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Revisiting the ALTMAN Z-Score in the Modern Economy: An EIGENVALUE-Based Analysis of Corporate Financial Structure

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ABSTRACT

In the year 1968, Professor Edward Altman from New York University Stern School of Business created the Altman Z-score formula, "A financial tool designed to assess the risk of bankruptcy in publicly traded companies," based on mid-20th-century manufacturing companies that focused on specific financial ratios to capture financial distress, excluding each company's business scale. However, the formula is highly outdated as cash flow patterns have changed over time, leading to companies with similar Z-scores having contradictory outcomes. Hence, this paper focuses on suggesting a new classification formula by enhancing the Altman Z-score formula based on modern corporate financial data. Previous bankruptcy prediction studies have generally relied on preprocessed data provided by commercial databases or summarized financial information websites. Although such sources offer high accessibility, they simplify the original reporting structure of corporate financial statements and limit the range of variables available for analysis. The 22 selected companies from the SEC EDGAR website are used as a sample to create a matrix with rows containing annual data for each of the 22 companies and columns containing all parts of the Altman Z-score formula and additional balance sheet measures. Eigenvalue Decomposition on the A^TA matrix is performed to identify the significant financial data from the balance sheet. On the other hand, the Altman Z-score formula contained minor variability, which leads to the conclusion that the newly chosen financial variables are more significant than the original Altman-score variables. This conclusion results in the fact that the errors in the Altman-Z-score formula are not due to statistical error, but more to structural change issues as time passed by. In conclusion, a more modern formula that explicitly accounts for specific firm size is needed for a modern bankruptcy risk prediction formula.

INTRODUCTION

Bankruptcy forecasting research has always been a crucial field of study in finance and accounting due to the potential costs that may arise when there is a situation of bankruptcy. It is easy to understand why, as being able to forecast companies that are likely to go bankrupt enables people to make informed decisions about whether they should invest their money into the company or lend it any money. With the complexity of modern corporations, the need for such prediction techniques becomes more obvious than ever.

Among the most prominent bankruptcy predicting models is the Altman Z-Score created by Professor Edward Altman in 1968. The model became rather popular due to the combination of several different factors into an easy-to-use single formula. As a result, despite being almost 50 years old, the Altman Z-Score is still considered one of the best methods for predicting financial distress due to its high accuracy and simplicity.

In the year 1968, Professor Edward Altman from New York University Stern School of Business created the Altman Z-score formula, "A financial tool designed to assess the risk of bankruptcy in publicly traded companies," based on mid-20th-century manufacturing companies that focused on specific financial ratios to capture financial distress, excluding each company's business scale.

However, today's business environment is markedly different from that in the Sixties in terms of capital structure, accounting standards, cash flows, and the growing role of intangibles in the asset base of modern companies. Therefore, there may be significant differences in financial performance for firms that have identical Z-scores, which calls into question the applicability of the model to the conditions faced by contemporary organizations.

Even though the formula still enjoys considerable use, surprisingly, there is not much literature devoted to the analysis of the relevance of the factors driving the success of the Altman Z-score formula for identifying companies at risk of financial distress. Indeed, in many modern organizations, most of their worth comes from intangibles, stock options, and capital market operations, whereas in Altman's time, his samples were made up of manufacturing businesses based on tangible asset-heavy structures. Does the lack of relevance of the Altman Z-score arise from the shortcomings of the statistics, or could it indicate something more significant?

Additionally, the formula is highly outdated as cash flow patterns have changed over time, leading to companies with similar Z-scores having contradictory outcomes. Hence, this paper proposes a new classification formula that enhances the Altman Z-score using modern corporate financial data.

The previous efforts to predict bankruptcy have made use of commercial databases and pre-processed financial data sets. Although such databases make financial data easily accessible, they tend to abstract from the complexities involved in the structure of corporate financial statements and constrain the set of variables under consideration. This can cause relevant financial indicators to go unnoticed.

