listed companies. In the first stage, multi-state models were developed to expect the state of health of a company. In the second stage, a contemporary approach was used to produce underlying information independent of the first stage model, so as to enable management to make a more meaningful state of the company. The financial health of the sampled companies is accurately predicted by using these models. Moyer, (1977) verified the accuracy of Altman's model on 27 non-failed and failed firms between1965-1975. These firms were paired on the basis of industry and assets size ranging from $15million to $1billion.The result of this study indicated that the forecasting accuracy on a genuinely post-dated sample of the firm collapse was 75% a year before bankruptcy, which conflicts with the 96%, proposed by Altman (1968). In re-estimating the Altman model parameters, Moyer used a new data set and the stepwise MDA approach.

Amoah-Gyarteng, (2014) employed the Altman's modified Z-Score and Beneish Models to detects bankruptcy and financial statements fraud of AngloGold Asante for the year 2010-2012. The Beneish model revealed the company was engaged in financial statement fraud. However, Altman's model was found effective in predicting the failure of AngloGold Asante. Maccarthy, (2017) used Altman Z-Score and Beneish model to evaluates financial statements fraud and bankruptcy of Enron corporation covering the period of 1996-2000. The study revealed that the financial statements for the study period were manipulated to give a good picture of the company's performance.

Soon *et al.* (2014) used Altman's financial bankruptcy model to predict the financial difficulties of 28 companies listed on trading services sector at the stock exchange of Malaysia for the period between 2003 and 2009, and this study concluded that Altman's score can be used to differentiate between failure companies and the non-failure and that it is very useful for investors to predict financial failure of companies. Johansson and Kumbaro, (2011) used what is called "multiple discriminant analysis" on a sample of 45 American companies between 2007 and 2010 by applying Altman's model, and the study concluded that these models could predict bankrupt firms for both one and the two-year period prior to bankruptcy.

Ohson (1980) used what is called "logit analysis " for 105 bankrupt firms and 2058 non-bankrupt firms for the period from 1970 to 1976 and the results of this study show that factors such as size, current liquidity, performance, and financial structure were important determinants of company's bankruptcy. Low, Nor and Yatim (2001) used the logit model in Malaysia and the results concluded that the probability of financial bankruptcy is related to the ratio of current assets to current liabilities, the ratio of sales to current assets, and the percentage change in net income of a company. And also the study of XU, ZHAO, and BAO (2015) in China used the partial least-squares logistic regression model to estimate the early warnings of financial bankruptcy on quoted firms in the real estate sector, the results showed that the partial least-squares logistic model is accurate in detecting early warning signs of corporate failure due to its elimination of multicollinearity problem as paralleled to the logistic regression model. Premachandra, Watson, and Chen (2011) used what is called the "data envelopment analysis" (DEA) model as a tool for predicting corporate failure and success. The results concluded that the DEA model is relatively weak in predicting corporate failures.

Gepp, A. and Kumar, (2015) used decision tree software called Classification and Regression Trees (CART) and the conclusions provided empirical evidence to support the use of survival analysis and decision tree techniques in financial bankruptcy warning systems that are very useful to most institutions in the financial market**.** Charitou *et al*. (2004) examined the incremental information content of operating cash flows in predicting organization bankruptcy by using logit analysis and neural networks on 51 matched pairs of failed and non-failed of United Kingdom companies from 1988 to 1997. They developed a parsimonious model with three financial ratios namely; financial leverage, profitability, and operating cash flow that resulted in an overall classification accuracy of 83%.

There are some studies that are conducted on mining companies that also used various financial bankruptcy predicting models. Such as Zlatanovic et al. (2016) that used the Altman Z-score model to study on a sample of two mining companies in Serbia. The conclusions of this study indicated that one of the two mines companies was in a state of financial bankruptcy. In addition, Saden and Prihatiningtias (2015) focused on 18 different mining companies listed on the Indonesian Stock Exchange, where some mining companies appeared to show signs of financial bankruptcy.

Some studies were conducted in South Africa that used several financial bankruptcy predictive models. For instance, Hlahla (2010) conducted a study on a sample of 28 companies listed on the Johannesburg Securities Exchange (JSE). The companies were grouped into failed and non-failed companies by using means of multiple discriminant analysis following normality tests. Three variables namely; cash to debt, working capital, and times interest earned to turnover was found to be significant. The model classified about 75% of failed and non-failed companies in the original and cross-validation procedures.

2.2.1. Theoretical Framework-Altman's (2000) Revised Model

This model was developed by Professor Edward Altman in the year 2000. The original Altman Z-score was later modified to overcome its shortcoming.

$$ALTMAN\ (Z) = 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4 + 0.998X5 \qquad (2.2.1.1)$$

The Altman Z-score model can now be used for both manufacturing and non-manufacturing, private companies and for those listed on the emerging markets. The model, for some reason, appears to create a lot of mixed emotions; some of these emotions are in favour of it while others are against it. The study of Grice and Ingram (2001) indicated that the accuracy of the Altman Z-score model is significantly lower in recent periods than reported in Altman's study. Most criticisms against this model focus on its over-reliance on accounting data; focus on failure rather than sustainability of the business; inadequate recognition of cash-flow as a relevant component; lack of consideration on non-financial ratios; the need for industry-specific or geography-specific model types and the danger of flexible interpretation or manipulation of financial results resulting in "window dressing" or inappropriate favourable report of financial position (Wilkinson, 2009). The first shortcoming of the Altman Z-score model necessitated for industry-specific or geography-specific model types. Specific industries have different characteristics; hence it would not be suitable to apply a general model for all these industries. This model assumes that financial ratios are taken from public financial information and that will be accurate. According to Panneerselvam, (2008). Firms in financial bankruptcy manipulate their financial statements to show good performance. Therefore, errors in these secondary data will influence the level of accuracy of the outcomes and will not be suitable for the present purpose. The interpretation of the Z-score as presented by Professor Altman's theory indicates that overall Score more than 2.9 represents a zone of creditworthiness or financial soundness. However, a score below 1.23 is classified as an insolvency or liquidation zone (Failed zone). Finally, the gap between 1.23 and 2.9 is the Zone of Ignorance or uncertainty.

$$X1 = (WORKING\ CAPITAL\ )/(TOTAL\ ASSETS) \qquad (2.2.1.2)$$

The working capital is ascertained by subtracting current liabilities from the current asset. This matrix of X_1 is used to estimates the net liquid asset as a ratio of the total book value of identifiable assets. In the ideal situation, continuous operating losses can lead to a deterioration of current assets with respect to total Assets.

$$X2 = (ACCUMULATED\ RETAINED\ PROFIT\ )/(TOTAL\ ASSETS) \qquad (2.2.1.3)$$

The matrix X_2 measures the firm-level leverage and it embodies the reinvest profit into the asset. The logic behind X_2 is that the accumulated profit of a firm is subject or prone to falsifications because of the reorganization and disbursement of dividends.

$$X3 = (OPERATING\ PROFIT\ )/(TOTAL\ ASSETS) \qquad (2.2.1.4)$$

The relation (X_3) examines the efficient utilization of assets in creating of worth. A lower ratio is an indication of inefficiency in the utilization of the company's assets. The ratio, therefore, produces the cash available for creditors settlement, Government and shareholder's payments.

$$X4 = (BOOK\ VALUE\ OF\ EQUITY\ )/(BOOK\ VALUE\ OF\ LIABILITIES) \qquad (2.2.1.5)$$

The book value of equity is calculated by adding the book value of ordinary and preference shares whereas the book value of total debts is estimated as either the addition of current and non-current debt or the total of long-term debts. The variable X_4 is the reversal of the equity ratio.

$$X5 = (TOTAL\ REVNUE)/(TOTAL\ ASSETS) \qquad (2.2.1.6)$$

This is the ratio that defines the activity of sales and assets. This ratio is used to assess the ability of asset in generating profit or earnings. Though the impact of X_5 was underscored by Altman (2000) however, it's inclusion will enhance the predictive ability of the Model.

2.2.2. Taffler (1983) Z-Score (Model 2)

Professor Taffler in 1983 suggested in his studies that failure models should reflect certain key variables of corporate solvency and performance such as profitability, working capital adequacy, financial risk, and liquidity. He thus formulated his Z-score as:

$$Z = 0.53X1 + 0.13X2 + 0.18X3 + 0.16X4 \qquad (2.2.2.1)$$

Where:

$X1$= *(PROFIT BEFORE TAX)/(CURRENT LIABILITIES)* *(2.2.2.2)*
$X2$= *(CURRENT ASSET)/(TOTAL LIABILITIES)* *(2.2.2.3)*
$X3$ *=(CURRENT LIABILITIES)/(TOTAL ASSET)* *(2.2.2.4)*
X4=(QUICK ASSET-CURRENT LIABILITY)/(OPERATING COST-DEPRECIATION) *(2.2.2.5)*

The weight $\mathbf{X_1}$, $\mathbf{X_2}$, $\mathbf{X_3}$, and $\mathbf{X_4}$ in the model are the explanatory variables employed to estimates the explained variable (Z- Value) in the model. $\mathbf{X_1}$ represents a measure of profitability, $\mathbf{X_2}$ is a measure of working capital position, $\mathbf{X_3}$, on the other hand, is a measure of financial risk and finally, $\mathbf{X_4}$ denotes the number of credit intervals. The benchmark for Taffler's model is subjected to Negative (-) and positive (+). A negative (-) score means the company has a financial profile similar to the previously failed business. While a positive (+) score indicates the company is safe from insolvency risk.

2.2.3. Beneish 1999 M-Score (Model 3)

Recent collapses of prominent businesses such as WorldCom, Lehman Brothers, and Enron Corp and many others despite their good looking financial statements provides justification that most financial statements published by organisations are prone to manipulations and fraud. Therefore, in other to guarantee shareholders, creditors, and bankers protections in their evaluations, required a balancing scientific tool to provides check and balances to the Z-Score Models. With this in mind, Professor Beneish developed a model called (M-score) in 1999. The model gained recognition and is widely used to spot areas of possible manipulation on the firm's financial statements by practitioners (accountants, auditors, and particularly the SEC). The overarching aim of the model is to bring forth companies that engages in financial statements fraud.

