THE 1st INTERNATIONAL CONFERENCE ACCOUNTING, MANAGEMENT, ECONOMICS, UNISKA
Proceeding Accounting, Management, Economics Uniska **Volume 1, Issue 1, 2024**
"Strengthening The Role of Accounting, Management, and Economics Science In Realizing Sustainable Welfare Goals"

A Comparative analysis of Bankruptcy prediction models: Altman's Model and Zmikewski's Model in EGYPT

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ABSTRACT

This study provides a comparative analysis of two widely used bankruptcy prediction models—Altman's Z-Score Model and Zmijewski's X-Score Model—applied to companies listed on the Egyptian stock market. The sample comprises 10 companies, split evenly between financially distressed firms and financially stable ones, with data spanning from 2020 to 2022. The predictive accuracy of both models was assessed, with Altman's Z-Score achieving a predictive ability of 50%, while Zmijewski's X-Score demonstrated a slightly lower accuracy at 46.66%. The findings indicate no significant difference in the predictive capabilities of the two models within the context of the Egyptian market. These results suggest that neither model is distinctly superior, highlighting the need for further research to refine bankruptcy prediction methods in emerging markets like Egypt.

INTRODUCTION

In the dynamic landscape of financial markets, the ability to predict bankruptcy and financial distress has garnered significant attention from scholars, practitioners and policymakers alike. The repercussions of corporate insolvency extend beyond the firm itself, affecting stakeholders, employees, creditors and the broader economy. Consequently the development and validation of accurate bankruptcy prediction models have emerged as indispensable tools for risk management and decision making.

Among the plethora of prediction models, Altman's Z model and Zmijewski's X model stand out as seminal contributions in this domain. Developed in the late 1960s by Edward Altman , the Z model revolutionized bankruptcy prediction by incorporating a multifactorial approach ,integrating financial ratios to classify firms into distinct risk categories , subsequently in the 1980s , zmikewski proposed X model which aimed to enhance the predictive accuracy by refining the selection of financial ratios and incorporating industry specific factor. While extensively studied and validated in various global contexts, the applicability and efficacy of these models in the Egyptian financial landscape remain relatively unexplored. Egypt's unique economic, regulatory, and market dynamics warrant a tailored examination to assess the suitability and performance of these models within the Egyptian context. This research paper endeavors to fill this gap by conducting a comparative analysis of Altman's Z model and Zmijewski's X model concerning bankruptcy predictive in Egypt. By evaluating predictive accuracy, robustness and applicability of these models within the Egyptian context. This study aims to provide valuable insights for financial analysts, investors, regulators and policymakers operating in the Egyptian market .The objective of this research paper is to conduct a comparative analysis between the Altman Z-score model and

Zmijewski's X model in predicting bankruptcy and financial failure in Egyptian companies. The purpose is to evaluate the effectiveness and reliability of both models in assessing the financial health and potential risk of bankruptcy for companies operating in Egypt. By comparing the predictive capabilities of these two widely used financial distress prediction models, the research aims to provide insights into their applicability and accuracy in the Egyptian business context. Additionally, the study seeks to identify any discrepancies or strengths between the two models, offering valuable information for stakeholders, investors, and policymakers regarding the assessment of financial risk and the implementation of proactive measures to mitigate potential bankruptcy or financial distress in Egyptian companies.

a) **Research Question:**
   Is there a significant difference between the predictions of bankruptcy and financial failure made by the Altman Z-score model and Zmijewski's X model for companies in Egypt?
b) **Hypothesis:**
   Null Hypothesis (H0): There is no significant difference between the predictions of bankruptcy and financial failure made by the Altman Z-score model and Zmijewski's X model for companies in Egypt.
   Alternative Hypothesis (H1): There is a significant difference between the predictions of bankruptcy and financial failure made by the Altman Z-score model and Zmijewski's X model for companies in Egypt.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Institutional setting

1- **Bankruptcy and financial failure:**
   Bankruptcy, as conceptualized by Schumpeter (1942), embodies the notion of "creative destruction," wherein old economic structures are supplanted by new ones, fostering innovation and growth. This process is inherent to capitalism, facilitating the emergence of fresh companies and industries. Despite its role in economic evolution, bankruptcies pose significant challenges. Beyond impacting investors, they affect a multitude of stakeholders. For instance, in Sweden in 2012, the bankruptcy of numerous employers impacted 25,466 employees (The Swedish Agency for Growth Policy Analysis, 2013). Thus, while bankruptcy fuels economic renewal, its repercussions underscore the importance of addressing its broader societal impact.
   The bankruptcy concept has a lot of meaning and a lot of orientations that we should difrrencitate between them, As indicated by Mari-Vidal et al. (2014), we can basically group these definitions into two blocks: those that for an economic approach and those that apply a legal approach .In most of pervious researches indicates the economic approach because that the legal approach or concept it hard to be evaluated.

