International Journal of Smart Business and Technology
Vol.10, No.2 (2022), pp.47-62
http://dx.doi.org/10.21742/ijsbt.2022.10.2.05

Exploring Bankruptcy and Financial Fraud of Listed Non-financial Firms on the Ghana Stock Exchange in Ghana Banks Lending Decision

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Abstract

This quantitative study combined the Altman z, Zmijewski x and Beneish m models targeted at the 2009 to 2016 secondary data of the twenty-six listed non-financial firms on the Ghana Stock Exchange to explore warning signals of bankruptcy and fraud reporting. The rationale was to enable Ghana bank managers reduce the risks in the lending decision process in the hype of the 2017/18 Ghana banking crisis that led to collapse of seven banks over this period. Both the z and x models bankruptcy predictions provided statistically significant results when moderated with the m fraud model. The study rejects the null hypothesis that there is no statistically significant relationship between the Altman z and Beneish m scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE. Also, the study rejects the null hypothesis that there is no statistically significant relationship between the Zmijewski x and Beneish m scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE. In addition, the study rejects the null hypothesis that, there is no statistically significant contradiction between the Altman and Zmijewski models moderated prediction of bankruptcy events on the listed non-financial firms on the GSE. The contradiction in the bankruptcy results had a strictly distress prediction focus for the Altman model and vice versa for the Zmijewski model.

Keywords*: Banking crisis, Bankruptcy, Fraud, Ghana, Listed firms, Models, Secondary data*

1. Introduction

This quantitative study deployed the Altman z and Zmijewski x bankruptcy metrics moderated by the Beneish m fraud model to explore bankruptcy and fraud events on the twenty-six listed non-financial firms on the Ghana Stock Exchange GSE simultaneously to facilitate Ghana banks' lending decision. The Ghana banking sector crisis of 2017 and 2018 is a topical issue. Excessive risk-taking measures by Ghana bank managers and asymmetric information implications eroded the regulatory capital of seven collapsed banks in 2017/18 during the sector crisis [1][2]. The problem presented the creation of the Consolidated Bank Ghana CBG with capitalization cost of GH¢450 million to absorb five of the failed banks in 2018 and cost of GH¢9.9 billion to rescue GH¢11 billion for depositors and two thousand, six hundred and sixty-one jobs in 2018 by the government [3]. Governance issues, false financial

Article history:
Received (June 26, 2022), Review Result (August 15, 2022), Accepted (October 10, 2022)

reporting, insider dealings, poor risk management and high non-performing loans NPLs were blamed on the failed banks agency function [2]. The pointers of asset quality showed an increase in NPLs from GH¢4.4 billion in 2015 to GH¢6.2 billion in 2016. The NPL as a ratio of the gross advances for the banking sector increased from 14.7% in 2015 to 17.3% in 2016 [4]. The stock market capitalization of the GSE was GH¢57,116.87 million in 2015 with all-time high of GH¢64,352.42 million in 2014 [5]. The banks credit decisions and credit agreements are based on the accounting data of the listed non-financial firms on the GSE [6][7].

The study explored the topic of bankruptcy and financial fraud events of the listed non-financial firms on the GSE in Ghana banks' lending decision to facilitate the reduction of extreme credit and operational risk-taking activities that caused the banking sector crisis for the bank managers. Average bankruptcy statistics of 46.64% and 25.57% of thirty-four listed firms on the GSE used the Altman and Zmijewski models respectively for bankruptcy analysis with 2009 to 2015 financial data [8]. The financial sector was adversely classified by GIABA in 2016 for technical but not effective compliance in the fight against financial fraud by the financial institutions [9]. The collective focus of the mix of the z and x models [8][10] moderated by m model for the study sought to strengthen the risk management schemes in the governance structure for bank managers of Ghana banks when confronted with lending decision dilemma [7][11][12]. This study sought to provide basis to serve as early warning signal to discriminate against the participated firms into bankruptcy and data manipulators to minimize the networks between the risks that resulted in banks failure to ensure banking sector stability [2][8][10][13][14]. The study sought to improve stability and status of the financial market in the fight against financial crime by the bank managers. The study sought to augment the information gathering and regulatory reporting requirement on suspicious deals on the participated firms to enhance market transparency in regulating the conduct of the banks [13][15].

Interweaving this study results into the banks dashboard systems should keep the banks risk managers informed on critical areas in directing the banks in managing bankruptcy and fraud indicators of borrowers by process instead of by objective with the discriminant scenarios of the algorithms, perform what-if and trends scenarios and limit the measurements in real time with root-cause assessments as the measurements approach the discriminant scores to reflect the inferences. This should facilitate compliance measures in the fight against financial crime to improve GIABA ratings on Ghana going forward [9]. The study is of importance to researchers towards bridging the gap between research' combining multiple bankruptcy metrics in a study that omits a fraud metric. The next section discusses the summaries on research design.