The 22 selected companies from the SEC EDGAR website are used as a sample to create a matrix with rows containing annual data for each of the 22 companies and columns containing all parts of the Altman Z-score formula and additional balance sheet measures. Eigenvalue Decomposition on the A^TA matrix is performed to identify the significant financial data from the balance sheet. On the other hand, the Altman Z-score formula contained minor variability, which leads to the conclusion that the newly chosen financial variables are more significant than the original Altman-score variables. This conclusion results in the fact that the errors in the Altman-Z-score formula are not due to statistical error, but more to structural change issues as time passed by. In conclusion, a more modern formula that explicitly accounts for specific firm size is needed for a modern bankruptcy risk prediction formula.

Following Edward Altman's invention of the Altman Z-score formula in 1968, it became one of the most effective bankruptcy prediction formulas. The following five key ratios played a crucial role in evaluating a company's financial health:

- X_1 (Working Capital / Total Assets): Measures a company's short-term liquidity and evaluates its capability to pay by analyzing the ratio of net working capital to total assets.
- X_2 (Retained Earnings / Total Assets): The accumulated profit of a company since its establishment, and represents a company's ability to leverage and its historical survivability
- X_3 (EBIT / Total Assets): A key performance indicator measuring a company's Actual Asset Utilization Efficiency, which represents the company's actual profit-generating capacity before debts and taxes.
- X_4 (Market Value of Equity / Total Liabilities): Measures the company's financial stability and the ability towithstand bankruptcy by calculating the ratio of the market value of assets to liabilities.
- X_5 (Sales / Total Assets): An asset turnover ratio, indicating the company's managerial efficiency in generating sales from its assets.

Due to the merit of its simple structure and easy interpretation, the Altman Z-score formula has been widely used in the field. Nevertheless, given that the formula is highly outdated and was based on 1960 asset-intensive manufacturing companies, we have to focus and reconsider whether the formula incorporates the characteristics of today's capital markets, where intangible assets and more complex financial structures are prevalent. This paper begins with the following question: Is the Altman Z-score formula sufficient to identify modern companies' risk of bankruptcy? The analysis target companies were 22 public companies: Bed Bath & Beyond, Big Lots, Container Store, Rite Aid, Tailored Brands, Whiting Petroleum, General Motors, JCPenney, etc., were selected by classifying them into bankrupt and non-bankrupt categories from the official SEC EDGAR website. More specifically, by downloading and parsing the sub.txt and num.txt files corresponding to all fiscal quarters within the sample period, quarterly financial data at the firm-year level within the 2009-2024 time range were constructed. After evaluating 22 corporations' financial statements, we determined that two contradicting examples turned out to be wrong, and that the original Altman Z-score formula is outdated for evaluating risks that today's businesses are facing. Given the calculation, only a few firms were analyzed below 1.8 Z-scores prior to bankruptcy(Figure 2), given that a substantial number of firms were observed to maintain scores exceeding 2.99 even before bankruptcy (Figure 1).

To begin with, a group of firms that went bankrupt despite having an Altman score over 1.8 was identified (FS: False Safe). Companies such as Bed Bath & Beyond, Rite Aid, and Whiting Petroleum maintained relatively low Z-scores in the "safe zone" range, just prior to bankruptcy. Meanwhile, there were companies that have remained financially feasible, containing low Z-scores (FD: False Distress). This event is exemplified by Axogen, CME Group, and Purple, classified with low Z-scores, yet having remained active in the market for several years. These kinds of inconsistencies do not indicate statistical error in the Altman Z-score, but rather a structural disconnect between the financial structures of 20th-century manufacturing companies and those of modern companies.

Moreover, especially in today's financial environment, the following new financial structures and cash flows are acting as critical factors for survival. False Safe (FS): Firms with relatively high Z-scores that eventually declared bankruptcy. False Distress (FD): Firms with persistently low Z-scores that remained financially viable.

Rather than evaluating only predictive accuracy, this study examines the underlying geometric structure of modern financial data using Principal Component Analysis (PCA). By decomposing the covariance matrix of financial variables, we identify the dominant axes of variability and assess whether traditional ratio-based variables remain structurally significant.