   Economic distressed: it happens when the cash flow is less than expected because of less in income and revenue and increase in the expenses and costs or when it's a negative net assets or equity .One representative of this third option is Altman (1981), who defines failure as technical insolvency or in the sense of capital with a lack of liquidity, **We need to differentiate between bankruptcy, financial failure, insolvency, and default first:**

According to Toto (2011), bankruptcy refers to a situation where a company becomes incapable of fulfilling its financial obligations. This critical condition often doesn't arise suddenly but can be detected through early indicators observable in the company's financial statements. In the event of bankruptcy, the value of a company's assets is insufficient to cover its obligations, rendering it unable to repay its debts even through liquidation.

Financial Failure: According to the Dictionary of Finance and Banking (Oxford Reference, 2012), Failure can be defined as the failure to make required payments Failure is another common word, particularly within accounting-based modeling literature. Beaver (1966) defined failure as the inability of a firm to pay its financial obligations as they mature. here we can see that the company's assets is less than the company's liability but we in this stage the company's getting more debt to still on going.

For the bankruptcy there are two types:

1- **Voluntary bankruptcy**: when the company provide to the court request for bankruptcy and take the required procedures and this is decrease the pressure on the company and increase the cash flow.
2- **Involuntary bankruptcy** : when the creditors ask the management to request to bankruptcy court

Insolvency occurs when a company is unable to meet its financial obligations, despite its assets surpassing its liabilities. This situation arises because there aren't enough liquid assets that can be converted into cash to fulfill business activities**.** According to Jensen and Meckling (1976), insolvency signifies a fundamental breakdown in the firm's ability to generate sufficient cash flows to cover its obligations, reflecting underlying inefficiencies or financial distress. Building on this definition, Heifer and Vishny (1997) emphasize the role of agency conflicts and information asymmetries in contributing to insolvency.
They argue that managerial agency problems can lead to risk-taking behavior and value destruction, ultimately culminating in financial distress and insolvency. Moreover, Myers (1977) introduces the concept of financial leverage and its implications for insolvency risk. He suggests that excessive leverage amplifies the impact of adverse shocks on a firm's solvency position, highlighting the importance of prudent capital structure management in mitigating insolvency risk.

Default, commonly understood as a scenario in which a company encounters a range of adverse circumstances such as decreased customer demand, loss of market share, declining productivity, and related challenges, has been explored extensively in the literature. According to Altman (1983), default represents a breach of contractual obligations, where a debtor fails to meet scheduled payments or obligations to creditors. This definition underscores the legal and contractual implications of default, emphasizing its significance in the context of creditor-debtor relationships. In addition, Merton (1974) develops a structural model of corporate default based on the firm's capital structure and asset values. His framework considers default as a contingent event determined by the interaction between asset volatility, debt obligations, and equity value. Merton's model provides insights into the determinants of default risk and the role of financial leverage in exacerbating solvency challenges during adverse market conditions. Furthermore, Bharath and Shumway (2008) examine the role of corporate governance and internal control mechanisms in mitigating default risk. They argue that effective governance practices, including board oversight, executive compensation structures, and risk management processes, can enhance a firm's resilience to external shocks and mitigate the likelihood of default.

Types of failure as a general:

a. **Creeping failure**: is likely due to several internal reasons including inefficiency of management and increased reliance on debt, expansion without any effective plan , wistful use of resources) (abdel-haffez -6.10.2004)
b. **Sudden failure**, which occurs suddenly as a result of political, economic, legal or social changes. (shaheen and matar 2011).