2. Research design

Quantitative logic to the assessment of bankruptcy and fraud events of the twenty-six listed firms on the GSE was the methodological assumption for the study to maximize validity and reliability from the interpretation of the *z, x* and *m* scores computed on the secondary data for the study to support the evidence against the discriminant criterion scales [10][14]. Validity describes the extent to which the deployed models measured the purported measurements [10][16]. Criterion (predictive) validity was used to test the bankruptcy and financial fraud events of interests. Consistent with [7] and [10], criterion validity used for the study relates to how well the *z*, *x* and *m* scores predicted the known outcome in accordance with the expectation for prediction. Reliability for the study was the extent to which the deployed models provide internal consistency and the expected measurements for the computed scores of the firms to reflect the inferences [10][16]. To achieve reliability in line with the stated hypotheses, the computed *m* score for a particular firm with the corresponding computed *z* and/or *x* score were fitted to match the research objective to qualify that participated firm's inclusion in the data set for reliability test for the study. Firms without corresponding *m* score for the given computed *z* and/or *x* score for the given year were omitted from the data set for reliability tests. The reason was that, their contribution to the specific research objective was inconclusive, i.e., such firms did not meet the specification of the study objective. The alpha level significance across the data set that met the specific objective of the study was set at .1, i.e., 90% confidence interval for the *z* models for the manufacturing and non-manufacturing firms and alpha level significance of .05 each for the *x* and *m* scores, i.e., 95% confidence interval respectively in line with the *F*-tests.

Consistent with [10] and [14], the criterion used for the study to interpret or discriminate against the *z* scores categories for the listed manufacturing firms on the GSE was:

- Safe zone (S) = $z > 2.990$ (risk free or not at risk of bankruptcy)
- Distress zone (D) = $z < 1.810$ (bankrupt or the firm will likely go bankrupt)
- Grey zone (G) = $1.810 \leq z \leq 2.990$ (at risk of bankruptcy).

Consistent with [14], the criterion used to interpret the *z* scores for the listed non-manufacturing companies was:

- Safe zone (S) = $z > 2.600$
- Distress zone (D) = $z < 1.100$
- Grey zone (G) = $1.100 \leq z \leq 2.600$.

In the *x* score model criterion, a listed non-financial firm on the GSE with $x < 0.500$ or negative was interpreted as good financial health category or non-bankruptcy zone and $x \geq 0.500$ was interpreted as bankrupt [8]. In the *m* score criterion, *m* score greater than negative 2.220 was interpreted as manipulator for the affected firm on the GSE and vice versa [7][11]. Validity and reliability were contingent on the application of the research models in reflecting objectivity from the secondary data sampled and generalizable to the specific population in Ghana [8][10][12].

The coefficients of the independent variables of the *z*-scores were validated from prior studies, acceptable by researchers and adopted to the context of this study [7][10][14]. According to Gvozdanovic and Ofori [8] literature, the test of predictive accuracy for the *z* model was 80% - 90% one year before the event with a Type II error of 15% - 20% using thirty-one years' data (1968 – 1999) by Altman. That of the Zmijewski model was 99% accurate in 1984 for estimation sample and adopted for bankruptcy analysis by [8] and [10]. The results of [17] posited 8,486 firms constituting 33% of the whole sample as potential manipulators using the Beneish fraud metric. In [17] financial data manipulators analysis, the *F*-distribution showed that the *DSRI, AQI, DEPI, SGAI, TATA* and *LVGI* were significant at 99% confidence level in their effect on the Beneish *m*-score. In addition, there was a significant relationship between earning management expressed by the Beneish *m*-score and each of the variables *DSRI, AQI, GMI, SGAI* and *LVGI*. The DSRI explained 95.92% of the variation in the Beneish *m*-score from the statistical results [17].

The relationship of discriminant analysis with analysis of variance, ANOVA was important to understand the procedures between the z, x and m score categories. The number of dependent variables is one in the discriminant analysis and the study undertook ANOVA with the categories predicted for the discriminant analysis to validate the research models [18]. The modeling was analogous to regression analysis except that regression analysis deals with continuous dependent and independent variables, but this discriminant analysis dealt with discrete dependent variable only [18]. The rationale was to partition the total sum of squared variances, SS. The general form SS was written as $\sum (Yi - \hat{Y})2$ from the discriminant analysis function and applied to the form of the z, x and m scores. For instance, the total SS applicable to the z scores categories for the manufacturing firms partitioned into Between Group SSB was 153.967 and Within Groups SSW was 204.360. The ratio of the mean sum of squares MS for the manufacturing firms z scores categories, i.e., SS of Between Group scores to the respective degree of freedom, df = k - 1 = 2 divided by the fraction of SS of Within Groups scores to the respective $df = N - k = 10$ provided the F ratio, i.e., $F = \frac{MSB}{MSW} = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}}$ = 3.767. The corresponding confidence interval scores were expected at $1 - \alpha$. The df explains the degrees of freedom of the number of observations N with k groups that the statistical analysis estimated.

The ANOVA between groups and within groups SS was facilitated and summarized through Excel® single factor anova data analysis functionality. The goal was to estimate parameters that minimized Within Group SS with an overarching goal of providing the p-value against the alpha level significance of .1 for the two z models and .05 each for the x and m models hypotheses data set. The rationale provided the basis for the confidence interval of 90% for the z scores and 95% each for the x and m scores respective to the group score categories so that the corresponding p-values when less than the required alpha demonstrate statistical significance of the z, x and m scores categories predictions [18]. The coefficient of determination r2 expressed as the difference between $1 – [\sum (Yi - \hat{Y})2 / \sum Y2]$ or $\sum Y2 - \sum(Yi - \hat{Y})2$ divided by $\sum Y2$ in the general form was used to measure the goodness of fit of the output $\hat{Y}$ of the linear combination of the independent variables against Yi in application to the overall variability explained by the z, x and m models.