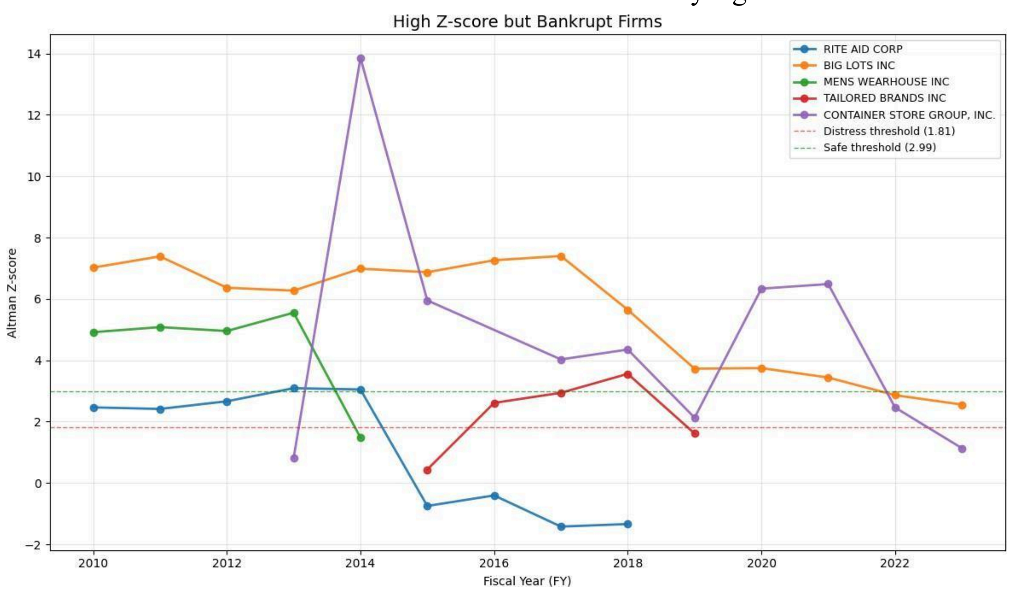

Figure 1. High Z-score and Bankrupt Firms

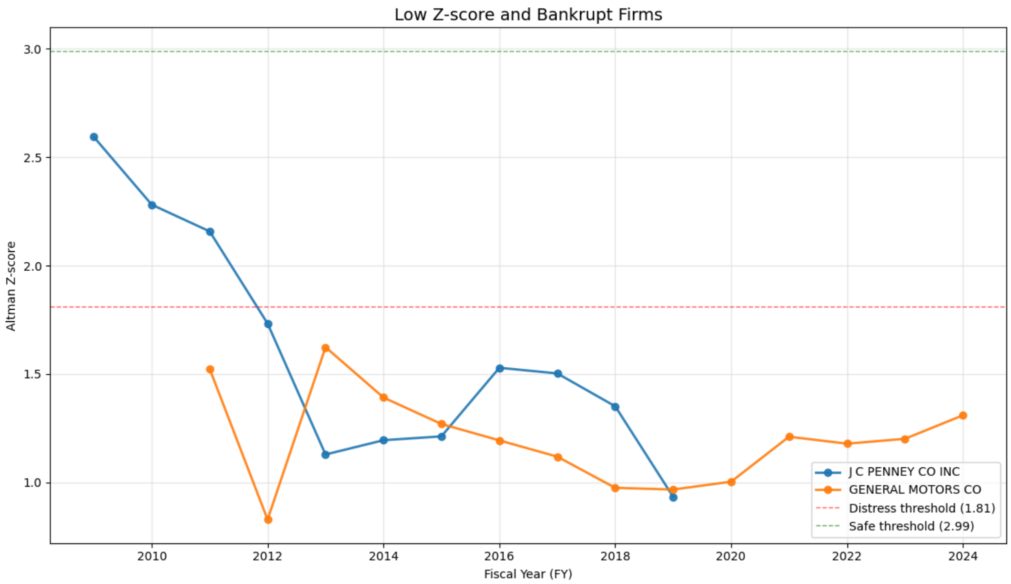

Figure 2. Low Z-score and Bankrupt Firms

Additionally, after calculating the Altman score of 2,700 companies, not including financial institutions, investment firms, state-owned enterprises, government-supported entities, and cryptocurrency-related companies, with scores below 1.8 were examined. As a result, a group of firms that recorded persistently low Z-scores yet have not declared bankruptcy to date was identified (Figure 3).

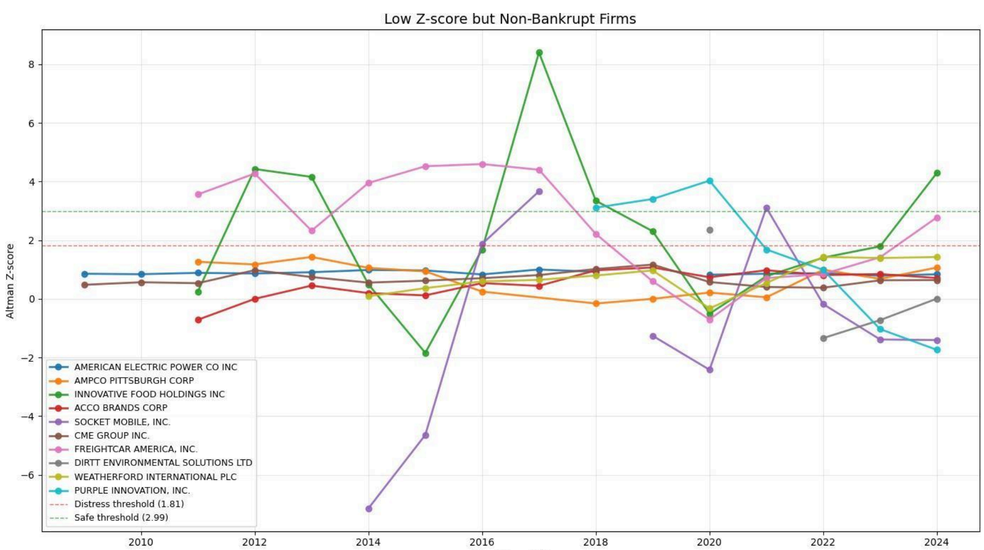

Figure 3. Low Z-score but Non-Bankrupt Firms

In this study, firms that went bankrupt despite having high Altman scores are defined as the FS (Failed despite high Score) group. Conversely, firms that did not go bankrupt despite having low scores are defined as the FD (Distressed but survived despite low Score) group. These cases suggest that the existing model may not fully explain the financial conditions of certain firms.