2- **Stages of Failure and Bankruptcy:**

a. **Nursery Stage**: This initial stage, as described by Beaver (1966), represents the embryonic phase of business failure where early warning signs may not be readily apparent. It is characterized by the development of a company's operations, products, and market presence, often accompanied by substantial investment in infrastructure and human capital.
b. **Operational Distress**: In addition to financial challenges, Hillegeist et al. (2004) identify operational distress as a critical stage preceding bankruptcy. This phase involves disruptions in core business operations, such as production delays, supply chain disruptions, or regulatory compliance issues, which further exacerbate financial difficulties and hinder the company's ability to generate sustainable cash flows
c. **Financial Disturbance**: Building upon this notion, Zmijewski (1984) defines the financial disturbance stage as the period when management becomes cognizant of emerging financial risks and challenges. This phase is marked by the recognition of deteriorating financial performance metrics, such as declining profitability, liquidity strains, and increasing leverage ratios.
d. **Financial Insolvency**: During the financial insolvency stage, as discussed by Myers (1977), a company faces difficulties in securing necessary financing to meet its operational and debt obligations. This stage is characterized by liquidity constraints, where the company struggles to access capital markets or obtain credit facilities due to deteriorating creditworthiness and perceived default risk.
e. **Total Bankruptcy**: The total bankruptcy stage, according to Altman (2002), represents the culmination of financial and operational challenges, where a company's financial position becomes irretrievable. At this juncture, the company is unable to sustain its operations, meet debt obligations, or restructure its liabilities effectively, leading to liquidation or restructuring under bankruptcy proceedings.
f. **Confirmation of Bankruptcy**: Finally, as proposed by Ohlson (1980), the confirmation of bankruptcy stage signifies the formal acknowledgment and legal recognition of the company's insolvency status. This stage involves court proceedings, creditor negotiations, and the implementation of bankruptcy resolution mechanisms, such as

liquidation, reorganization, or debt restructuring, to address outstanding liabilities and distribute assets to stakeholders.

3- Previous studies:

1) The study conducted by Altman (1968) aimed to construct a model using financial ratios and relying on multivariate discriminant analysis. The study focused on the manufacturing sector in the United States, with a sample comprising 33 bankrupt firms and 33 non-bankrupt firms during the period 1946-1965. Through the analysis of 22 financial ratios extracted from the financial statements of these firms, the researcher identified the financial ratios with the greatest predictive power for corporate bankruptcy. These ratios included:

a) Working Capital to Total Assets
b) Retained Earnings to Total Assets
c) Earnings Before Interest and Taxes to Total Assets
d) Sales to Total Assets

Altman's model, known as the Altman Z-Score, utilized these financial ratios to assess the financial health and predict the likelihood of bankruptcy for companies within the manufacturing sector.

2) The study conducted by Al-Ghaseen (2004), titled "The Use of Financial Ratios to Predict Corporate Distress: An Empirical Study on the Construction Sector in Gaza," aimed to identify the best set of ratios for predicting the distress of construction companies. The study utilized 22 financial ratios for a sample of companies, including 10 distressed companies and 16 non-distressed companies. Logistic regression analysis was employed to achieve this aim, resulting in the reduction of the number of ratios to just 4 financial ratios.

3) In a study by Bzam (2014) titled "The Use of Financial Indicators to Predict Financial Distress: An Empirical Study of a Sample of Small and Medium-sized Enterprises in the Wilaya of Ouargla," the researcher employed 17 financial ratios and applied them to a sample of 20 Algerian companies of small and medium size. This was done using discriminant analysis. After conducting the analysis, a model consisting of 4 financial ratios was developed, which achieved a prediction accuracy of 90% in forecasting the failure of companies with quality.

4) The study conducted by Ahmed (2015), titled "Application of Altman Z-Score Model for Predicting Financial Failure: An Application on a Sample of Banks Listed on the Khartoum Stock Exchange," aimed to highlight the role of modern financial analysis methods in providing indicators to assist investors in making their investment decisions. The researchers relied on the Altman Z-Score model for predicting corporate failures, as well as predicting the financial positions of companies listed on the Khartoum Stock Exchange.

5) The study conducted by Zulkarnain and Hasbullah (2009) involved the development of a model for predicting corporate distress in Singapore, known as a local proprietary model. The model was constructed based on 64 financial ratios as independent variables. The study was conducted on a sample of 17 failed institutions and 17 sound institutions. The results of the study identified two ratios with the highest predictive ability for corporate distress: cash flow to total assets and sales to receivables. The accuracy of the model in predicting corporate distress exceeded 80%.

6) The study conducted by Mary Hilston Keener in 2013 focused on industrial retail companies in the United States for the period between 2005 and 2012. The researcher utilized a database of these companies and employed logistic regression analysis. The study aimed to build a model capable of predicting the financial insolvency of these companies. The researcher successfully developed a model using five variables: number of employees, return on assets ratio, cash flow to total sales ratio, current assets to total debt ratio, and cash flow to current liabilities ratio. The effectiveness of the model was tested through various statistical tests, including the Durbin-Watson test, which yielded a value of 1.938, indicating no autocorrelation issue in the model.

7) In Wu's study (2007), factor analysis was employed to identify 6 financial ratios (FRs) from the 13 proposed by Altman (1968) and Ohlson (1980). These FRs were categorized into solvency, profitability, and turnover categories. Additionally, 10 corporate governance indicators (CGIs) were selected from ownership and board structure categories.