The model was developed base on eight variable estimated from the financial statements with an intercept. This study employed the same principles to obtained the eight variables from the firm's financial statements and used to determine the M-score of this companies. When an M-score is greater than -2.22 indicates that the firm's financial statements may have been manipulated (Warshavsky, 2012). Hence, when the score that is obtained from the computation of the eight variables from understudy firm's financials is greater than the cut-off point of negative 2.22, then it concludes that the financial statements were manipulated. M-score model is a probability model, and such cannot provide 100% justification (MacCarthy, 2017). Beneish concluded that it is possible to determine 76% manipulators accurately and 17.5% incorrectly is considered as non-manipulator. According to Beneish *et al.*, (1999), the indices have varying rationales as described below.

$$BENEISH\ (M) = -4.84 + (0.92 * DRI) + (0.528 * GMI) + (0.404 * AQI) + (0.892 * RGI) + (0.115 * DEPI) - (0.172 * SGAI) + (4.679 * TATA) - (0.327 * LVGI) \qquad (2.2.3.1)$$

where:

Day Sales Receivable Index (DRI)

This index measures the ratio of A/C receivable stability with the variations in revenue. The bench mark is set between 1.031 and 1.465. A score below or equal 1.031 is an indication of fraud free financial statements. However, a score of 1.465 and above represent a manipulated financial statement. When this does not show a fair consistent trend then it suggests that either the majority of revenue is on credit terms rather than cash or the company has difficulty in the collection of receivables (MacCarthy, 2017). A rising DRI may be the perfect legal activity of the firm extending more credit to customers and the firms that overstated revenue. Therefore, a sharp rise in the DRI score provides signals to auditors that, the financial statements of the firms are manipulated or terms of credit have changed. Empirically described as:

$$DRI = \frac{\text{ACCOUNT RECEIVABLE(CY)/SALES(CY)}}{\text{ACCOUNT RECEIVABLE(PY)/SALES(PY)}} \qquad (2.2.3.2)$$

Gross Margin Index (GMI)

According to Harrington, (2005), the GMI score of 1.041 or lower suggests gross profit of the current period is not manipulated however a score of 1.193 is an indication that gross profit of the firm is manipulated. Financial Analyst orated that earning quality is considered a very important aspect for assessing the firm's financial fitness and therefore, can create an avenue for earnings manipulations especially when performance is downgraded (MacCarthy, 2017). The numerical representation is shown below.

$$GMI = \frac{\text{Sales(PY) - Cost oF Sales(PY)/Sales(PY)}}{\text{Sales(CY) - Cost oF Sales(CY)/Sales(CY)}} \qquad 2.2.3.3$$

Asset Quality Index (AQI)

The AQI is calculated as the percentage of total assets of the current year (CY) to the preceding year (PY). According to Pustylnick (2009) cited by MacCarthy, (2017), a ratio greater than 1.0 is a signal of overheads and intangible assets capitalization. Harrington 2005, suggested that growth in AQI suggests additional expenses have been capitalized to avoid writing-off to the comprehensive income statement in order to preserve profit. This is the mathematical representation;

$$AQI = \frac{\text{Total Asset - PPE(cy)/Total Asset(cy)}}{\text{Total Asset - PPE(Py)/Total Asset(Py)}} \qquad (2.2.3.4)$$

Sales Growth Index (SGI)

SGI is calculated by dividing sales or revenue for the current year (CY) by sales or revenue of the preceding year (PY). Benchmark value of 1.134 or below forecast non-manipulation and a value above 1.607 predicts the possibility of sales or revenue manipulations. Harrington (2005) noted that, firms with higher growth rate find themselves highly motivated to commit fraud when the trends reverse. Below is the mathematical representation;

$$SGI = \frac{\text{Sales(cy)}}{\text{Sales(py)}} \qquad (2.2.3.5)$$

Depreciation Index (DEPI)

DEPI is calculated as the ratio of the depreciation expense against the firm's value of PPE in the current year against that of the preceding year. DEPI ratio of 1.001 or lower is an indication of DEPI manipulations. However, a score above 1.077 indicates the value of the assets has been revalued or the useful life of the assets has been adjusted upward (Beneish, 1999). The ratio is described as follows:

$$DEPI = \frac{\text{Depreciation. exp (cy)/Depreciation. exp + PPE(cy)}}{\text{Depreciation. exp (py)/Depreciation. exp + PPE(py)}} \qquad (2.2.3.6)$$

Sales, General, and Administrative Expenses Index (SGAI)

SGAI is the ratio of sales, general and administrative expenses for the current year over the preceding year. When a score of 1.001 or below is obtained, it indicates that SGAI has not been manipulated. According to Lev, and Thiagarajan. (1993), a disproportional increase in SGAI is considered as an indicator of a negative signal about the firm's upcoming prospects. A positive relation gives an indication of possible manipulations.

$$SGAI = \frac{\text{Sales, General and Administrative Cost (cy)/Sales (cy)}}{\text{Sales, General and Administrative Cost (py)/Sales (py)}} \qquad (2.2.3.7)$$

Leverage Index (LEVI)

LEVI can be used to measure the firm's ratio in terms of total debt to total assets for the current year is divided over the preceding year's ratio. When a LEVI is greater than 1 it indicates there is an increase in leverage position in the firm and that the firm has taken more debt to operate or to run the business for the period under review. Empirically;

$$LEVI = \frac{TotalLiability}{TotalAsset} \qquad (2.2.3.8)$$

Total Accruals to Total Assets Index (TATAI)

TATAI is the ratio of change in working capital other than cash and less depreciation. The increase in TATAI may indicate that goodwill and amortization numbers in the financial statements of the company have been tampered with. When a mean score is 0.018, it indicates there are non-financial manipulations in respect of TATAI while as a mean score of 0.031 and above is an indicator that the financial data have been tampered with. Mathematically presented as:

$$TATAI = \frac{\text{Working Capital - Depreciation}}{\text{Total Asset}} \quad (2.2.3.9)$$

3. Methodology

3.1. Sample and Research Method

The study adopted Altman (2000), Taffler (1983) and Beneish (1999) style of predicting corporate failure and detecting financial statement fraud using 17 listed consumer goods and service companies in Ghana. The study evaluates the effectiveness of Altman, Taffler, and Beneish M-Score model in predicting failure and detecting earnings manipulation in a survey setting. The study uses numerical investigation on the dataset extracted from the financial position (Balance sheet), and Comprehensive income statement (profit and loss account) of the sample firms. The financial statements were taken from the website of the companies, Ghana Stock Exchange(GSE) and Annual Report Ghana. The time spinning from 2014 to 2018 was considered as the covered period for the study and long enough to detect any financial or insolvency risk. The selection of the consumer goods sector was purposively considered by the authors due to the current instability and inefficiency in the sector. The analytical tools adopted for this study include; excel for the computations of variables, Z-Scores, M-score and Eviews version ten for descriptive and correlation analysis. Altman (2000) Z-Score and Taffler (1983) Z-Score model were applied for the detection and establishment of the financial soundness of the firms under review. And the Beneish M-Score model was employed to investigates the possibility of earnings Manipulations for the understudy years.

3.2. Hypotheses

All the empirical theories and studies being highlighted in the literature such as Sulub S.A (2014), Soon *et. al,* (2014), Soon and Mohammed (2012), Gyimah, P. and Boachie (2018), Naidoo and du Toit, (2007), Alareeni and Branson (2013) and Maccarthy (2017) -have proved that Altman Z-Score model can successfully predict corporate failure particularly in the presence of error-free financial statements. According to Zavgren, (1985), MDA models are suitable to a certain extent in predicting company bankruptcy. As a result, a more suitable approach based on less or no assumption should be considered apparent; other methods should rank alongside the above statistical tools, which motivated the inclusion of Beneish (1999) and Taffler (1983) model. According to Macarthy 2017, Gyarteng 2014, and Beneish 1999 which concluded that financial ratios taken from public financial information will not be accurate considering the fact that firms with financial distress manipulate their financials to show healthier performance as in the case of Enron Corporation. Consequently, manipulations in these financial data will affect the level of accuracy of the outcomes and will not be appropriate for the failure prediction (Panneerselvam, 2008). Giving the background, the hypotheses of the study can be specified as follows:

H_1: Altman's (2000) model can accurately predict the bankruptcy status of the listed consumer goods and service companies in Ghana.

H_2: Taffler's (1983) model can accurately predict the bankruptcy status of the listed consumer goods and service companies in Ghana.

H_3: The annual financial statements published by the sample firms are likely to exhibit signs of manipulation.

4.Empirical Results

4.1. Descriptive Statistics

Table, -1 provides a summary of the descriptive statistics of the explanatory variables for all the Models employed for this study. This report the average indicators of variables computed from the annual financial statements for the sample firms. The working capital/total assets (X1), retained earnings/total assets (X2), earnings before interest and taxes/total assets (X3), market value of equity/book value of total debt (X4) and sales/total assets (X5) reveals an average of **-0.078**, **0.158, 0.202, 1.354** and **1.999** respectively for Altman computations. These results suggest a poor performance in working capital management during the period under study. However, operating profit/current liability (x1), current asset/total liabilities (x2), current liabilities/total asset (x3), and credit interval (x4) reported an average of 80%, 92%, 29%, and 53% respectively as indicated by Taffler's Computations. The results suggest a good performance in working capital positions and profitability ratio with a lower financial risk ratio. Finally, the Beneish model recorded the highest variable mean score value of **1.790** with a maximum of **43.601** and this score is attributed to Sales, General, and administrative expenses index (SGAI). This indicates a high probability of **SGAI** manipulation since it is greater than the benchmark figure of **1.041**.

Tables- 2, 3, and 4, provide summary of the descriptive statistics of the explained variables (Z-Scores and M-Score). The tables report the average of Z-Scores and M-Scores computed from the annual financial statements for the period under review. From **Table 2,** it can be observed that the Z-score reported banks chronicled a maximum value of 12.817 in 2014 and a minimum value of **-0.295** in 2018. Except for the year 2014, the mean Z-score recorded the least value of 3.098 in 2018 and this observation could possibly mean the firms were financially not healthy in the year 2018 as compared to the remaining years under review. The results presented in **table 3** recorded a maximum Z-score of 17.088 in 2018 and a minimum of **-2.102** in 2017. However, the mean z- score recorded the least value **0.146** in 2014 followed by 2017 then 2015, and 2016, and the highest mean (1.899) was recorded in 2018. This result may indicate a sign of financial distressed among the firms in the year 2014 according to Taffler's Z- scores and the observation is contrary to that of Altman model (see table 2 above). Finally, Beneish M-score (**Table 4**), registered a maximum M-Score of 6.443 in 2014 and a minimum of -7.911 in 2018. However, the mean M-Score recorded a peak value of **-1.457** in 2016 and the lowest value of **-2.262** in 2015. This result illustrates a clear indication of higher earnings manipulations in **2016** among the sample firms.