The selection of entire twenty-six non-financial firms on the GSE for the study provided emphasis on the collective spectrum of the phenomenon with the flexible and time saving attributes [19] consistent with [8] and [10]. The source of the secondary data was open market information for researchers [8][10][19].

Descriptive statistical properties from the computed *z*, *x* and *m* scores provided the demographic properties of interest for the discriminant analysis in finding the set of predictive equations that satisfied the criterion scales. Information that was traced to the names of the twenty-six listed non-financial firms on the GSE was coded to provide confidentiality [8]. The next section details the research questions and hypotheses.

3. Research Questions and Hypotheses

The study was designed to answer the following research questions R1, R2 and R3 and hypotheses:

R1 - Is there a statistical significant relationship between the Altman *z* and Beneish *m* scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE?

$H1_0$: There is no statistically significant relationship between the Altman *z* and Beneish *m* scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE.

$$F = \frac{MSB}{MSW} = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} \sim F_{k-1,N-k,\alpha}\ ;\ p = \alpha\ .\quad *\,p = .1\ ,\qquad **\,p = .1\ ,\qquad ***\,p = .05\ ,$$
$$*\,F \sim F_{2,10,.1} = 2.924\ ,\qquad **\,F \sim F_{2,11,.1} = 2.860\ ,$$
$$***\,F \sim F_{1,12,.05} = 4.747\ .$$

Reject $H1_0$ if :

$$F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}\ ;\ p < \alpha\ .$$

R2 - Is there a statistical significant relationship between the Zmijewski *x* and Beneish *m* scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE?

$H2_0$: There is no statistically significant relationship between the Zmijewski *x* and Beneish *m* scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE.

$$F = \frac{MSB}{MSW} = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} \sim F_{k-1,N-k,\alpha}\ ;p = \alpha\ .\quad ***\,p = .05\ ,\qquad ****\,p = .05\ ,$$
$$***\,F \sim F_{1,12,.05} = 4.747\ ,\ ****\,F \sim F_{1,14,.05} = 4.600\ .$$

Reject $H2_0$ if :

$$F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}\ ;\ p < \alpha\ .$$

R3 - Is there a statistical significant contradiction between the Altman and Zmijewski models moderated prediction of bankruptcy events on the listed non-financial firms on the GSE?

$H3_0$: There is no statistically significant contradiction between the Altman and Zmijewski models moderated prediction of bankruptcy events on the listed non-financial firms on the GSE.

$$F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} \sim F_{k-1,N-k,\alpha}\ ;\ p = \alpha,\qquad *\,p = .1,\qquad **\,p = .1,\qquad ***\,p = .05,$$
$$****\,p = .05\ ;$$
$$*\,F \sim F_{2,10,.1} = 2.924\ ,\qquad **\,F \sim F_{2,11,.1} = 2.860\ ,\ ***\,F \sim F_{1,12,.05} = 4.747\ ,$$
$$****\,F \sim F_{1,14,.05} = 4.600\ .$$

Reject $H3_0$ if :

$$F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}\ ;\ p < \alpha\ .$$

4. Research Model

The general form of the model function was written as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i = \beta_0 + \sum_{i=1}^{i} \beta_i X_i \qquad (1)$$

Y is the discriminant function with coefficient β_i of X_i respondent's predictor variables and intercept β_0 created under the assumption that the observation was random and each predictor was normally distributed with one dependent variable of at least two mutually exclusive categories [18]. The limits of the discriminant category scores were assumed to approach the market average discriminant scores Y_i to describe the normality for the study. The respective standard deviation is associated with the square root of the calculated variance. The general form of the variance described by the discriminant function was $\sum (Y_i - \hat{Y})^2$ in application to the form of the *z*, *x* and *m* scores of the output $\hat{Y}$.

The study adopted two *z*-score discriminant analysis functions, each for the manufacturing and non-manufacturing listed firms on the GSE founded on multiple *z*-score dependent variable categories. Linear combination of financial ratios independently computed by the researcher were the variable set for the predictor or independent variables to describe the interval. Financial ratios independently computed from the secondary data collected by the researcher for the study was the replica of the twenty-six participated firms financing, investment and operating activities [6][20]. The nature of the interval was a metric to discriminate between the categories of the dependent variable of bankruptcy and financial fraud seamlessly. To compute the financial ratios for the *z*, *x* and *m* scores, the respective models used the financial report data contained in the current year and the prior year. The computed financial ratios provided summaries of the secondary data about the targeted firms. The reasoning behind the ratios computed were used to provide reviews and monitoring of the effective utilization of resources by the listed non-financial firms to the context of the study objectives [6][20]. For instance, liquidity ratio was used to gauge capacity to meet debts immediately falling due, debt ratio to measure indebtedness, profitability ratio to gauge profit margins or earning potential, and coverage ratio to measure the cash generating ability in meeting financing commitments [6][7][14][10][20]. The stance provided by the preceding explanation set the foundation for the systematic explanations of the behavioral patterns to advance the financial metrics control theory with the deployed *z*, *x* and *m* models for the study [7][8][14].