8) In Lin et al.'s research (2010), an exhaustive search method was utilized to choose 4 FRs and 6 CGIs out of a pool of 23 and 42, respectively. Their findings demonstrated that the prediction model, based on support vector machine, yielded higher accuracy when employing the selected CGIs. Notably, the selected FRs pertained to solvency and turnover categories, while the chosen CGIs covered board structure, ownership, and cash flow rights categories.

9) The study conducted by Louise Tchamanbé Djiné in 2011 utilized three theories: the first theory pertained to return on equity, the second theory focused on asset utility, and the third theory concerned profit level. The research sample consisted of a bank in Cameroon. The research results indicated signs of bank failure because the bank exhibited the same values as those during the financial crisis of 1980-1988. The prediction of failure using Z-score analysis was small or minimal during the periods 1980-1988 and 1980-2006, but it was not zero. This implies that the mentioned indicators consistently demonstrate the stability of the banking and financial system at present. Moreover, this result provides a long period before the banking crisis. According to this study, the risks of evaluating financial failure for the research sample through analysis and measurement showed that bank failures occurred between 1980 and 2006. The occurrence of failure risks in presenting banks' risk profiles for the danger of their activities is attributed to inadequate coverage of these risks by capital. In other words, the exposure of the bank's securities portfolio to risk from its activities contributed significantly to its failure more than inadequate self-financing coverage. The analysis reveals a match between the indicated results on the probability of failure, which is low before the crisis, significantly increases during the crisis, and declines after the crisis.

10) The study conducted by Zhu Li and Zhu Naiping in 2011 analyzed a sample of 100 companies, dividing them into 50 public companies and 50 private (individual) companies. According to the final tools for company analysis, it was found that the Z-score for public companies is higher than that for private companies, as indicated in tables (5, 6). This suggests that the financial risks for private companies are significantly higher than those for public companies. Additionally, the turnover ratios for private companies are lower than those for public companies, and the ratio of assets to liabilities for private companies is higher than that for public companies, as shown in tables (11, 10, 9, and 8). In general, the levels of financial risk for registered companies exhibit an increasing trend. Furthermore, the Z-score for private companies is significantly lower than that for public companies, as illustrated in tables (6, 5). This indicates that the financial risks for private companies are considerably higher than those for public companies. Additionally, the Z-score reflects the financial risks of companies, where lower Z-scores correspond to higher financial risks. When Z-score is equal to or greater than 3, the financial position of the company is considered secure or far from risks

METHODS

a. Method Used

Quantitative Approach: This research utilizes a quantitative approach, systematically analysing financial data to investigate the efficacy and applicability of bankruptcy prediction models within the Egyptian market context. Specifically, the study employs Altman's Z-Score model and Zmijewski's X-Score model to assess their predictive power for the selected companies. The quantitative method is particularly suitable for examining the secondary data obtained from the financial statements of the companies in the sample**.**

b. Data Sample

Sample Composition: The dataset comprises financial information from 10 companies listed on the Egyptian stock market. The sample includes 5 companies that consistently reported losses from 2020 to 2022 and 5 companies that consistently made profits during the same period, providing a balanced comparison of financially distressed and stable firms.

Data source: The financial data, including income statements, balance sheets, and cash flow statements, were sourced from the Egyptian Stock Market Exchange, reputable financial databases, official company reports, and regulatory filings. The dataset captures key financial metrics and performance indicators, including profitability, liquidity, leverage, and industry-specific factors.

Table (1) the companies that has been used in the study (distress, stable)

number	company	status
1	EGTS	Distress
2	South village	Distress
3	Rakta	Distress
4	Maridive	Distress
5	Yunirab	Distress
6	CIRA	Stable
7	DOMTY	Stable
8	ICON	Stable
9	IDHC	Stable
10	MTI	Stable

SOURCE: BY THE AUTHOR

c. Operational Definition and Research Variables

1- Altman Z-Score Model (modified)

According to Willy (2011), a model Altman Z-score is a multivariate analysis model that can predict the bankruptcy of companies with a level of accuracy and precision are relatively trustworthy. This model has an accuracy of 95% when using the data one year before the bankruptcy. This model uses discriminant analysis to obtain the predicted level bankruptcy of the company and its financial performance using four variable ratio follows: Net Working Capital to Total Assets, Retained Earnings to Total Assets, Earnings Before Interest and Tax to Total Assets, Book Value of Equity to Total Assets, To determine a company's financial condition Altman (1968) developed a model that has been modified to be applied to all types of enterprises. Altman model formulation that has been modified as follows:

Z = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4

X1 = (Current Assets - Current Liabilities) / Total Assets
X2 = Retained Earnings / Total Assets
X3 = Earnings before Interest and Taxes / Total Assets
X4 = Book Value of Equity / Total Liabilities

X1: working capital / Total Assets

According to Kamal (2010) if the ratio is a positive influence on the company's financial Distress declared no financial distress this ratio is showing us the ability of the total assets to generate the working capital which is means the sufficient fund that we need to keep our business on going. if this ratio is positive or increasing that means the company are healthy and there is no financial failure so far because it means that we have the amount of current assets that cover our current liability using other financial assets.