Table 1. *Descriptive statistics of the independent variables for all Models*

ALTMANMODEL 2014-2018								
STATISTICS	**X1**		**X2**		**X3**		**X4**	**X5**
Mean	(0.078)		0.158		0.202		1.354	1.999
Median	0.077		0.176		0.052		0.890	0.989
Maximum	0.823		1.683		1.259		6.122	12.126
Minimum	(5.859)		(0.680)		(0.324)		(0.104)	0.054
Std. Dev.	0.883		0.351		0.304		1.318	2.228
TAFFLER MODEL (2) 2014-2018								
STATISTICS	**X1**		**X2**		**X3**		**X4**	
Mean	0.800		0.923		0.299		0.536	
Median	0.220		0.767		0.275		(0.073)	
Maximum	6.673		5.547		0.818		103.394	
Minimum	(1.023)		0.032		0.046		(14.536)	
Std. Dev.	1.405		0.833		0.192		11.727	
BENEISH MODEL (3) -2018								
STATISTICS	**DSRI**	**GMI**	**AQI**	**SGI**	**DEPI**	**SGAI**	**TATAI**	**LEVI**
Mean	1.259	1.048	1.062	1.006	1.441	1.790	0.022	0.512
Median	1.040	0.998	1.008	1.019	1.023	0.990	0.040	0.528
Maximum	12.543	5.840	4.104	1.916	10.804	43.601	0.689	1.116
Minimum	0.045	(4.790)	0.318	0.009	0.002	0.009	(1.228)	0.039
Std. Dev.	1.408	1.304	0.474	0.325	1.800	4.912	0.284	0.192

Source: Financial Reports (2014 – 2018)

Table 2. *Descriptive statistics (Altman Z-Scores)*

	MEAN	**MEDIAN**	**MINIMUM**	**MAXIMUM**	**Std.Dev.**
2014	3.458	2.272	0.322	12.817	3.237
2015	3.394	3.156	0.910	8.979	2.374
2016	3.198	2.851	0.857	8.119	1.728
2017	3.190	2.964	0.218	9.535	2.183
2018	3.098	3.058	(0.295)	7.448	2.012

Table 3. *Descriptive Statistics (Taffler Z-Scores)*

	MEAN	**MEDIAN**	**MINIMUM**	**MAXIMUM**	**Std.Dev.**
2014	0.146	0.166	(1.310)	1.967	0.708
2015	0.460	0.287	(2.077)	2.015	0.950
2016	0.476	0.467	(1.723)	2.310	0.996
2017	0.431	0.434	(2.102)	2.098	0.881
2018	1.899	0.602	(0.008)	17.088	4.053

Table 4. *Descriptive Statistics (Beneish M-Score).*

	MEAN	**MEDIAN**	**MINIMUM**	**MAXIMUM**	**Std.Dev.**
2014	(2.251)	(3.217)	(5.708)	6.443	3.055
2015	(2.262)	(2.712)	(6.732)	2.620	2.120
2016	(1.457)	(1.575)	(3.987)	1.512	1.329
2017	(2.037)	(2.061)	(3.828)	(0.372)	1.013
2018	(2.021)	(1.375)	(7.911)	1.421	2.180

Source: Financial Reports (2014 – 2018)

4.2 Correlation Matrix Analysis

4.2.1. Correlation of the Independent Variables to the Z-Scores

The correlation of the independent variables to the Z-Scores basically explain what variables or ratios are the main drivers of the Z-score. Therefore, knowing the main drivers of the Z-scores, management can enhance those ratios or variables to affect the performance of the firm. Table, - 5 (Altman Model) shown a strong correlation between asset turnover ratio (X5) and Z- Score, suggesting that, a high asset turnover ratio was a major driver for the Z-Score determination. Except for working capital/Total asset (x1) and market value of equity/total debt (X4) which showed a negative correlation with the Z-Score, the remaining ratios x2 and x3 indicated a weak positive correlation with the Z-Score.

Table, -6 (Taffler's model) revealed a strong positive correlation between credit interval (x4) and the Z-Score indicating that credit interval is the major determinants of business survival. However, with the exception of the financial risk ratio (x3), the remaining ratios (profitability and working capital position) indicated a weak positive correlation with the Z-Score.

Table 5. *Correlation matrix of independent variables to the Z-scores (Altman-Model)*

	X1	X2	X3	X4	X5	ZSCORE
X1	1	0.173	-0.273	0.16	-0.285	-0.051
X2	0.173	1	0.16	0.028	-0.046	0.204
X3	-0.273	0.16	1	-0.239	0.122	0.413
X4	0.16	0.028	-0.239	1	-0.259	-0.059
X5	-0.285	-0.046	0.122	-0.259	1	0.866
Z-SCORE	-0.051	0.204	0.413	-0.059	0.866	1

Source: Financial Reports (2014 – 2018)

Table 6. *Correlation matrix of independent variables to the Z-scores (Taffler-Model 2)*

	X1	X2	X3	X4	Z-SCORE
X1	1	-0.11	-0.139	-0.036	0.325
X2	-0.11	1	0.006	0.418	0.399
X3	-0.139	0.006	1	-0.072	-0.101
X4	-0.036	0.418	-0.072	1	0.932
Z-SCORE	0.325	0.399	-0.101	0.932	1

Source: Financial Reports (2014 – 2018)

Table, - 7 presents the correlation results of the independent variables to the M-Score computed using Beneish Model. The results indicated a significant positive correlation between total accruals to total asset index (TATAI), days Sales receivable index (DSRI), Gross margin index (GMI), Asset quality index (AQI), and Sales growth index (SGI) to M-Score. However, Sales, General and Administration index (SGAI), leverage index (LEVI), and depreciation index (DEPI) showed a significant negative correlation to the M-Score.

The result suggests TATAI as the major driver for earnings Manipulations among the sample firms. In general, we observed that all the independent variables of the models are substantially correlated with the dependent variables (Z and M scores), and this guarantees the suitability and reliability of Altman (2000), Taffler (1983) and Beneish (1999) models, meaning the explanatory variables are important factors for determining the Z and M Scores.

Table 7. *Correlation matrix of the independent variables to M-scores (Beneish Model)*

	DSRI	**GMI**	**AQI**	**SGI**	**DEPI**	**SGAI**	**LEVI**	**TATAI**	**M-SCORE**
DSRI	1	0.039	0.136	-0.079	-0.064	0.477	0.111	0.057	0.48
GMI	0.039	1	0.339	-0.185	-0.052	0.005	-0.079	0.004	0.366
AQI	0.136	0.339	1	-0.247	0.026	-0.055	-0.09	0.148	0.384
SGI	-0.079	-0.185	-0.247	1	-0.004	-0.072	-0.024	0.215	0.177
DEPI	-0.064	-0.052	0.026	-0.004	1	0.039	0.16	-0.157	-0.078
SGAI	0.477	0.005	-0.055	-0.072	0.039	1	0.059	0.034	-0.101
LEVI	0.111	-0.079	-0.09	-0.024	0.16	0.059	1	-0.472	-0.314
TATAI	0.057	0.004	0.148	0.215	-0.157	0.034	-0.472	1	0.717
M-SCORE	0.48	0.366	0.384	0.177	-0.078	-0.101	-0.314	0.717	1

4.2.2 Correlation of Z-scores (Altman and Taffler) to Beneish M-Score

The rationale of knowing the correlation between Z-Scores and Beneish M-Score will go a long way to assist scholars and management in decision making. To scholars, it will give reasons for the need to use both models in corporate failure prediction research. Management, shareholders, auditors, and investors on the other hand will appreciate the importance of using Altman and Taffler's model to assess the performance of corporate entities. As reported in Table, - 8 below, it can be observed that there is a significant positive correlation between Beneish M-Score and the Z-Scores models employed for this study (Altman 2000 and Taffler 1983 model). Note, the fact there is such a positive correlation between the Z-Scores and the M-Score serves as a reasonability check, as the upwards trend in M-Score indicates the possibility of earning manipulations. Hence, a positive correlation suggests that the firms under review manipulate their financial statements to vehicle a good performance. Therefore, as the banks manipulate their earnings, Altman and Taffler's Z-Scores improve from distress to safe zone.

Table 8. *Correlation matrix of the Z-scores (Altman and Taffler) to Beneish M-Score*

	BENEISH M-SCORE	ALTMAN Z-SCORE	TAFFLER Z-SCORE
BENEISH M-SCORE	1	0.009	0.231
ALTMAN Z-SCORE	0.009	1	0.118
TAFFLER Z-SCORE	0.231	0.118	1

Source: Financial Reports (2014 – 2018)

4.3 Z-Models and Scores Analysis

Examining the annual financial statements using Altman and Taffler Z-Scores provides justifications for appreciating the outcomes of business operations and understands how well the firm has performed. In this regard, Altman (2000) and Taffler (1983) Z-Score models were employed to examine the bankruptcy status of 17 listed consumer Goods and service sectors in Ghana.