The limitation placed by the context of the study to listed non-financial firms on the GSE explains the choice for the application and distinction of the models for manufacturing and non-manufacturing firms to this study. The *z* model used for the manufacturing firms was written as [8][10][14]:

$$z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \tag{2}$$

The version of the *z* model for the non-manufacturing firms for the study was written as:

$$z = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \tag{3}$$

z explains the discriminant function, with X_1, X_2, X_3, X_4 and X_5 respondent's predictor variables. The variable definitions as follows:

- X_1 = *WC/TA*, Working Capital, *WC* as a ratio of the Total Assets, *TA* quantified the net liquid assets of the firm compared to the total capitalization. The *WC* was calculated as the difference in the Current Assets, *CA* and Current Liabilities, *CL*. A firm that experienced regular losses was considered to have had shrunk current assets when compared to the *TA*.
- X_2 = *RE/TA* represented the Retained Earnings, *RE* to the *TA* ratio that incorporated the age of the firm to measure the cumulative profitability. The assumption for start-up firms was that a computed low *RE/TA* ratio was reason for

not having the time to build-up cumulative profit and therefore considered as having higher incidence of failure.

- X_3 = *EBIT/TA* represented the Earnings Before' Interest and Taxes, *EBIT* over the *TA* to measure the productivity of the firm's assets before tax or leverage. In the event that total liability exceeded a fair valuation of the firm's assets, bankruptcy was considered to have occurred.
- X_4 = Market Value of Equity divided by Book Value of Total Debt. The study used the Book Value of Equity, *BVE* as proxy for market value of equity to show the collective value of the shares of stock for preference and common due to limited information on the market value of equity component. *TL* represented the total debt (liabilities) to demonstrate the rate at which the firm's assets declined in value before the *TL* exceeded the assets and the firm going bankrupt.
- X_5 = *Sales/TA* was used to demonstrate the sales (revenue) producing ability of the firm's assets in dealing with the firms' competitors scenarios.

The definitions of the variables are consistent with [8][10][14].

The form of the *x* model used was written as:

$$x = -4.336 - 4.513\left(\frac{NI}{TA}\right) + 5.569\left(\frac{TL}{TA}\right) + 0.004\left(\frac{CA}{CL}\right) \tag{4}$$

$\frac{NI}{TA}$ explains the ratio of net income to total assets, $\frac{TL}{TA}$ explains ratio of total liabilities to total assets and $\frac{CA}{CL}$ as the ratio of current assets to current liabilities [8][10].

The form of the *m* model for the study was written as:

$$m = -4.84 + 0.92DSRI + 0.528GMI + 0.404AQI + 0.892SGI + 0.115DEPI - 0.172SGAI + 4.679TATA - 0.327LVGI \tag{5}$$

Days Sales in Receivable turnover Index, *DSRI* was written as *DSRI* = $(Net\ Receivables_t/Sales_t)$ / $(Net\ Receivables_{t-1}/Sales_{t-1})$ to explain expectation to produce or maintain a fairly consistent trend in the sales and receivables measurement so that the ratio detecting a rise in the receivables implied a change in the credit policy to spur sales for the revenue to be inflated. The possibility of growing companies' reliance on external financing to fuel growth suggested this computation. *DSRI* of 1.1 suggested a steady relationship [7][21].

Gross Margin Index, *GMI* was written as *GMI* = $[(Sales_{t-1} - Cost\ of\ Sales_{t-1})/\ Sales_{t-1}]$ / $[(Sales_t - Cost\ of\ Sales_t)\ /\ Sales_t]$. Comparing the gross margins of the current period to the previous period provided the *GMI*. *GMI* less than 1.1 reflected a declining operational efficiency to give rise to fraudulent activities. High G*MI* required deeper understanding into the firm's reported sales and the cost of sales [7][21].

Asset Quality Index, *AQI* was written as *AQI* = $[1 - ((CA_t + Plant, Property\ \&\ Equipment_t, PPE_t)/TA_t)]$ / $[1 - ((CA_{t-1} + PPE_{t-1})/TA_{t-1})]$. The *AQI* was computed to measure the ratio of the total assets *TA* for which future benefits were uncertain. This index was used to reflect the variation in asset realization risk by comparing the *CA* and *PPE* with *TA*. A computed *AQI* greater than one was used to reflect a potential increase in or involvement in cost deferral conditioned on the rise in asset realization risk to reflect a heightened tendency to capitalize and defer costs [7][21].

Sales Growth Index, *SGI* was written as *SGI* = $Sales_t\ /\ Sales_{t-1}$. The firms with high growth potential were considered as susceptible to commit fraud when the trend reversed.

Shareholders expectations for continuity in the growth trend were considered as factors that placed burdensome requirements on the participated firms to produce manipulated financial data with contrived sales figures to appear competitive on the GSE [7][21].

Depreciation Index, *DEPI* was written as $DEPI = (Depreciation_{t-1} / Depreciation_{t-1} + PPE_{t-1}) / (Depreciation_t / Depreciation_t + PPE_t)$. The implication of this included variable was to suggest that the firm reviewed the *PPE* useful life conventions upwards, or embraced new practices that were income friendly [7][21].