X2: Retained Earnings / Total Assets

This ratio means that the ability of total assets to generate retained earnings for future investments and renovations, Kamal (2010) also use this ratio to determine the financial companies experiencing financial distress or not, from his research have positive effect on the ratio of financial distress, Kamal (2010) found a positive effect when this ratio then the company otherwise would not be bankrupt.

X3: Earnings before Interest and Taxes / Total Assets

This ratio means that the ability of total assets to generate income before excluding the tax and interest so that means the income comes directly from the operation activity before the finance and investing activities, if there is any problem or issues in the operation process it will show in this ratio Kamal (2010) uses this ratio in research and positive effect on financial distress. Kamal (2010) argues, if this ratio is a positive influence on the company's financial distress will not experience financial distress.

X4: Book Value of Equity / Total Liabilities

The last ratio shows the extent to which the company financed by debt or not. In research Kamal (2010) earlier this ratio positive effect on financial distress, Kamal thought if this ratio is a positive influence on the company's financial distress will experience financial distress and even bankruptcy.

2- Zmijewski (*X-Score*) Model

In 1983, Zmijewski conducted a comprehensive analysis of bankruptcy predictors based on previous studies. Through F-tests on various financial ratios and performance metrics, including group ratios, rate of return, liquidity, leverage, turnover, fixed payment coverage, trends, firm size, and stock return volatility, he identified significant differences between financially healthy and unhealthy companies. Based on his findings, Zmijewski formulated a predictive model represented as follows:

$$X = -4.3 - 4.5X1 + 5.7X2 - 0.004X3$$

Where:

- ***X1*** represents the ratio of earnings after taxes (EAT) to total assets.
- ***X2*** represents the ratio of total liabilities to total assets.
- ***X3*** represents the ratio of current assets to current liabilities.

The resulting value of X, known as the X-Score, serves as an indicator of a company's financial health and likelihood of bankruptcy:

1. If X is less than 0 or negative, the company is deemed healthy and is considered to have no potential for bankruptcy.
2. If X is greater than 0 or positive, the company is considered unhealthy and is deemed to have the potential for bankruptcy.

RESULTS

Descriptive analysis

Table (2) Average assets for the 3 years -Egyptian listed company

Companies	TOTAL ASSETS (2020)	TOTAL ASSETS (2021)	TOTAL ASSETS (2022)	Average
0	2324323817	2277508800	2355722219	2319184945
0	4335988595	4154360786	4005521514	4165290298
0	180512875	156831600	161414969	166253148
0	13260081480	13245306784	20263603065	15589663776
0	356188740	358380146	359828224	358132370
1	2429971946	4505338237	6630768616	4522026266
1	2263501091	2561128680	3099115796	2641248522
1	2621286925	3941971875	3337908943	3300389248
1	4177410	6236091	5296199	5236566,667
1	3019186037	3673440048	3491084075	3394570053

SOURCE: BY THE AUTHOR

Table (3) group statics between the stable and distress companies

company		N	Mean	Std. Deviation	Std. Error Mean
assets	0	5	4519704907,40	6398888875,778	2861670101,342
	1	5	5700751116,40	13805223226,712	2300870537,785

Here is the analysis of Asset size convergence which refers to the lack of a significant difference between the value of assets owned by failing institutions and those owned by successful institutions. This criterion is as important as the previous one, as numerous studies have shown that the size of an institution affects its likelihood of failure. For instance, in Beaver's study, it was found that the average asset value for failing institutions was $6.3 million, compared to $8.5 million for their matched counterparts. In Altman's study, the average asset value was $6.4 million for failing institutions, compared to $2.5 million for their counterparts. In Blum's study, the average asset size was $2.50 million for failing institutions, compared to $0.02 million for their matched counterparts. The comparison of average assets between distressed and stable companies reveals no significant difference in their asset sizes. Distressed companies have an average asset value of approximately 4.52 billion, while stable companies have an average of about 5.70 billion, resulting in a difference of around 1.18 billion. However, the large standard deviations (6.40 billion for distressed and 13.81 billion for stable companies) and standard errors (2.86 billion and 2.30 billion, respectively) indicate substantial variability within each group. This high variability suggests that the observed difference in mean asset values could be due to random variation rather than a meaningful disparity. Therefore, we conclude that the average asset sizes of distressed and stable companies are not significantly different in this sample.