Table 9. *Results of Z-Score using Altman's (2000) Model*

COMPANY CODE	2014	2015	2016	2017	2018	AVERAGE
	Z-SCORE	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**
PZ	2.224	3.966	3.633	3.721	3.559	**3.421**
CMLT	5.805	3.781	4.085	4.622	2.73	**4.205**
ALW	4.487	2.852	1.451	3.513	4.244	**3.309**
BOPP	1.683	3.247	2.709	2.964	2.315	**2.584**
CPC	2.272	1.459	1.212	0.218	0.638	**1.160**
FMLK	3.112	3.702	4.347	4.006	3.273	**3.688**
GGBL	8.751	8.893	8.119	9.535	7.234	**8.506**
SWL	0.322	1.447	2.761	1.06	-0.295	**1.059**
MMH.GH	0.815	1.023	2.882	1.817	3.008	**1.909**
HORD	1.978	1.634	2.579	1.567	2.114	**1.975**
MLC	1.133	2.048	2.929	2.983	3.271	**2.473**
DIGICUT	0.652	0.91	0.857	1.163	1.02	**0.921**
PBC	1.719	2.278	2.317	2.113	3.156	**2.317**
SAMBA	2.361	3.406	2.242	2.102	1.623	**2.347**
ACI	3.526	3.156	3.826	4.402	4.267	**3.835**
UNIL	12.817	8.979	5.561	5.784	7.448	**8.118**
AYRTON	5.121	4.919	2.851	2.664	3.058	**3.722**

***Table 10**. Results of Z-Score using Taffler (1983) Z-Score Model*

COMPANY CODE	2014	2015	2016	2017	2018	AVERAGE
	Z-SCORE	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**
PZ	0.369	0.933	0.945	0.818	0.756	**0.764**
CMLT	0.306	0.248	2.021	0.086	2.108	**0.954**
ALW	(1.089)	(2.077)	(1.723)	(2.102)	1.420	**(1.114)**
BOPP	0.234	0.890	0.472	0.664	0.661	**0.584**
CPC	(1.310)	0.458	0.467	0.379	0.602	**0.119**
FMLK	0.563	0.700	0.818	0.722	0.330	**0.627**
GGBL	1.967	1.987	1.822	2.098	3.173	**2.209**
SWL	(0.306)	(0.290)	0.486	0.131	0.048	**0.014**
MMH.GH	0.166	0.064	2.310	1.002	3.585	**1.425**
HORD	0.202	1.139	(0.880)	1.596	17.088	**3.829**
MLC	0.063	0.209	0.653	0.647	0.514	**0.417**
DIGICUT	0.089	0.106	(0.453)	(0.006)	0.023	**(0.048)**
PBC	0.138	(0.244)	0.405	0.396	0.576	**0.254**
SAMBA	(0.163)	2.015	0.071	(0.448)	(0.008)	**0.293**
ACI	0.274	0.287	0.084	0.589	0.396	**0.326**
UNIL	0.833	0.084	0.177	0.317	0.328	**0.348**
AYRTON	0.150	1.308	0.413	0.434	0.680	**0.597**

Source: Financial Reports (2014 – 2018)

***Table 11.** Firms correctly classified as Safe on a year-on-year Z-score (Altman Model)*

	2014		**2015**		**2016**		**2017**		**2018**	
	CODE	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**
	CMLT	5.805	PZ	3.966	PZ	3.633	PZ	3.721	PZ	3.559
	ALW	4.487	CMLT	3.781	CMLT	4.085	CMLT	4.622	ALW	4.244
	FMLK	3.112	BOPP	3.247	FMLK	4.347	ALW	3.513	FMLK	3.273
	GGBL	8.751	FMLK	3.702	GGBL	8.119	BOPP	2.964	GGBL	7.234
	ACI	3.526	GGBL	8.893	MLC	2.929	FMLK	4.006	MMH.GH	3.008
	UNIL	12.817	SAMBA	3.406	ACI	3.826	GGBL	9.535	MLC	3.271
	AYRTON	5.121	ACI	3.156	UNIL	5.561	MLC	2.983	ACI	3.835
			UNIL	8.979			ACI	4.402	UNIL	8.118
			AYRTON	4.919			UNIL	5.784	AYRTON	3.722
No. of firms	**7**		**9**		**7**		**9**		**9**	
%	**41%**		**53%**		**41%**		**53%**		**53%**	

Source: Financial Reports (2014 – 2018)

***Table 12.** Firms classified into Grey zone on a year-on-year Z-score (Altman Model).*

	2014		**2015**		**2016**		**2017**		**2018**	
	CODE	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**
	PZ	2.224	ALW	2.852	ALW	1.451	MMH	1.817	CMLT	2.73
	BOPP	1.683	CPC	1.459	BOPP	2.709	HORD	1.567	BOPP	2.315
	CPC	2.272	SWL	2.761	SWL	2.761	PBC	2.113	HORD	2.114
	HORD	1.978	MMH	2.882	MMH	2.882	SAMBA	2.102	SAMBA	1.623
	PBC	1.719	HORD	2.579	HORD	2.579	AYRTON	2.664		
	SAMBA	2.361	MLC	2.048	PBC	2.317				
			PBC	2.278	SAMBA	2.242				
					AYRTON	2.851				
No. of firms	**6**		**7**		**8**		**5**		**4**	
%	**35%**		**41%**		**47%**		**29%**		**24%**	

Source: Financial Reports (2014 – 2018)

Table 13. *Firms correctly classified as Safe using Average Z-Scores (Altman model)*

	COMPANY CODE	AVERAGE Z-SCORE
	PZ	3.421
	CMLT	4.205
	ALW	3.309
	FMLK	3.688
	GGBL	8.506
	ACI	3.835
	UNIL	8.118
	AYRTON	3.722
No. of firms	**8**	
%	**47%**	

Table 14. *Firms classified into Grey zone using average z-Scores (Altman Model)*

	COMPANY CODE	AVERAGE Z-SCORE
	BOPP	2.584
	MMH.GH	1.909
	HORD	1.975
	MLC	2.473
	PBC	2.317
	SAMBA	2.347
No. of firms	**6**	
%	**35%**	

Source: Financial Reports (2014 – 2018)

Table 15. *Non-Failed Firms classified as failed on year-on-year Z-Score (Altman model) (Type II Error)*

	2014		2015		2016		2017		2018	
	CODE	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**
	SWL	0.322	MMH	1.023	CPC	1.212	CPC	0.218	CPC	0.638
	MMH.GH	0.815	DIGICUT	0.91	DIGICUT	0.857	SWL	1.06	SWL	-0.295
	MLC	1.133					DIGICUT	1.163	DIGICUT	1.02
	DIGICUT	0.652								
No. of firms	**4**		**2**		**2**		**3**		**3**	
%	**24%**		**12%**		**12%**		**18%**		**18%**	

Source: Financial Reports (2014 – 2018)

Table 16. *Non-Failed Firms classified as failed using average Z-Score (Altman model).*

	COMPANY CODE	AVERAGE Z-SCORE
	CPC	1.160
	DIGICUT	0.921
	SWL	1.059
No. of firms	**3**	
%	**18%**	

Source: Financial Reports (2014 – 2018)

Table 17. *Firms correctly classified as Safe on year-on-year Z-Score. (Taffler model)*

	2014		**2015**		**2016**		**2017**		**2018**	
	CODE	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**
	PZ	0.369	PZ	0.933	PZ	0.945	PZ	0.818	PZ	0.756
	CMLT	0.306	CMLT	0.248	CMLT	2.021	CMLT	0.086	CMLT	2.108
	BOPP	0.234	BOPP	0.890	BOPP	0.472	BOPP	0.664	ALW	1.420
	FMLK	0.563	CPC	0.458	CPC	0.467	CPC	0.379	BOPP	0.661
	GGBL	1.967	FMLK	0.700	FMLK	0.818	FMLK	0.722	CPC	0.602
	MMH.GH	0.166	GGBL	1.987	GGBL	1.822	GGBL	2.098	FMLK	0.330
	HORD	0.202	MMH.GH	0.064	SWL	0.486	SWL	0.131	GGBL	3.173
	MLC	0.063	HORD	1.139	MMH	2.310	MMH.GH	1.002	SWL	0.048
	DIGICUT	0.089	MLC	0.209	MLC	0.653	HORD	1.596	MMH	3.585
	PBC	0.138	DIGICUT	0.106	PBC	0.405	MLC	0.647	HORD	17.088
	ACI	0.274	SAMBA	2.015	SAMBA	0.071	ACI	0.589	MLC	0.514
	UNIL	0.833	ACI	0.287	ACI	0.084	UNIL	0.317	DIGICUT	0.023
	AYRTON	0.150	UNIL	0.084	UNIL	0.177	AYRTON	0.434	PBC	0.576
			AYRTON	1.308	AYRTON	0.413	PBC	0.396	ACI	0.396
									UNIL	0.328
									AYRTON	0.680
No. of firms	**13**		**14**		**14**		**14**		**16**	
%	**76%**		**82%**		**82%**		**82%**		**94%**	

Source: Financial Reports (2014 – 2018)

Table 18. *Non-Failed Firms classified as failed on the year-on-year score (Taffler)*

	2014		2015		2016		2017		2018	
	CODE	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**	**CODE**	**Z-SCORE**
	ALW	(1.089)	PBC	(0.244)	ALW	(1.723)	ALW	(2.102)	SAMBA	(0.008)
	SWL	(0.306)	SLW	(0.290)	HORD	(0.880)	DIGICUT	(0.006)		
	BOPP	(0.163)	ALW	(2.077)	BOPP		SAMBA	(0.448)		
No. of firms	**3**		**3**		**3**		**3**		**1**	
%	**18%**		**18%**		**18%**		**18%**		**6%**	

Source: Financial Reports (2014 – 2018)

Table 19*. Firms correctly classified using Average Z-Scores (Taffler model)*

	COMPANY CODE	**AVERAGE Z-SCORE**
	PZ	0.764
	CMLT	0.954
	BOPP	0.584
	CPC	0.119
	FMLK	0.627
	GGBL	2.209
	SWL	0.014
	MMH.GH	1.425
	HORD	4.181
	MLC	0.417
	PBC	0.254
	SAMBA	0.293
	ACI	0.326
	UNIL	0.348
	AYRTON	0.597
No. of firms	**15**	
%	**88%**	

Source: Financial Reports (2014 – 2018)

Table 20. *Non-Failed Firms classified as failed by Taffler's model using average Z-Score*

	COMPANY CODE	AVERAGE Z-SCORE
	ALW	(1.114)
	DIGICUT	(0.048)
No. of firms	**2**	
%	**12%**	

Source: Financial Reports (2014 – 2018)

4.4 M-Score Model Analysis

Investigating the accuracy of annual financial statements used for computing the Z-Score provides explanations for appreciating and assessing whether earnings were manipulated. To achieved these, the Beneish M-Score model was employed to establish whether the annual statements were manipulated and the output is presented below in Tables 21, 22, and 23.