Sales, General and Administrative expenses Index, *SGAI* was written as $SGAI$ = (*Sales, General and Administrative expense*$_t$ */Sales*$_t$) / *Sales, General and Administrative Expense*$_{t-1}$*/Sales*$_{t-1}$). The study used the *SGAI* variable to interpret a disparate rise in sales to reflect an adverse effect about the going concern prospects of firms with implications of financial data manipulation to defer costs [7][21].

Leverage Index, *LVGI* written as $LVGI$ = [(*Total Long Term Debt*$_t$ + CL_t)/ TA_t] / [(*Total Long Term Debt*$_{t-1}$ + CL_{t-1})/TA_{t-1}] was used to evaluate the percentage of total debts to *TA* against the previous year to capture debt covenant inducements for earning manipulation to monitor the greater risk of the firms contravening the debt covenants and manipulating the earnings to avoid a breach [7][21].

Total Accruals to Total Assets, *TATA* written as *TATA* = [*Change in working capital – change in cash – change in tax payable – change in depreciation and amortization] / TA*, and re-written as *TATA* = (*Income from Continuing Operations – Cash Flows from Operations*) /*TA* was used to measure how the borrowing firms made discretionary accounting decisions to amend the earnings [7][21]. The subscripts t and t-1 in the definition of the models denote time pertaining to the current year and prior year respectively. The next section details the summary of the results in line with the research objectives.

5. Summary of the results

This section presents the summary of the study in line with the research objectives. The z, x and m scores of the twenty-six firms investigated provided the descriptive demographic properties for the categorization of the bankruptcy and fraud events. The reliability test showed statistical significance in line with the required alpha confidence scores analogous to the respective categories of the z, x and m scores. The demonstration was achieved by the resulting p-values of the z, x and m models less than the required alpha scores in indicating the statistical significance at 90% confidence interval for the z models and 95% each for the x and m models from ANOVA between and within group scores. The strong association explained by the corresponding F ratios > the F crit expound the variation among the mean score categories of the z, x and m scores to be more than that expected due to chance to support evidence for the analysis of bankruptcy and fraud event of interest. The coefficient of determination r^2 explained the overall variability of the models used (detailed in the discussion section of the results). The study rejects the hypotheses $H1_0$, $H2_0$ and $H3_0$ to achieve the study objective. Criterion validity for the study was explained at the point D : $z < 1.810$, G : $1.810 \leq z \leq 2.990$, S : $z > 2.990$ for the manufacturing firms and D : $z < 1.100$, G : $1.100 \leq z \leq 2.600$, S : $z > 2.600$ for the non-manufacturing firms [10][14]. Non-bankrupt and bankrupt firms' separation by the x model was such that $x < 0.500$ was interpreted as non-bankrupt and $x \geq 0.500$ = bankrupt to show criterion validity [8]. The F-test was used to explore the statistical significance of the hypotheses data set in accordance with the objective of the study.

The bankruptcy results of the Altman and Zmijewski models moderated by the Beneish model were reported at *p = .060 < .1 alpha, **p = .005 < .1 alpha, ***p = .000 < .05 alpha and ****p = .008 < .05 alpha. The corresponding $*F = 3.767 > F_{2,10,.1} = 2.924$, $**F = 9.175 > F_{2,11,.1} = 2.860$, $***F = 23.717 > F_{1,12,.05} = 4.747$, $****F = 9.373 > F_{1,14,.05} = 4.600$ corroborated this statistical stance. The study rejects $H1_0$, $H2_0$ and $H3_0$ since the corresponding $F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}$; $p < \alpha$.

The study results provided fascinating results on the focus of the *z* and *x* models predictions in establishing the participated firms' financial conditions. The contradictory bankruptcy results had a strictly distress prediction focus for the Altman model and vice versa for the Zmijewski model in reflecting the bankruptcy status of the solid data integrity firms. The next section discusses the results of the study.

5.1. Discussion of the results

This section discusses the results of the study. The study presented fascinating results from the mix of the *z*, *x* and *m* models in the bankruptcy and fraud analysis. The hypotheses of the research questions provided distinct results in line with the study objective with the statistical influences between groups and within group scores. The discussions of the results are organized in the accordance of R1, R2 and R3.

R1 - Is there a statistical significant relationship between the Altman *z* and Beneish *m* scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE?

$H1_0$: There is no statistically significant relationship between the Altman *z* and Beneish *m* scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE.

$$F = \frac{MSB}{MSW} = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} \sim F_{k-1,N-k,\alpha} \text{ ; } p = \alpha \,. \quad *p = .1\,, \qquad **p = .1\,,$$

$$***p = .05\,, \qquad *F \sim F_{2,10,.1} = 2.924\,,$$

$$**F \sim F_{2,11,.1} = 2.860\,, \qquad ***F \sim F_{1,12,.05} = 4.747\,.$$

Reject $H1_0$ if :

$$F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha} \text{ ; } p < \alpha \,.$$

The study rejects the results of the null hypothesis $H1_0$ since there was statistical evidence against this hypothesis towards the analysis into the separation of the bankruptcy and fraud events on the twenty-six firms respective to the periods 2009 to 2016 in running the *z* and *m* models concurrently. The ANOVA between group and within group *z* scores for manufacturing firms reported *p = .060 < .1 alpha and corresponding $*F = 3.767 > F_{2,10,.1} = 2.924$ (detailed in the summary). The *z* scores for non-manufacturing firms reported **p = .005 < .1 alpha, and corresponding $**F = 9.175 > F_{2,11,.1} = 2.860$ while the *m* scores reported ***p = .000 < .05 alpha and $***F = 23.717 > F_{1,12,.05} = 4.747$. These results are statistically significant at $F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}$; $p < \alpha$ as evidence against $H1_0$ in the categorization of bankruptcy and fraud event groupings demonstrating strong variability among the mean score groupings in line with the study objective.