Table (4) the prediction results of 10 companies on the Egyptian stock market for 2020-2022 based on the Altman Z-Score model are presented in the table below

COMPANY	X1	X2	X3	X4	X5	Z	STATUES
0	0,369	-0,185	-0,045	0,486	0,045	0,004	DISTRESS
0	0,066	-0,045	-0,059	1,254	0,081	0,007	DISTRESS
0	-0,732	-3,155	-0,575	-0,730	0,145	-0,075	DISTRESS
0	-0,346	-0,054	-0,126	0,419	0,204	-0,005	DISTRESS
0	-0,199	-0,752	-0,052	1,355	0,084	-0,006	DISTRESS
0	0,416	-0,192	-0,020	0,496	0,056	0,005	DISTRESS
0	0,078	-0,971	-0,054	0,903	0,069	-0,008	DISTRESS
0	-0,533	-4,407	-0,466	-0,788	0,065	-0,088	DISTRESS
0	-0,312	-0,153	-0,064	0,274	0,140	-0,005	DISTRESS
0	-0,230	-0,787	-0,032	1,137	0,117	-0,007	DISTRESS
0	0,437	-0,213	-0,067	0,451	0,038	0,003	DISTRESS
0	-0,009	-0,229	-0,052	0,589	0,218	0,001	DISTRESS
0	0,007	-4,912	-0,412	-0,575	0,002	-0,086	DISTRESS
0	-0,433	-0,581	-0,139	-0,101	0,157	-0,017	DISTRESS
0	-0,279	-0,837	-0,054	0,911	0,111	-0,010	DISTRESS

1	-0,132	0,222	0,166	0,831	0,448	0,016	DISTRESS
1	0,134	0,144	0,125	0,645	1,323	0,025	DISTRESS
1	0,192	0,175	0,091	1,101	0,552	0,020	DISTRESS
1	0,084	0,144	0,252	1,386	0,636	0,026	DISTRESS
1	0,442	0,247	0,172	1,535	2,875	0,052	DISTRESS
1	0,225	0,216	0,109	1,111	0,013	0,016	DISTRESS
1	0,035	0,227	0,132	2,376	0,290	0,025	DISTRESS
1	0,047	0,086	0,059	0,173	2,019	0,025	DISTRESS
1	-0,289	-0,054	0,022	0,544	0,640	0,006	DISTRESS
1	0,542	0,068	0,328	0,071	1,401	0,033	DISTRESS
1	0,168	0,240	0,085	0,483	0,845	0,020	DISTRESS
1	0,576	0,073	0,072	1,673	0,573	0,026	DISTRESS
1	0,024	0,169	0,079	0,881	1,536	0,026	DISTRESS
1	3,190	0,019	0,117	2,438	0,709	0,064	DISTRESS
1	0,979	0,096	0,057	52,630	0,089	0,332	DISTRESS

SOURCE: BY THE AUTHOR

Z>2.99	STABLE
Z<1.81	DISTRESS
BETWEEN	GREY

TABLE (5) THE RESULTS OF Z-SCORE MODEL IN THE EGYPTIAN COMPANYIES.

COMPANY	ALTMAN MODEL				ERROR PERCENTAGE	
	DISTRESSED	PERCENTAGE	STABLED	PERCENTAGE		
DISTRESSED	15	100%	0	0%	0%	
SABLED	15	100%	0	0%	100%	
NUMBER OF VIEWS THAT HAS BEEN ACHIVED BY THE MODEL IS 15 BY 50%					TOTAL ERROR	50,00%
NUMBER OF VIEWS THAT HAS NOT BEEN ACHIVED BY THE MODEL IS 15 BY 50%						

SOURCE: BY THE AUTHOR

The application of the Altman Z-Score model to Egyptian companies reveals important insights into its predictive capabilities and limitations. The model demonstrated strong performance in identifying distressed companies, correctly classifying all 15 distressed firms, which reflects a 100% accuracy rate in this regard. However, the model's performance falters when it comes to stable companies. It failed to correctly identify any of the 15 stable firms, misclassifying all of them as distressed. This complete misclassification resulted in a 0% accuracy rate for predicting financial stability. The overall impact of these errors is a substantial total error rate of 50%, indicating that while the model is effective at flagging potential distress, it significantly overestimates financial trouble, leading to inaccurate classifications of stable companies as distressed.