Table 21. *Results of M-Score (Beneish 1999).*

COMPANY CODE	2014 **M-SCORE**	2015 **M-SCORE**	2016 **M-SCORE**	2017 **M-SCORE**	2018 **M-SCORE**	AVERAGE **M-SCORE**
PZ	(3.611)	(2.712)	(1.575)	(2.591)	(3.084)	**(2.715)**
CMLT	(2.709)	(2.842)	(2.326)	(2.621)	(1.964)	**(2.492)**
ALW	(3.373)	(3.322)	(3.987)	(3.252)	(5.485)	**(3.884)**
BOPP	6.443	(6.732)	(1.287)	(1.901)	(7.911)	**(2.278)**
CPC	(5.708)	2.620	0.793	(2.205)	0.293	**(0.841)**
FMLK	(3.217)	0.034	(1.906)	(0.867)	(1.209)	**(1.433)**
GGBL	2.783	(2.195)	(1.961)	(2.061)	(0.972)	**(0.881)**
SWL	(2.954)	(3.024)	1.512	(3.828)	(1.371)	**(1.933)**
MMH.GH	(2.445)	(3.061)	(2.402)	(2.461)	(3.193)	**(2.712)**
HORD	(3.978)	(0.001)	(0.411)	(0.513)	1.421	**(0.696)**
MLC	(1.625)	(0.889)	(2.918)	(2.500)	(0.068)	**(1.600)**
DIGICUT	(4.856)	(4.717)	(0.519)	(1.607)	(2.467)	**(2.833)**
PBC	(4.206)	(3.122)	(2.331)	(3.437)	(3.124)	**(3.244)**
SAMBA	(4.040)	(0.695)	(1.183)	(1.815)	(1.209)	**(1.788)**
ACI	(1.894)	(2.456)	(1.399)	(1.977)	(1.375)	**(1.820)**
UNIL	(3.993)	(3.960)	(2.106)	(0.372)	(1.044)	**(2.295)**
AYRTON	1.119	(1.386)	(0.768)	(0.627)	(1.597)	**(0.652)**

Table 22. *Assessments of signs of manipulation on year-on-year M-score (Note, ** indicates a sign of possible manipulation)*

COMPANY CODE	2014	2015	2016	2017	2018
	M-SCORE	**M-SCORE**	**M-SCORE**	**M-SCORE**	**M-SCORE**
PZ	(3.611)	(2.712)	(1.575)**	(2.591)	(3.084)
CMLT	(2.709)	(2.842)	(2.326)	(2.621)	(1.964)**
ALW	(3.373)	(3.322)	(3.987)	(3.252)	(5.485)
BOPP	6.443**	(6.732)	(1.287)**	(1.901)**	(7.911)
CPC	(5.708)	2.620**	0.793**	(2.205)**	0.293**
FMLK	(3.217)	0.034**	(1.906)**	(0.867)**	(1.209)**
GGBL	2.783**	(2.195)**	(1.961)**	(2.061)**	(0.972)**
SWL	(2.954)	(3.024)	1.512**	(3.828)	(1.371)**
MMH.GH	(2.445)	(3.061)	(2.402)	(2.461)	(3.193)
HORD	(3.978)	(0.001)**	(0.411)**	(0.513)**	1.421**
MLC	(1.625)**	(0.889)**	(2.918)	(2.500)	(0.068)**
DIGICUT	(4.856)	(4.717)	(0.519)**	(1.607)**	(2.467)
PBC	(4.206)	(3.122)	(2.331)	(3.437)	(3.124)
SAMBA	(4.040)	(0.695)**	(1.183)**	(1.815)**	(1.209)**
ACI	(1.894)**	(2.456)	(1.399)**	(1.977)**	(1.375)**
UNIL	(3.993)	(3.960)	(2.106)**	(0.372)**	(1.044)**
AYRTON	1.119**	(1.386)**	(0.768)**	(0.627)**	(1.597)**
No. of firms	**5**	**7**	**12**	**10**	**11**
%	**29%**	**41%**	**71%**	**59%**	**65%**

Table 23. *Assessments of signs of manipulation based on Average M-scores.*

COMPANY CODE	AVERAGE M-SCORE	ZONE OF DISCRIMINATION
PZ	**(2.715)**	Non- Manipulation
CMLT	**(2.492)**	Non- Manipulation
ALW	**(3.884)**	Non- Manipulation
BOPP	**(2.278)**	Non- Manipulation
CPC	**(0.841)**	Manipulation
FMLK	**(1.433)**	Manipulation
GGBL	**(0.881)**	Manipulation
SWL	**(1.933)**	Manipulation
MMH.GH	**(2.712)**	Non- Manipulation
HORD	**(0.696)**	Manipulation
MLC	**(1.600)**	Manipulation
DIGICUT	**(2.833)**	Non- Manipulation
PBC	**(3.244)**	Non- Manipulation
SAMBA	**(1.788)**	Manipulation
ACI	**(1.820)**	Manipulation
UNIL	**(2.295)**	Non- Manipulation
AYRTON	**(0.652)**	Manipulation

Source: Financial Reports (2014 – 2018)

4.5. Discussion of Results

Tables, - 9, and 10 show the results of Z-Scores computed from the secondary data collected from 2014 to 2018. Altman Z-Score computation reported that on average 47% of the firms showed an impressive Z-Score performance of being financially sound. In the case of a year-on-year score, the result showed a Z-Score performance of 41% of the firms classified as safe from distressed for 2014 and 2016 while recorded 53% in the remaining years. Also, the result classified 35%, 41%, 47%, 29%, and 24% not financially distressed but in the zone of distress or Grey Zone in the year 2014 through 2018 respectively. Note, it is important to report that the model misclassified (Type II error) 24%, 12%, 12%, 18%, and 18% of the firms in the year 2014 to 2018 respectively. In general, the model reported a predictive power of 66% on average. These findings accept the hypotheses (**H_1**) which states that Altman's (2000) model can Accurately predict the bankruptcy status of the listed consumer goods and service companies in Ghana and this is consistent with the findings of Sulub S.A (2014), Soon *et. al,* (2014), Soon and Mohammed, (2012), and Gyimah, P. and Boachie, (2018), which concluded that Altman’s model can successfully predict corporates failure.

Table, -10 (Taffler model) revealed that on average 88% of the firms showed outstanding Z-Score performance of being safe from bankruptcy. Using a year-on-year score to determine distress revealed an impressive Z-Score performance of 82% of the firms classified as safe from distressed through 2015 to 2017 except 2014, and 2018 which recorded 76% and 94% respectively as healthy. However, the model constantly misclassified three non-failed firms as failed for the period 2014 to 2017 representing (18%) error rate except 2018 which recorded one (6%) non-failed as failed. In general, the model does extremely well in predicting the success of the firms with a predictive power of 83% for consumer goods and service companies in Ghana. This finding supports hypotheses (**H_2**) which states that Taffler’s model can Accurately predict the bankruptcy status of the listed consumer goods and service companies in Ghana and this conclusion is consistent with the findings of Taffler (1983).

Tables, - 21, 22, and 23 reports the result and assessments of m-score calculated from the financial data of 17 listed firms starting from 2014 to 2018. A carefully look at Tables, - 21 and 22 indicated that financial statements of two firms (Aryton drugs manufacturing company and Guinness Ghana Breweries limited) showed signs of possible manipulations as far back 2014 to 2018 as their M-Score figure is above the standard score for non- manipulated earning figures of negative 2.22. Five firms on the other hand (**SAMBA, ACI, HORD, FMLK,** and **CPC**) showed signs of manipulation for a four-years score whereas **MLC** and BOPP reported three years of manipulations. The remaining firms only reported one or two-year manipulation sign except for **MMH.GH** and **ALW** who were found to be free from financial statement fraud in all the five-year study period. The Five-year Average M-Score in table, - 23 revealed 53 % of the firms engaging in earnings manipulation as their average M-Score lies above the benchmark figure of negative 2.22. Therefore, a detailed overview of the results in table, - 21 as confirmed by Tables, 22 and 23 revealed that financial statement fraud was found to be common among the sample firms. This result is similar to McCarthy, J, (2017), who reported that, the financial statements for the five years studied were manipulated by the management of

Enron corporation to hide the true picture of the company's distress status, hence hypotheses (**H_3**) is accepted. Contrary to these findings is Amoa-Gyarteng, K., (2014), who analysed listed firms in Ghana for early warning signs of bankruptcy and financial statement fraud with the Beneish model. His findings revealed that the companies were not engaging in financial statement fraud.

4.6. Assessments of Classification Power of Altman and Taffler Z-Score Model

The classification accuracy of Altman (2000) and Taffler's (1983) Z-Score models was evaluated using a sample of 17 firms from the consumer goods sector. The z-scores are obtained for both models using five years' annual financial data. The accuracy is calculated by dividing the number of firms correctly classified by the total number of firms in the sample (Predictive Power= TCA ÷ NO). The tenacity of Altman's (1968) study was to develop a model that could predict a corporate future in the light of failed, non-failed and zone of ignorance. However, the question of the accuracy determination method was not dealt with due to his failure to authenticate his model. Therefore, in other to confirm the model in dissimilar countries and circumstances, we consider the accuracy calculation imperative. To meritoriously evaluate the predictive ability between the two models, it is statistically appropriate to include the greyzone count area thus zone which cannot be regarded as failed or non-failed.

Table- 24 presents the results of the calculation of both Taffler (1983), and Altman (2000) predictive power. The Altman model was found to be accurate with an average predictive power of 66% for the study period of five years**.** In the case of using the overall average Z- scores of each firm in the study sample, the model showed a classification power of 65%. In the case of Taffler (1983), the model does equally well for predicting the firms with an average predicting accuracy of 83%. However, using the overall average Z- scores of each firm, the model does improve its classification accuracy to 88%. In general, it can be concluded that Taffler (1983) model has a high predictive power than that of Altman's (2000) model in the consumer goods industry with a statistical difference of 17% (83%-66%).