Meantime, the EDGAR financial dataset contains a wide range of financial variables. Within those datasets, this study focuses on the selected 13 additional variables that were considered significant enough to explain each firm's characteristics. The following variables are represented as X6 ~ X18; definitions and descriptions of each variable are presented in Table 1.

Variable	**Formula**	**Description**	**Economic Interpretation**
X6	Cash / Assets	Cash intensity	Measures liquidity buffer relative to total assets
X7	Δ Cash / Assets	Change in cash intensity	Captures annual liquidity adjustment or financing shocks
X8	Accounts Payable / Assets	Payables intensity	Reflects reliance on supplier financing
X9	Inventory / Assets	Inventory intensity	Indicates working capital tied up in inventory
X10	PPE / Assets	Tangible asset intensity	Measure capital intensity and fixed-asset concentration
X11	Capex/ Assets	Capital expenditure intensity	Captures the scale of investment in fixed assets
X12	Other Noncurrent Assets/ Assets	Long-term asset composition	Reflects the proportion of miscellaneous long-term assets
X13	Comprehensive Income/ Assets	Comprehensive performance ratio	Incorporates net income and valuation-based gains/losses
X14	AOCI/ Stockholders' Equity	Accumulated OCI leverage	Measures the extent to which equity is driven by valuation adjustments