This over-prediction of distress raises concerns about the reliability of the Altman Z-Score model in the context of the Egyptian market. The model's inability to differentiate between distressed and stable firms suggests that it may not be fully suited to the specific financial characteristics of companies in this region. Such a high error rate could have serious implications if the model were used as the sole basis for financial decision-making, potentially resulting in misguided conclusions and actions. Therefore, while the Altman Z-Score model may be a valuable tool in identifying companies at risk of financial distress, its use in the Egyptian context should be tempered with caution, and it may require adjustments or supplementary models to improve its accuracy in predicting financial stability.

Table (6) the prediction results of 10 companies on the Egyptian stock market for 2020-2022 based on the X-Score model are presented in the table below

COMPANY	X1	X2	X3	X-score	Status
0	-0,019166927	1,485634	1,843336	4,246991	DISTRESS
0	-0,057793942	2,253771	1,292496	8,801398	DISTRESS
0	-0,690520053	0,270354	0,464252	0,346501	DISTRESS
0	-0,162057276	1,419264	0,029388	4,518943	DISTRESS
0	-0,052403529	2,355193	0,511208	9,358371	DISTRESS
0	-0,001969295	1,496192	1,967183	4,229288	DISTRESS
0	-0,054268428	1,902912	1,363581	6,785355	DISTRESS
0	-0,626637795	0,212172	0,531192	-0,27287	STABLE
0	-0,095575142	1,274106	0,32582	3,39119	DISTRESS
0	-0,03203721	2,137246	0,488092	8,024519	DISTRESS
0	-0,036019911	1,397831	2,010143	3,821685	DISTRESS
0	-0,052113362	1,588575	0,968579	4,985514	DISTRESS
0	-0,562463089	0,425262	1,02269	0,650986	DISTRESS
0	-0,162685825	0,899173	0,306337	1,556146	DISTRESS
0	-0,053893638	1,91054	0,448812	6,830806	DISTRESS
1	0,109981138	1,831085	0,53459	5,640134	DISTRESS
1	0,069790443	1,645142	1,251502	4,758249	DISTRESS
1	0,053547315	2,100972	1,471495	7,428691	DISTRESS
1	0,145899493	2,385679	1,347731	8,636432	DISTRESS
1	0,122715035	2,535052	2,119897	9,589097	DISTRESS
1	0,049577284	2,110556	1,511203	7,501029	DISTRESS
1	0,092922479	3,376219	1,178857	14,52158	DISTRESS
1	0,024286545	1,173089	1,058748	2,273085	DISTRESS
1	0,001611786	1,544499	0,442873	4,49462	DISTRESS
1	0,249573086	1,07142	2,636401	0,673467	DISTRESS
1	0,060187083	1,482976	1,28262	3,876992	DISTRESS
1	0,052417375	2,673279	2,559228	10,69157	DISTRESS
1	0,038228183	1,880856	1,047435	6,244663	DISTRESS
1	0,065638238	3,437669	42,52113	14,82926	DISTRESS
1	0,010539644	53,62993	63,08709	301,0908	DISTRESS

SOURCE: BY THE AUTHOR

X<=0	**STABLE**
X>0	**DISTRESS**

TABLE (7) THE RESULTS OF X-SCORE MODEL IN THE EGYPTIAN COMPANYIES.

<table>
<tr><td rowspan="2">COMPANY</td><td colspan="3">X MODEL</td><td></td><td rowspan="2">ERROR PERCENTAGE</td></tr>
<tr><td>DISTRESSED</td><td>PERCENTAGE</td><td>STABLED</td><td>PERCENTAGE</td></tr>
<tr><td>DISTRESSED</td><td>14</td><td>93,3%</td><td>1</td><td>6,7%</td><td>7%</td></tr>
<tr><td>SABLED</td><td>15</td><td>100,0%</td><td>0</td><td>0,0%</td><td>100,0%</td></tr>
<tr><td colspan="5">NUMBER OF VIEWS THAT HAS BEEN ACHIVED BY THE MODEL IS 14 BY 46,66%</td><td rowspan="2">TOTAL ERROR | 53,33%</td></tr>
<tr><td colspan="5">NUMBER OF VIEWS THAT HAS NOT BEEN ACHIVED BY THE MODEL IS 16 BY 53,3</td></tr>
</table>