Table 24*. Calculations of Classification Power of Model 1&2 including Grey-zone count*

YEAR	ALTMAN (2000) MODEL			Taffler (1983) model	
	NO. OF FIRMS CLASSIFIED AS SAFE	NO. OF FIRMS CLASSIFIED INTO GREY ZONE	PREDICTIVE POWER (%)	NO. OF FIRMS CLASSIFIED AS SAFE	PREDICTIVE POWER (%)
2014	7	6	10/17=59%	13	13/17=76%
2015	9	7	12.5/17=74%	14	14/17=82%
2016	7	8	11/17=65%	14	14/17=82%
2017	9	5	11.5/17=68%	14	14/17=82%
2018	9	4	11/17=65%	16	16/17=94%
Average:			**66%**		**83%**
USING AVERAGE Z-SCORES	8	6	**11/17=65%**	**15**	**88%**

Source: Financial Reports (2014 – 2018)

5. Conclusion and Recommendations

In this paper, we investigated the predictive power of applying Altman's (2000) revised model and Taffler's (1983) model to 17 listed non-failed consumer goods and service companies in Ghana. These firms were purposively sampled for the analysis. The study also investigated financial statement fraud by applying Beneish's (1999) M-Score model on the data set extracted from the annual financial data of the sample firms. Professor Edward Altman's (2000) Revised model was found to be accurate for listed Consumer goods and service companies in Ghana at a predictive power range from 65% to 66% on average. Professor Richard J. Taffler (1983) model was equally found to be accurate for the listed consumer goods and service sector in Ghana at a high predictive power ranges from 83% to 88% on average. Professor Messod Beneish (1999) model also revealed that financial statements fraud was common among the sample firms, some for all the five years and others show signs of manipulations for four and three years. Generally, the findings confirmed the assumptions under the hypotheses H_1, H_2, and H_3.

This study adds to the literature of finance and accounting particularly on failure and insolvency prediction from the viewpoint of an emerging economy. The study is however restricted to the extent that, it relies on only seventeen (17) listed consumer goods and service firms in Ghana. Also, Taffler and Altman's models were developed based on UK and US-GAAP whilst the data for the study were based on IAS and IFRS standards. Furthermore, considering the relatively high firms classified into the grey zone using the Altman model with 17% type II error rate documented, criticizers or critics, of this paper, may argue that the investigation was biased considering the sample size used for the analysis and other relevant limitations of the model. Giving the above reproaches, it would be appropriate to consider the following for further studies: How applicable is Altman's (2000), Taffler (1983) and Beneish's (1999) model in predicting bankruptcy and detecting financial statement fraud in the banking and mining sectors in Ghana taking into account the frequent collapse, mergers, and acquisitions in the aforementioned sectors? Furthermore, at what degree can corporate failure be predicted in Ghana using a new set of models? Finally, a detailed experimental study that would test the existing models and estimate a new model based on the characteristics of Ghanaian firms, which will be appropriate for predicting bankruptcy in Ghana.

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Appendix

Appendix A. Description of Companies Used For The Studies

COMPANY	SYMBOL	SECTOR
ALUWORKS	ALW	CONSUMER GOODS
BENSO OIL PALM PLANTATION	BOPP	CONSUMER GOODS
COCOA PROCESSING COMPANY	CPC	CONSUMER GOODS
FAN MILK	FML	CONSUMER GOODS
GUINNESS GHANA BREWERIES	GGBL	CONSUMER GOODS
HORDS	HORDS	CONSUMER GOODS
PRODUCE BUYING COMPANY	PBC	CONSUMER GOODS
PZ CUSSONS GHANA	PZC	CONSUMER GOODS
SAMBA FOODS	SAMBA	CONSUMER GOODS
UNILEVER GHANA	UNIL	CONSUMER GOODS
DIGICUT PRODUCTION AND ADVERTISING	DIGICUT	CONSUMER SERVICES
MECHANICAL LLOYD COMPANY	MLC	CONSUMER SERVICES
MERIDIAN-MARSHALLS HOLDINGS	MMH.GH	CONSUMER SERVICES
SAM WOODE	SWL	CONSUMER SERVICES
CAMELOT GHANA	CMLT	CONSUMER GOODS
Ayrton Drug	AYRTON	CONSUMER GOODS
African Champion Industries	ACI	CONSUMER GOODS

Appendix B. Data Presentation of Altman Z-Score Computations

CODE	YEARS	X1	X2	X3	X4	X5
PZ	2014	0.13341	0.47911	0.12334	1.14984	0.85891
	2015	(0.06319)	0.45429	0.79818	0.89485	0.77832
	2016	(0.04558)	0.44100	0.71575	0.88765	0.70224
	2017	(0.05791)	0.46527	0.75278	0.81946	0.69222
	2018	(0.06987)	0.52635	0.65352	0.93048	0.74831
CMLT	2014	0.07280	(0.45938)	0.02365	0.45841	5.88789

	2015	0.08100	(0.63646)	0.03528	0.51214	3.94563
	2016	0.04348	(0.61415)	0.37607	0.62605	3.15113
	2017	0.09697	(0.61934)	(0.00873)	0.59889	4.86217
	2018	(5.85940)	(0.68026)	0.41849	0.68220	5.93557
ALW	2014	(0.17647)	(0.19767)	(0.03416)	0.74357	4.58379
	2015	(0.20949)	0.42668	0.10420	0.53082	2.09889
	2016	(0.15693)	0.63886	0.09638	0.89902	0.34665
	2017	(0.28686)	(0.44137)	(0.12236)	0.36102	4.32873
	2018	0.80267	0.11078	0.07692	5.91079	0.85550
BOPP	2014	0.22555	0.20127	0.03530	0.60451	0.98913
	2015	0.05805	0.23476	0.53603	0.70757	1.05012
	2016	(0.00679)	0.25007	0.35103	0.71023	1.11798
	2017	0.02322	0.21189	0.43059	0.70926	1.13782
	2018	(1.22734)	0.20744	0.42736	0.61816	1.43757
CPC	2014	(0.42364)	(0.40678)	0.11334	0.09317	2.53509
	2015	0.29015	(0.23465)	0.02761	0.91901	0.98019
	2016	0.25248	(0.27204)	0.04014	0.84680	0.78312
	2017	0.23952	(0.28931)	(0.03262)	0.80714	0.05395
	2018	0.64473	(0.27720)	(0.01753)	0.88600	0.09277
FMLK	2014	(0.19520)	0.57315	0.17535	1.88895	1.43239
	2015	0.41637	0.51480	0.30982	1.28042	1.47240
	2016	0.08532	0.67076	0.35728	2.46699	1.57674
	2017	0.11104	0.70533	0.21265	2.82631	1.48600
	2018	0.38183	0.68803	0.04924	2.55453	1.19334
GGBL	2014	0.09489	0.10617	0.74508	0.49369	6.08779
	2015	0.05747	0.14083	0.74911	0.55934	6.18741
	2016	0.07694	0.13201	0.72233	0.55595	5.48980
	2017	0.07945	0.18979	0.88706	0.71510	6.27912
	2018	(4.59374)	0.19135	1.25862	0.65065	6.20293
SWL	2014	(0.13637)	0.12219	(0.32433)	0.11715	1.27460
	2015	(0.03352)	0.01982	(0.04764)	3.44549	0.15505
	2016	0.20922	0.01133	(0.01397)	6.12190	0.07405
	2017	(0.13173)	0.09791	0.07774	(0.10383)	0.87543
	2018	(1.37060)	0.08914	(0.02804)	0.11182	0.65317
MMH.GH	2014	0.07710	(0.23864)	0.02020	1.14679	0.41833
	2015	0.00829	0.24624	0.00077	0.89012	0.43306
	2016	0.03137	0.24798	0.57745	1.01415	0.43404
	2017	0.07536	0.22222	0.23021	1.05778	0.41718
	2018	0.02428	0.17593	0.67280	0.79676	0.42229
HORD	2014	(0.24719)	0.10365	0.32924	0.26207	0.93866
	2015	0.39889	0.03519	0.00871	1.70226	0.57739
	2016	0.42637	0.14199	0.02928	3.29794	0.67867
	2017	(1.35036)	0.17814	0.03655	3.72844	0.70695
	2018	(0.12762)	0.02966	0.00792	2.89227	0.94278
MLC	2014	0.25392	0.12096	0.05054	0.74335	0.37992
	2015	0.16388	0.24949	0.13701	1.49927	0.66626
	2016	(0.04480)	0.22432	0.42126	1.58062	0.80312
	2017	(0.01796)	0.16898	0.61795	0.99977	0.51837
	2018	0.43657	0.12944	0.55046	0.89324	0.76874
DIGICUT	2014	(0.06028)	(0.27416)	0.00419	0.86865	0.55102
	2015	(0.13928)	0.28287	0.00056	0.64530	0.49876
	2016	(0.13984)	0.29182	0.00040	0.71161	0.41108
	2017	0.07536	0.22222	0.00016	1.05778	0.47657
	2018	0.12077	0.17593	0.00121	0.79676	0.44725
PBC	2014	(0.38888)	0.13556	(0.00283)	0.16573	1.82619
	2015	(0.23691)	0.20330	0.15506	0.26283	1.68830
	2016	0.41445	0.19803	0.14079	0.25306	1.31162
	2017	0.13064	0.25417	0.13947	0.34651	1.22861
	2018	0.82254	0.40421	0.34456	0.68423	0.87015

SAMBA	2014	0.08895	(0.02719)	(0.06544)	4.89041	0.47012
	2015	0.25627	0.10395	0.16764	5.08902	0.47792
	2016	0.32827	0.03913	(0.04697)	4.42818	0.25972
	2017	0.20077	(0.04542)	(0.10930)	4.78461	0.32684
	2018	0.20534	(0.07119)	(0.01984)	2.87018	0.39253
ACI	2014	0.13008	(0.01918)	0.02031	1.10670	2.92663
	2015	0.14194	0.05611	0.01174	1.31869	2.42141
	2016	0.13918	0.03404	(0.01018)	1.29671	3.19100
	2017	0.17766	0.01986	0.05192	1.26208	3.57406
	2018	0.16848	0.01849	0.03563	1.25090	3.50133
UNIL	2014	(0.13421)	0.42657	0.02870	0.85915	12.12634
	2015	(0.23510)	0.57725	(0.00841)	1.68138	7.99408
	2016	(0.15344)	0.56384	0.02687	1.58342	4.45389
	2017	0.41063	0.47755	(0.01212)	1.08507	4.67648
	2018	0.38126	0.48133	0.01239	1.10831	6.27609
AYRTON	2014	(0.22866)	1.68335	0.02601	0.33612	3.64460
	2015	0.15299	0.21810	1.16862	0.72755	0.69719
	2016	0.29223	0.34010	0.11896	1.34560	1.42193
	2017	0.33884	0.38465	0.10874	1.41722	1.16520
	2018	0.55059	0.45004	0.15522	1.73476	1.07412