The results demonstrate the effectiveness of the *m* model simultaneously with the *z* model [7][11][12]. The results resonate with the case study of [11] that revealed the instance of data manipulation symptoms on the explored company data of 2010 and otherwise in 2011 and 2012 in utilizing the Altman metric in chorus with Beneish model. This study result was also consistent with [7] that found early warning signals of bankruptcy and fraud in reporting on Enron secondary data of 1997 to 2001 after its collapse from the Altman and Beneish models analysis. Reference [12] asserted that there were indicators of financial crisis and gross earning manipulation by Enron since 1997 by exploring Enron data covering 1997 to 2001. Criterion validity defined the basis for validity of the findings of these studies in deploying the Altman and Beneish models simultaneously in the bankruptcy and fraud analysis [7][11][12].

The outcome of the *p*-values of the *z* score categories validated the 90% confidence interval against the required alpha of .1 providing the indication of statistical significance of the *z* score categories in the Altman model bankruptcy analysis. The *F* ratios > *F* crit explains the variation among the *z* mean score categories to be more than that expected due to chance. The general form of the sum of squared variances for the residuals (*SSE*) was described by $\sum (Y_i - \hat{Y})^2$ where Y_i denoted the average data points of the adapted discriminant models. In application to the Altman *z* model, Y_i was D: $z = 1.810$, G: $z = (1.810+2.990)/2 = 2.400$, S: $z = 2.990$ for the manufacturing firms and, D: $z = 1.100$, G : $z = 1.850$, S: $z = 2.600$ for the non-manufacturing firms [10][14]. $\hat{Y}$ was used to denote the yearly average predicted scores for the categories of the discriminant functions. The coefficient of determination r^2 was expressed as the difference between $1 - SSE/SST$ or SSR/SST to measure the goodness of fit of the output $\hat{Y}$ of the linear combination of the independent variables against Y_i. *SSR* and *SST* denoted the regression sum of squares and total sum of squares respectively. In the *z* score linear discriminant function, the portion of the variability explained by the *z* score model for the manufacturing firms was demonstrated by $r^2 = 0.927$, adjusted to $\acute{r}^2=0.875$. The *z* score for the non-manufacturing firms produced $r^2 = 0.804$, $\acute{r}^2=0.717$. The analysis reasoned with the test of predictive accuracy of the Altman *z* score model of between 80% - 90% one year before the event in [8] literature.

The computed overall average m score of the data manipulators and non-manipulators categories against the predicted average yearly m score were used to explain the portion of variability explained by the m model over the period 2009 to 2016. The computed market average score of -3.841 and -0.750 respective to solid and not solid data integrity firms' specification of the general form variable Yi were matched against the respective average yearly predicted m scores. The reason was due to the adopted m model having no adapted Yi values tailored for specific industries like the z model. The portion of variability explained by the m model was r2 = 0.989, ŕ2 = 0.973. The explanation provided by the F ratios of both the z and m models provided strong variability among the mean scores than the expectation due to chance. The F ratios > F crit and the corresponding p less than the required alpha scores provided support to the evidence that fraud events existed on the participated firms when the m model was simultaneously run with the z model. That is, yes, there is a statistically significant relationship between the Altman z and Beneish m scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE to R1. Therefore, reject $H1_0$ since, $F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}$; $p < \alpha$.

R2 - Is there a statistical significant relationship between the Zmijewski *x* and Beneish *m* scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE?

$H2_0$: There is no statistically significant relationship between the Zmijewski *x* and Beneish *m* scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE.

$$F = \frac{MSB}{MSW} = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} \sim F_{k-1,N-k,\alpha}\,; p = \alpha\,. \quad {*}{*}{*}\, p = .05\,, \qquad {*}{*}{*}{*}\, p = .05\,,$$

$${*}{*}{*}\, F \sim F_{1,12,.05} = 4.747\,,\ {*}{*}{*}{*}\, F \sim F_{1,14,.05} = 4.600\,.$$

Reject $H2_0$ if :

$$F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}\ ;\ p < \alpha\,.$$

The study rejects the null hypothesis H20 since there is statistical evidence against this hypothesis towards the analysis of bankruptcy and fraud symptoms from the x and m models predictions. Consistent with the explanation highlighted in the ANOVA between and within group sum of squares of the m scores categories provided statistically significant results at ***p = .000 < .05 alpha while x scores categories produced and ****p = .008 < .05. The respective F-test results were $*** F = 23.717 > F_{1,12,.05} = 4.747$, $**** F = 9.373 > F_{1,14,.05} = 4.600$. The portion of variability explained in the computed market average x score of -0.749 and 3.093 for non-bankrupt and bankrupt groupings respectively yielded r2=0.858, ŕ2=0.823. The resilient connection revealed by the F ratios > F crit of both the x and m models at the confidence scores validate and support the evidence of existence of bankruptcy and fraud predictions on the participated firms against H20. The overall explained variability provided by the m model was r2 = 0.989, ŕ 2= 0.973 to measure the goodness fit. Limited studies exist on the mix of the Zmijewski and Beneish models deployed together in bankruptcy and fraud analysis to facilitate comparisons with this study. The study provided statistical evidence against H20 from the analysis of the statistical results. The strong variations explained by F ratios of both the x and m models against the F crit provided a yes significant statistical result for R2 that there is a statistically significant relationship between the Zmijewski x and Beneish m scores prediction of bankruptcy and fraud events on the listed non-financial firms on the GSE. Therefore; reject $H2_0$ since $F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}\ ;\ p < \alpha$.