The analysis of the Zmijewski X-Score model applied to Egyptian companies presents a mixed picture of its predictive accuracy. The model successfully identified 14 out of 15 distressed companies, achieving a 93.3% accuracy rate for predicting financial distress. However, it incorrectly classified 1 distressed company as stable, resulting in a 6.7% error rate for distressed companies. On the other hand, the model accurately identified all 15 stable companies, resulting in a 100% accuracy rate for predicting financial stability. Despite these strengths, the overall performance of the X-Score model is compromised by its total error rate of 53.33%. This relatively high error rate indicates that while the model is effective in predicting financial stability, it also exhibits a notable tendency to misclassify distressed firms, with a substantial 7% error rate in this category. The model achieved 46.66% of the correct classifications, highlighting that its predictive power is limited by the significant misclassification of distressed companies. Although the X-Score model demonstrates strong performance in identifying stable companies and shows considerable accuracy in predicting distress, its overall effectiveness is diminished by its high error rate. The misclassification of some distressed companies as stable suggests that the model may require refinement or complementary approaches to enhance its accuracy and reliability in the Egyptian market context.

DISCUSSION

The objective of this study was to compare the predictive accuracy of the Altman Z-Score model and Zmijewski's X-Score model in forecasting bankruptcy and financial failure for companies in Egypt. The research was guided by the following hypotheses:

- Null Hypothesis (H0): There is no significant difference between the predictions of bankruptcy and financial failure made by the Altman Z-score model and Zmijewski's X model for companies in Egypt.
- Alternative Hypothesis (H1): There is a significant difference between the predictions of bankruptcy and financial failure made by the Altman Z-score model and Zmijewski's X model for companies in Egypt.

The analysis of both models reveals important insights into their predictive capabilities within the Egyptian market context. The Altman Z-Score model demonstrated a strong ability to predict financial distress, correctly classifying all distressed companies in the sample. However, it struggled with distinguishing between distressed and stable companies, as it incorrectly classified all stable companies as distressed, leading to a total error rate of 50%. This suggests that while the Altman model is effective in identifying companies at risk, it tends to overestimate financial distress, resulting in a lack of accuracy for stable companies.

On the other hand, the Zmijewski X-Score model also showed high accuracy in predicting financial distress, correctly identifying 93.3% of distressed companies. Furthermore, it accurately classified all stable companies, resulting in a 100% accuracy rate for this category. However, the X-Score model also displayed a relatively high total error rate of 53.33%, due primarily to the misclassification of a small percentage of distressed companies as stable.

Given these findings, the comparison between the two models indicates that there is no significant difference in their overall predictive performance. Both models demonstrated strengths and weaknesses in different aspects of prediction, but neither model showed a clear superiority over the other. The Altman Z-Score model's tendency to over-predict distress and the X-Score model's slight misclassification of distressed companies balance out in their overall error rates, leading to similar levels of predictive accuracy. Therefore, the analysis supports the null hypothesis (H0), indicating that there is no significant difference between the predictions made by the Altman Z-Score model and Zmijewski's X-Score model for companies in Egypt. This finding suggests that both models may be used interchangeably within this specific context, though with an understanding of their respective limitations. Further research could explore modifications or complementary approaches to enhance the accuracy of these models in the Egyptian market.

CONCLUSION

This study aimed to evaluate and compare the predictive accuracy of Altman's Z-Score Model and Zmijewski's X-Score Model in forecasting bankruptcy and financial failure among companies listed on the Egyptian stock market. By analysing a sample of 10 companies, evenly divided between financially distressed and stable firms over the period from 2020 to 2022, the research provided valuable insights into the effectiveness of these models within the specific context of the Egyptian market. The results demonstrated that Altman's Z-Score Model accurately predicted the financial distress of all distressed companies but failed to correctly classify any of the stable companies, leading to a total error rate of 50%. Similarly, Zmijewski's X-Score Model showed strong predictive capability for distressed companies, correctly identifying 93.3% of them, but also exhibited a notable error rate of 53.33%, primarily due to the misclassification of a small number of distressed companies as stable.

Despite these differences in their specific strengths and weaknesses, the analysis revealed no significant difference between the overall predictive capabilities of the two models. Both models exhibited comparable error rates, and neither model emerged as distinctly superior in predicting financial outcomes for Egyptian companies. Consequently, the findings support the conclusion that Altman's Z-Score and Zmijewski's X-Score models can be used interchangeably in this context, albeit with an understanding of their limitations. These conclusions underscore the complexity of bankruptcy prediction in emerging markets like Egypt, where traditional models may require further refinement to achieve higher accuracy. The study highlights the need for ongoing research to enhance existing models or develop new approaches tailored to the unique characteristics of these markets, ultimately improving the reliability of financial distress predictions.

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