Appendix C. Data Presentation of Taffler Z-Score Computations

CODE	YEARS	X1	X2	X3	X4
PZ	2014	0.41608	0.92412	0.29644	(0.15804)
	2015	1.75036	0.74433	0.45601	(1.08534)
	2016	1.51165	0.80775	0.47349	(0.28704)
	2017	1.52804	0.79097	0.49264	(1.14868)
	2018	1.41491	0.75677	0.46188	(1.09806)
CMLT	2014	0.21951	0.26329	0.10773	0.85115
	2015	0.36351	0.28026	0.09706	0.00750
	2016	3.53947	0.26506	0.10625	0.57451
	2017	(0.07368)	0.33068	0.11844	0.37815
	2018	3.50567	0.31071	0.11937	1.17838
ALW	2014	(0.12408)	0.30148	0.27533	(6.94701)
	2015	0.27932	0.26002	0.37306	(14.53634)
	2016	0.37279	0.21440	0.25852	(12.46713)
	2017	(0.44155)	0.14715	0.27712	(12.10503)
	2018	1.07896	5.54708	0.07129	0.71320
BOPP	2014	0.08009	0.90305	0.44072	(0.02979)
	2015	1.34734	0.87245	0.39784	(0.05700)
	2016	0.77734	0.89758	0.45158	(0.10625)
	2017	0.89527	0.94287	0.48096	(0.12425)
	2018	0.88650	0.91848	0.48208	(0.09298)
CPC	2014	0.20210	0.15464	0.56083	(9.61420)
	2015	0.09680	1.11400	0.28527	1.30779
	2016	0.13240	1.06551	0.30314	1.27320
	2017	(0.10112)	1.06836	0.32263	1.47510
	2018	(0.05554)	1.21618	0.31565	2.60324
FMLK	2014	0.58976	1.46510	0.29732	0.04121
	2015	0.76260	1.62056	0.40627	0.07204
	2016	1.38900	1.26045	0.25722	(0.79939)
	2017	0.93594	1.48625	0.22720	(0.04848)
	2018	0.19305	1.41005	0.25504	(0.01149)
GGBL	2014	3.52711	0.48582	0.21124	(0.02477)
	2015	3.65406	0.46350	0.20501	(0.28960)
	2016	3.32633	0.48343	0.21716	(0.26691)
	2017	3.84234	0.51439	0.23087	(0.29388)
	2018	5.88050	0.48278	0.21403	(0.27918)
SWL	2014	(0.57644)	0.49019	0.56265	(1.03504)

	2015	(0.52830)	0.22330	0.09018	(0.34671)
	2016	(0.30301)	1.84381	0.04612	2.49143
	2017	0.18872	0.21605	0.41190	(0.44248)
	2018	(0.08724)	0.37294	0.32144	(0.12071)
MMH.GH	2014	0.19422	0.34210	0.10399	0.00070
	2015	0.00798	0.29202	0.09597	0.02562
	2016	4.25646	0.33471	0.13567	(0.08407)
	2017	1.78454	0.34640	0.12900	(0.07302)
	2018	6.67262	0.27112	0.10083	(0.02777)
HORD	2014	1.02402	0.32777	0.32152	(2.75279)
	2015	0.03181	1.46347	0.27378	5.51472
	2016	0.19941	2.42837	0.14684	(8.30115)
	2017	0.27263	2.90208	0.13407	6.56427
	2018	0.03279	3.72611	0.24160	103.39375
MLC	2014	0.10335	1.00512	0.48903	(1.31330)
	2015	0.37018	1.20426	0.37012	(1.31433)
	2016	1.19592	1.09254	0.35225	(1.16180)
	2017	1.38646	0.89939	0.44570	(1.78112)
	2018	1.13776	0.84748	0.48381	(1.78730)
DIGICUT	2014	0.03506	0.06396	0.11946	0.25132
	2015	0.00507	0.04721	0.11025	0.48373
	2016	0.00249	0.03218	0.15964	(3.04255)
	2017	0.00126	0.34640	0.12900	(0.46843)
	2018	0.01199	0.27112	0.10083	(0.22694)
PBC	2014	(0.00345)	0.76742	0.81816	(0.67052)
	2015	0.20242	0.90219	0.76603	(3.78866)
	2016	0.18225	0.91378	0.77247	0.31312
	2017	0.19509	1.01966	0.71490	0.19524
	2018	0.59829	1.34992	0.57591	(0.12515)
SAMBA	2014	(0.69140)	1.28424	0.09464	0.12368
	2015	3.07411	1.88240	0.05453	0.82238
	2016	(0.40058)	1.55579	0.11726	0.37576
	2017	(1.02344)	0.70276	0.10679	(0.10146)
	2018	(0.14404)	0.79472	0.13777	(0.37252)
ACI	2014	0.23021	0.45988	0.08822	0.47469
	2015	0.20833	0.45977	0.05635	0.66416
	2016	(0.12229)	0.51076	0.08321	0.41992
	2017	0.76681	0.55506	0.06771	0.61515
	2018	0.41298	0.57340	0.08627	0.54497
UNIL	2014	0.05801	0.67022	0.49471	3.91311
	2015	(0.02550)	0.25375	0.32974	0.03336
	2016	0.07707	0.50434	0.34866	0.04685
	2017	(0.02644)	1.81204	0.45842	0.07949
	2018	0.02802	1.73574	0.44202	0.04806
AYRTON	2014	0.03475	0.69448	0.74843	(0.58170)
	2015	2.01886	1.26429	0.57885	(0.19109)
	2016	0.27904	1.68546	0.42633	(0.18899)
	2017	0.26616	1.80664	0.40856	(0.09374)
	2018	0.69183	2.11930	0.22436	(0.01867)

Appendix D. Data Presentation of Beneish M-Score Computation

CODE	YEARS	DSRI	GMI	AQI	SGI	DEPI	SGAI	LEVI	TATAI
PZ	2014	0.5935	1.0826	0.9347	0.0090	1.0368	4.1618	0.4652	0.1013
	2015	1.1261	1.0167	0.9951	0.9509	0.7302	1.1852	0.5277	(0.0861)
	2016	0.9751	0.9524	1.2477	1.0026	9.5775	0.9336	0.5298	(0.0644)
	2017	1.1067	1.0171	1.0000	0.9854	1.0014	1.0094	0.5496	(0.0749)
	2018	0.9139	0.9702	0.8465	0.9424	0.1498	1.0170	0.5180	(0.0967)
CMLT	2014	0.7996	0.8072	0.9310	0.9422	0.9776	0.4277	0.6857	(0.0132)
	2015	0.9084	0.9544	0.9472	0.7761	1.1550	1.2407	0.6613	(0.0257)

	2016	1.2766	1.1050	0.9602	1.0192	1.0232	0.7673	0.6150	(0.0696)
	2017	0.8212	0.7367	1.1325	1.0602	1.0964	0.9896	0.6254	(0.0170)
	2018	1.0768	1.1379	1.0195	0.8743	0.8712	1.3583	0.5945	0.0899
ALW	2014	0.6460	0.9005	1.0492	1.3243	0.8935	1.2649	0.5735	(0.1935)
	2015	1.1361	0.8010	0.9818	1.0237	1.7255	0.7213	0.6532	(0.2395)
	2016	0.4794	0.9902	0.6640	0.8831	0.9368	1.3240	0.5266	(0.1869)
	2017	0.8458	0.1625	0.9591	1.2159	0.7653	0.6129	0.7347	(0.1048)
	2018	1.1524	(4.7900)	0.6755	0.7398	0.8958	1.6769	0.5060	0.0517
BOPP	2014	12.5432	0.5387	0.7828	1.2158	0.0027	16.2423	0.6232	0.2255
	2015	3.7080	1.1379	0.9671	0.9000	2.7975	43.6006	0.5856	0.0579
	2016	0.9070	0.9608	1.0254	1.0677	10.8039	0.9811	0.5847	(0.0082)
	2017	1.3948	0.8926	1.0131	1.0525	0.7778	0.9605	0.5850	0.0222
	2018	1.1254	1.1425	1.0082	1.0212	0.8482	1.0257	0.6180	(1.2282)
CPC	2014	1.0145	0.0782	0.6853	0.6048	1.2588	2.0842	0.9148	(0.4587)
	2015	1.4472	5.0781	4.1037	0.7659	0.8967	0.6524	0.5211	0.2749
	2016	1.0957	5.8399	0.9939	0.4792	0.9909	1.9446	0.5415	0.2372
	2017	1.0972	(1.1861)	1.0247	1.1064	0.9805	0.7757	0.5534	0.2250
	2018	1.2656	(1.9087)	1.0908	1.9158	0.9840	0.4169	0.5302	0.6324
FMLK	2014	0.9651	0.8319	1.3067	1.2772	1.1884	0.3040	0.3461	(0.2869)
	2015	0.6934	1.0868	1.3964	1.7770	1.0392	0.8573	0.4385	0.3599
	2016	1.2587	1.0112	0.5145	1.2251	0.5073	0.8890	0.2884	0.0279
	2017	2.1683	0.9173	1.0647	1.1541	1.2438	1.2451	0.2613	0.0408
	2018	0.9829	0.8165	1.0193	0.8734	1.2425	1.8461	0.2813	0.2931
GGBL	2014	5.1655	2.4777	3.5156	0.0435	1.3713	0.8787	0.6695	0.0675
	2015	0.8532	0.9992	1.0076	1.1421	0.6880	0.8805	0.6413	0.0404
	2016	1.1260	1.0238	1.0079	0.9796	1.0197	0.9788	0.6427	0.0603
	2017	0.8333	1.0184	0.9966	1.1581	0.7596	0.9939	0.5831	0.0669
	2018	1.0400	1.0094	1.0018	1.0176	1.3040	1.0287	0.6058	0.2759
SWL	2014	2.5725	0.3766	0.6015	0.7031	0.3719	1.0819	0.8951	(0.2380)
	2015	0.4444	0.5205	2.0348	0.7758	1.2858	1.1246	0.2249	(0.0562)
	2016	1.6459	5.7908	1.0210	0.8672	0.4492	2.0796	0.1404	0.2021
	2017	0.3294	1.2827	0.3179	1.4257	1.2414	0.6833	1.1159	(0.2199)
	2018	1.0831	0.6399	1.1948	0.8654	1.0019	0.7566	0.8994	0.2542
MMH.GH	2014	0.8414	0.8614	1.0945	0.9871	1.1616	0.2965	0.4658	(0.0187)
	2015	0.8404	1.0108	0.9308	0.8873	1.0476	1.1419	0.5291	(0.0955)
	2016	0.9329	1.3188	1.0592	1.0802	1.0487	0.6454	0.4965	(0.0759)
	2017	1.1810	0.9575	0.9249	1.0045	0.9479	1.7432	0.4860	(0.0285)
	2018	0.8130	0.8725	1.1585	0.9334	1.1115	2.3451	0.5566	(0.0864)
HORD	2014	0.7785	1.0296	0.5723	1.2342	1.1033	1.6693	0.7924	(0.2800)
	2015	1.4040	0.8625	1.3342	1.1389	1.0363	1.2819	0.3701	0.3760
	2016	0.7585	0.9980	1.0181	1.1421	1.6170	0.9065	0.2327	0.3891
	2017	0.8658	0.8769	1.0456	1.0771	1.0652	0.8853	0.2115	0.3811
	2018	1.4838	1.0095	1.0786	1.0841	1.0089	0.9272	0.2852	0.6618
MLC	2014	0.5979	0.9313	1.0067	0.7977	3.0173	1.2402	0.5736	0.2370
	2015	1.3073	0.9202	0.8630	1.5286	0.9128	0.6061	0.4001	0.1454
	2016	0.8077	0.6014	0.9002	1.0881	1.1641	0.9199	0.3875	(0.0687)
	2017	1.2499	1.2727	1.0801	0.6780	1.0364	1.6657	0.5001	(0.0411)
	2018	0.8741	1.0050	0.9875	1.4336	1.0004	0.6732	0.5282	0.4131
DIGICUT	2014	1.1813	0.3766	0.9634	0.7031	0.9038	0.4163	0.5351	(0.4649)
	2015	0.9611	0.5205	1.0248	0.7758	1.0079	1.3058	0.6078	(0.3922)
	2016	1.1621	5.7908	1.0020	0.8672	0.0082	0.8039	0.5842	(0.1401)
	2017	0.8320	1.2827	1.0083	1.4257	1.1307	1.2281	0.4860	0.0752
	2018	0.8769	0.6399	0.9970	0.8654	0.9273	2.5295	0.5566	0.1206
PBC	2014	1.0967	0.8447	1.0085	1.2691	8.6413	0.5777	0.8578	(0.6356)
	2015	1.2456	1.2592	1.0411	1.2638	0.2197	0.9519	0.7919	(0.2657)
	2016	1.4153	1.0670	0.9792	0.9568	6.7943	1.0500	0.7980	(0.2020)
	2017	1.0037	0.9948	1.0333	1.1601	0.8836	0.8272	0.7427	(0.2595)
	2018	2.0700	1.0003	1.0584	1.0979	1.3965	1.1016	0.5937	(0.4063)
SAMBA	2014	0.0447	(0.0027)	1.0470	0.0900	2.0783	0.0094	0.1698	0.0161