X15	Share-Based Compensation / Equity	Equity compensation burden	Reflects reliance on stock-based compensation
X16	Diluted Shares / Basic Shares	Dilution ratio	Captures potential equity dilution pressure
X17	Shares Issued/ Basic Shares	Issuance expansion ratio	Measures active expansion of share count
X18	Shares Issued/ Authorized Shares	Issuance progress ratio	Indicates how much authorized equity has been utilized

Furthermore, financial data were collected from the U.S. Securities and Exchange Commission (SEC) EDGAR database for fiscal years 2009–2024. For each firm-year observation, financial variables were extracted to construct a matrix A: n*m matrix. Where n represents the annual data for each of the 22 companies, and m represents all parts of the Altman Z-score formula and additional balance sheet measures, more specifically, $X1 \sim X5$ representing the original Altman components, and $X6 \sim X18$ representing the additional significant variables selected from the SEC EDGAR website. The structure of the matrix is illustrated in Figure 4, and the list of included companies is summarized in Table 2.

	$X1$	$X2$	$X3$	$X4$	$X5$	$X6$	$X7$	. . .
(FIRM$_1$**, FY**$_{(1)}$)	a^11	a^12	a^13	a^14	a^15	a^16	a^17	. . .
(FIRM$_1$**, FY**$_{(2)}$)	a^21	a^22	a^23	a^24	a^25	a^26	a^27	. . .
(FIRM$_2$**, FY**$_{(1)}$)	a^31	a^32	a^33	a^34	a^35	a^36	a^37	. . .
.	.	.	.	.	.	.	.	
.	.	.	.	.	.	.	.	
.	.	.	.	.	.	.	.	

Rows	Company	Fiscal Years Included
1 - 14	Bed Bath & Beyond	2009 - 2022
15 - 28	Big lots	2010 – 2023
29 - 38	Container Store	2013 – 2015, 2017 – 2023
39 - 47	Rite Aid	2010 – 2018
48 - 57	Tailored Brands	2010 – 2018
58 - 71	General Motors (GM)	2011 - 2014
72 - 82	JC Penny	2009 – 2019
83 – 88	Toys R Us	2011 - 2016
89 - 102	Acco	2011 - 2024
103 - 118	American Electric	2009 - 2024
119 - 131	Ampco	2011 - 2016, 2018 - 2024
132 - 135	Axogen	2020 - 2023
136 - 151	CME	2009 - 2024
152 - 156	Dirt	2020 - 2024
157 - 161	Flotek	2018 - 2022
162 - 175	Freight Car	2011 - 2024
176 - 189	Innovative Food	2011 - 2024
190 - 196	Purple	2018 - 2024
197 - 210	Socket Mobile	2011 - 2024
211 - 221	Weatherford	2014 - 2024

METHODS

Eigenvalue Decomposition

In order to distinguish the most significant variable within the X6-X18 variables, we evaluated the PCA(Principal Component Analysis). PCA: a method to distinguish the structure of the data matrix by evaluating eigenvalue decomposition of the covariance matrix(or its proportional ATA matrix). An eigenvalue reflects the volatility of its components, following the idea that each eigenvector represents the linear combination structure of the original variables. Starting off by evaluating the eigenvector corresponding to the largest eigenvalue, we can note that the absolute value of the largest coefficient in the vector indicates that the variable is crucial for explaining the variance in the data. Thus, by conducting the eigenvalue decomposition of ATA, the loading of the leading eigenvectors was analyzed, and the most influential values–$X10$, $X14$, $X16$, $X17$– were selected within the $X6$~$X18$.