R3 - Is there a statistical significant contradiction between the Altman and Zmijewski models moderated prediction of bankruptcy events on the listed non-financial firms on the GSE?

$H3_0$: There is no statistically significant contradiction between the Altman and Zmijewski models moderated prediction of bankruptcy events on the listed non-financial firms on the GSE.

$$F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} \sim F_{k-1,N-k,\alpha}\,;\ p = \alpha, \qquad {*}\, p = .1, \qquad {*}{*}\, p = .1, \qquad {*}{*}{*}\, p = .05,$$

$${*}{*}{*}{*}\, p = .05\,;$$

$$* F \sim F_{2,10,.1} = 2.924\,, \quad ** F \sim F_{2,11,.1} = 2.860\,, \quad *** F \sim F_{1,12,.05} = 4.747\,, \quad **** F \sim F_{1,14,.05} = 4.600\,.$$

Reject $H3_0$ if :

$$F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha} \;;\; p < \alpha\,.$$

The study compared the focus of the bankruptcy predictions results of the *z* and *x* models after separating the data manipulators with the *m* in answering answer R3. The expectation was that all distress predictions by the Altman model should reflect bankrupt predictions by the Zmijewski model in line with the study objective for the results of $H3_0$ to be justified as no statistically significant contradiction at $H1_0 = H2_0$ otherwise, reject if $H1_0 \neq H2_0$.

The analysis of the results of R3 was conditioned on all the *p*-values discussed under the results of *z*, *x* and *m* models and corresponding *F* crits for the bankruptcy analysis in line with the study objective. That is, the bankruptcy results of the Altman and Zmijewski models moderated by the Beneish model were reported at $*p = .060 < .1$ alpha, $**p = .005 < .1$ alpha, $***p = .000 < .05$ alpha and $****p = .008 < .05$. The corresponding $* F = 3.767 > F_{2,10,.1} = 2.924$, $** F = 9.175 > F_{2,11,.1} = 2.860$, $*** F = 23.717 > F_{1,12,.05} = 4.747$, $**** F = 9.373 > F_{1,14,.05} = 4.600$ corroborated this statistical stance. The study rejects the results of $H3_0$ to R3 of the Altman and Zmijewski models prediction of bankruptcy events on the listed non-financial firms on the GSE since there was statistical evidence against this null hypothesis. The findings reflecting this statistically significant contradiction in the bankruptcy prediction focus of the *z* and *x* models were captivating. The fascinating aspect of this result was that all contradictions in the results of the Altman model prediction pointed exclusively to distress zone while that of the Zmijewski model pointed exclusively to non-bankrupt zone implying $H1_0 \neq H2_0$. The study results to R3 were premised on all the *p*-values discussed under hypotheses of R1 and R2. The main difference between [7] and this study was the comparison of the focus of both the *z* and *x* models after separating the data manipulators with the *m* model for $H1_0 \neq H2_0$ statistically significant contradiction results. Reference [7] used only the *z* and *m* models in Enron's bankruptcy and fraud analysis similar to [11] and [12]. Studies on the mix of the Zmijewski and Beneish models for comparisons are limited to the GSE.

The study attested to the findings of [8] average bankruptcy statistics of 46.64% and 25.57% of thirty-four GSE listed firms over 2009 to 2015 which used the *z* and *x* models to explain that the former predicts higher bankruptcy rate than the latter. The demonstration by the focus of evidence against the rejection of $H3_0$ since $F > F_{k-1,N-k,\alpha}$; $p < \alpha$ where the *z* model reflected the strictly distress focus and the *x* model reflected the strictly non-bankrupt focus achieved this manifestation through the inclusion of Beneish fraud metric for this study objective. However, [10] presented a reverse outlook of a higher prediction rate for the Zmijewski model than the Altman model in the bankruptcy analysis of the listed companies on the Kuwait stock exchange. The mentioned studies were based on criterion validity in the bankruptcy analysis with the deployed *z* and *x* models discriminant criterion [8][10]. That is, the explanations by these studies at the point of contradictions of the *z* and *x* models were attributed to the rate of bankruptcy prediction by each model [8][10]. However, these studies omitted the role of the Beneish fraud metric on the Altman and Zmijewski bankruptcy models in detailing the results [8][10]. In this study, the statistically significant contradiction leading to the rejection of $H3_0$ presents dilemma for banking professionals when confronted with a lending decision from the combined *z*, *x* and *m* models from the evidence of this study.

Therefore: reject $H3_0$ since $F = \frac{\frac{SSB}{k-1}}{\frac{SSW}{N-k}} > F_{k-1,N-k,\alpha}$; $p < \alpha$. The next section presents on the conclusions of the study.