	2015	0.9780	1.6799	1.0393	1.2622	1.1301	0.5702	0.1642	0.1783
	2016	1.4595	0.4536	1.0667	0.7344	0.8104	1.9856	0.1842	0.2773
	2017	0.6043	1.0929	0.8776	1.1540	0.9490	1.0474	0.1729	0.1358
	2018	0.5373	1.3669	0.8672	1.3376	0.0018	0.0249	0.2584	0.2052
ACI	2014	1.1270	1.0317	1.0677	0.8762	0.9484	1.0457	0.4747	0.0808
	2015	0.5413	1.0597	1.0490	0.8345	0.9322	1.5527	0.4313	0.0981
	2016	1.4465	1.0630	0.8567	1.1029	1.1561	0.8766	0.4354	0.0812
	2017	0.6284	1.0264	0.9903	1.0995	1.0417	0.9251	0.4421	0.1166
	2018	1.4853	0.9692	1.0145	0.9829	0.9725	1.0474	0.4443	0.1098
UNIL	2014	0.4011	0.6206	0.9446	1.0474	1.1520	0.9077	0.5379	(0.2064)
	2015	1.0879	1.5577	1.0047	0.4704	0.6633	2.4529	0.3729	(0.2781)
	2016	2.1365	1.9919	1.0767	0.5655	1.2805	1.8521	0.3871	(0.1977)
	2017	1.1349	0.5852	1.1031	1.2024	1.6577	0.7755	0.4796	0.3625
	2018	0.5420	0.6394	0.9373	1.3239	0.6089	0.6955	0.4743	0.3431
AYRTON	2014	0.7464	0.7495	1.0492	1.4492	0.8072	0.8410	0.0386	0.6891
	2015	1.7627	1.3928	0.9737	0.6115	2.0096	2.1954	0.5789	0.1056
	2016	0.5055	1.0885	0.9817	1.8170	1.0396	0.5092	0.4263	0.2399
	2017	1.3439	1.1378	1.0542	0.9031	1.1007	1.1534	0.4137	0.2889
	2018	1.3108	1.0721	1.0228	1.0343	4.0280	0.9199	0.3657	(0.0107)
CODE	YEARS	0.5935	1.0826	0.9347	0.0090	1.0368	4.1618	0.4652	0.1013

Appendix E.
Results of Z-Score Using Altman's (2000) Model

COMPANY CODE	2014	2015	2016	2017	2018	AVERAGE
	Z-SCORE	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**
PZ	2.224	3.966	3.633	3.721	3.559	**3.421**
CMLT	5.805	3.781	4.085	4.622	2.73	**4.205**
ALW	4.487	2.852	1.451	3.513	4.244	**3.309**
BOPP	1.683	3.247	2.709	2.964	2.315	**2.584**
CPC	2.272	1.459	1.212	0.218	0.638	**1.160**
FMLK	3.112	3.702	4.347	4.006	3.273	**3.688**
GGBL	8.751	8.893	8.119	9.535	7.234	**8.506**
SWL	0.322	1.447	2.761	1.06	-0.295	**1.059**
MMH.GH	0.815	1.023	2.882	1.817	3.008	**1.909**
HORD	1.978	1.634	2.579	1.567	2.114	**1.975**
MLC	1.133	2.048	2.929	2.983	3.271	**2.473**
DIGICUT	0.652	0.91	0.857	1.163	1.02	**0.921**
PBC	1.719	2.278	2.317	2.113	3.156	**2.317**
SAMBA	2.361	3.406	2.242	2.102	1.623	**2.347**
ACI	3.526	3.156	3.826	4.402	4.267	**3.835**
UNIL	12.817	8.979	5.561	5.784	7.448	**8.118**
AYRTON	5.121	4.919	2.851	2.664	3.058	**3.722**

Results of Z-Score using Taffler (1983) Z-Score Model.

COMPANY CODE	2014	2015	2016	2017	2018	AVERAGE
	Z-SCORE	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**	**Z-SCORE**
PZ	0.369	0.933	0.945	0.818	0.756	**0.764**
CMLT	0.306	0.248	2.021	0.086	2.108	**0.954**
ALW	(1.089)	(2.077)	(1.723)	(2.102)	1.420	**(1.114)**
BOPP	0.234	0.890	0.472	0.664	0.661	**0.584**
CPC	(1.310)	0.458	0.467	0.379	0.602	**0.119**
FMLK	0.563	0.700	0.818	0.722	0.330	**0.627**
GGBL	1.967	1.987	1.822	2.098	3.173	**2.209**
SWL	(0.306)	(0.290)	0.486	0.131	0.048	**0.014**
MMH.GH	0.166	0.064	2.310	1.002	3.585	**1.425**
HORD	0.202	1.139	(0.880)	1.596	17.088	**3.829**
MLC	0.063	0.209	0.653	0.647	0.514	**0.417**
DIGICUT	0.089	0.106	(0.453)	(0.006)	0.023	**(0.048)**
PBC	0.138	(0.244)	0.405	0.396	0.576	**0.254**

SAMBA	(0.163)	2.015	0.071	(0.448)	(0.008)	**0.293**
ACI	0.274	0.287	0.084	0.589	0.396	**0.326**
UNIL	0.833	0.084	0.177	0.317	0.328	**0.348**
AYRTON	0.150	1.308	0.413	0.434	0.680	**0.597**

Results of M-Score (Beneish 1999)

COMPANY CODE	2014	2015	2016	2017	2018	AVERAGE
	M-SCORE	**M-SCORE**	**M-SCORE**	**M-SCORE**	**M-SCORE**	**M-SCORE**
PZ	(3.611)	(2.712)	(1.575)	(2.591)	(3.084)	**(2.715)**
CMLT	(2.709)	(2.842)	(2.326)	(2.621)	(1.964)	**(2.492)**
ALW	(3.373)	(3.322)	(3.987)	(3.252)	(5.485)	**(3.884)**
BOPP	6.443	(6.732)	(1.287)	(1.901)	(7.911)	**(2.278)**
CPC	(5.708)	2.620	0.793	(2.205)	0.293	**(0.841)**
FMLK	(3.217)	0.034	(1.906)	(0.867)	(1.209)	**(1.433)**
GGBL	2.783	(2.195)	(1.961)	(2.061)	(0.972)	**(0.881)**
SWL	(2.954)	(3.024)	1.512	(3.828)	(1.371)	**(1.933)**
MMH.GH	(2.445)	(3.061)	(2.402)	(2.461)	(3.193)	**(2.712)**
HORD	(3.978)	(0.001)	(0.411)	(0.513)	1.421	**(0.696)**
MLC	(1.625)	(0.889)	(2.918)	(2.500)	(0.068)	**(1.600)**
DIGICUT	(4.856)	(4.717)	(0.519)	(1.607)	(2.467)	**(2.833)**
PBC	(4.206)	(3.122)	(2.331)	(3.437)	(3.124)	**(3.244)**
SAMBA	(4.040)	(0.695)	(1.183)	(1.815)	(1.209)	**(1.788)**
ACI	(1.894)	(2.456)	(1.399)	(1.977)	(1.375)	**(1.820)**
UNIL	(3.993)	(3.960)	(2.106)	(0.372)	(1.044)	**(2.295)**
AYRTON	1.119	(1.386)	(0.768)	(0.627)	(1.597)	**(0.652)**