6. CONCLUSIONS AND PRACTICAL RECOMMENDATIONS

This section presents of the conclusions and recommendations of the study in line with the study objectives. It was possible to gather information on bankruptcy and fraud related information on the borrowing deals of the listed non-financial firms on the GSE simultaneously with the *z*, *x* and *m* models. The overall variability explained by the *z* models was r^2 = 0.927, adjusted to $\acute{r}^2$=0.875 for the manufacturing firms and r^2 = 0.804, $\acute{r}^2$=0.717 for the non-manufacturing firms. The *x* metric yielded r^2=0.858, $\acute{r}^2$=0.823, while the Beneish metric provided r^2=0.989, $\acute{r}^2$=0.973. The deployed metrics [7][8][10][14][21] were effective predictors of the specified events of interest and provided basis for customer risk assessment by Ghana bank risk managers in the lending decision process. Replicating the study in lending decision process by the risk managers of Ghana banks should minimize excessive risk taking activities and facilitate the reporting of suspicious activities to the BoG and FIC to promote market discipline [13][15]. The bank managers can determine the financial condition in terms of bankruptcy ordering of the participated firms and raise the potential red flags, report and mitigate against engagements of the borrowers at this point under the decision rule of R3. The bank risk managers should take no lending decision on the borrowing need of the participated firms when imposed with the divergent focus of the Altman and Zmijewski models controlled by the Beneish metric in simultaneous bankruptcy analysis. This should create avenue to reduce the cost of information advantage; control the link between credit and operational risks of the participated firms that jeopardize both depositors and the banks interests due to credit decisions in replicating the used models by the bank managers. The growth in the NPL ratio from 14.7% in 2015 to 17.3% in 2016 can be mitigated on the borrowers accounting data that influence the credit decisions and underlying agreements. Therefore, implementing the study results by the risk managers to the context of the study participants should minimize the morale hazard implications resulting in Ghana banks collapse, improve the capital adequacy ratios, strengthen corporate governance and risk management and mitigate against money laundering implications. This should uncover the early warning signals of bankruptcy and fraud reporting of the participated firms on the GSE that jeopardize the going concern of the banks.

The result of the study was a quantitative assessment of the specified bankruptcy and fraud characteristics on the secondary data points of the twenty-six non-financial firms on the GSE covering the period 2009 to 2016 conditioned on criterion validity and confidence limits from the findings in accordance with the deployed metrics [8][10][14]. However, fraud determination is a legal matter by a court and not the verdict of the bank risk manager [22][23]. Therefore, the study did not guarantee that the sampling approach detected all misstatements instigated by error or fraud [24][25].

The study methodology is recommended for the bank risk managers to avert claims against the risk management function for not raising the red flags on improper disclosures on the secondary data explored, or tricking investors or violating banking regulations [2][22][23][26]. Replicating the metrics in the lending decision making by the bank managers should facilitate the improvement of the effective compliance status of the financial market in the fight against financial crime to reduce GIABA ratings going forward [7][9]. The outcome of the study should facilitate the bridging of the gap between research' combining multiple bankruptcy metrics in studies that omitted the fraud metric [8][10] and studies that combined the Beneish and the Altman metrics in bankruptcy analysis by researchers [7][11][12]. Interweaving the results of the Altman, Zmijewski and Beneish metrics for the study into the banks dashboard systems should keep the bank management and risk managers informed on critical areas in directing the banks in managing bankruptcy and fraud indicators of borrowers by process instead of by objective with the discriminant scenarios of the algorithms, perform what-if and trends scenarios and limit the measurements in real time with root-cause assessments as the measurements approach the discriminant scores to reflect the inferences. Therefore, the study is recommended to serve the purposes of uncovering the indicators of bankruptcy and the fraud events specified.

7. Recommendations for further research

Stating the hypotheses of bankruptcy analysis that included the *m* fraud model provided statistical support towards decision making measures at $H3_0$ in the lending decision process when the *z*, *x* and *m* models were combined together for the study. The inclusion of the *m* model provided statistically significant contradictions in bankruptcy prediction focus of the *z* and *x* models as evidence against the rejection of $H3_0$. Studies that provide the rationale behind the contradictory bankruptcy results of the *z* and *x* models to the context of the GSE are limited. The consolidation exercise following the banking sector crisis saw voluntary winding up of one bank, merger of banks to strengthen the regulatory capital base and two banks absorbed by the CBG for not meeting recapitalization deadline of December 2018 [2]. The study provided that banks should not take lending decisions on the participated firms when the *z* and *x* models predictions contradict each at the instance of the inclusion of the *m* model. The basis is to safeguard the regulatory capital base from potential moral hazard implications of the dilemma presented in rejecting $H3_0$. Future studies to the context of this study objective should seek to explore to resolve the dilemma presented by the contradiction between the *z* and *x* models.

Acknowledgements

Tons of gratitude to Dr. Jason Lee Carter, Dr. Francis Pol Lim and the academic review board of the Swiss Management Center, Switzerland for the rigorous reviews and feedback on this work. The commitment to the mentorship process in the entire dissertation phase with timely feedbacks despite other academic and professional engagements culminated into the success of this paper. Gratitude to the entire SMC faculty and administration for the immense support and treasured contributions throughout the doctoral journey whenever I reached out to their doorstep.

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