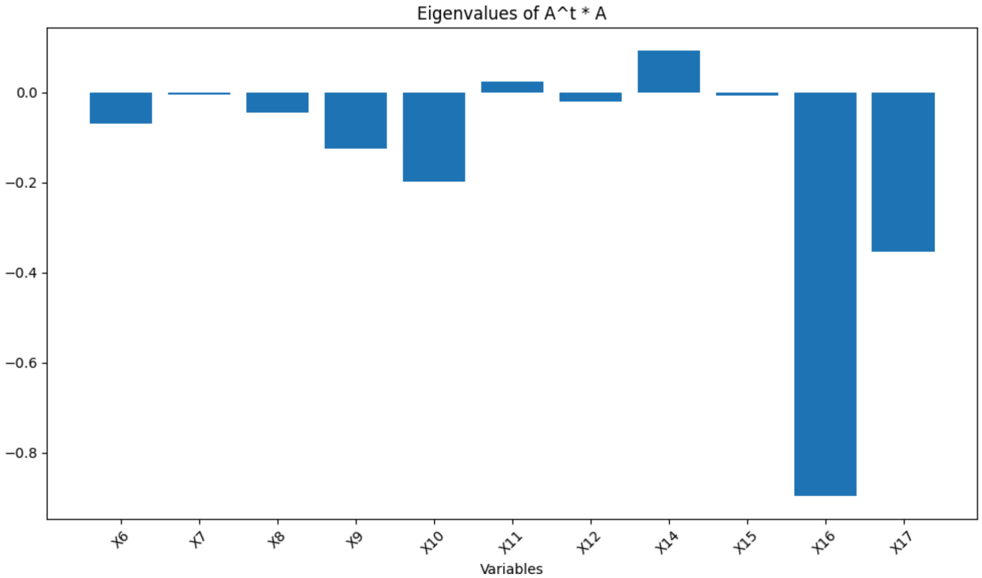

Figure 4. Eigenvalues of A^TA

Specifically, $X10$, the proportion of tangible assets, indicates if a firm's structure is centered on fixed assets such as equipment and factories. $X14$ reflects the sensitivity of capital to shifts in market valuation. $X16$ captures potential for future equity dilution. $X17$ denotes the equity issuance ratio, which indicates the degree of reliance on external capital financing. In modern firms, capital strategy tends to play a more critical role than asset scale. Although in the past, if physical assets such as factories, equipment, and inventory determined corporate competitiveness, nowadays, investment and ownership structures are playing a significant role in shaping a firm's financial characteristics. In other words, the main way of explaining the differences between companies is moving from a structure centered on physical assets to a structure centered on financial assets. Moreover, modern firms are significantly affected by market value fluctuation. Since the rise of startup companies and technology companies, components such as stock options, equity compensation, and new stock issuance are becoming crucial. In real life, recently bankrupt companies have been observed to have a high frequency of capital increases, significant share dilution, and a high dependence on valuation gains. In this respect, the fact that variables selected through PCA analysis are related to capital structure and equity policy suggests that the primary factors explaining financial differences among modern firms may lie not in traditional profitability measures, but rather in variables related to capital market structure.

Regression Model

The next step is to utilize 9 variables: $X1$, $X2$, $X3$, $X4$, $X5$, $X10$, $X14$, $X16$, $X17$ to implement a new Altman-type scoring function. Each number variables represent one score for each firm, which is calculated as a linear combination form. The main purpose of these variables is to ensure that the FS group and the FD group exhibit distinct score distributions. In other words, to identify a scoring system that distinguishes between the two groups, select coefficients that represent high average scores for the FD group and low average scores for the FS group. Coefficient estimation was performed using Ridge regression, and the calculation was conducted using Python. The estimated scoring function is as follows.

Equation 1: NewScore metric

$\text{NewScore} = b_0 + \sum i^k Xi$

i

The estimated coefficient values are as follows:

$b0$	$X1$	$X2$	$X3$	$X4$	$X5$	$X10$	$X14$	$X16$	$X17$
1.8845	0.3421	-2.0188	1.7218	-0.4631	0.6409	-2.4512	0.4849	-0.7953	2/8400

Using this new scoring function, the annual average scores of firms in the FS group and the FD group were calculated, and the results are presented in Figure 6 below.

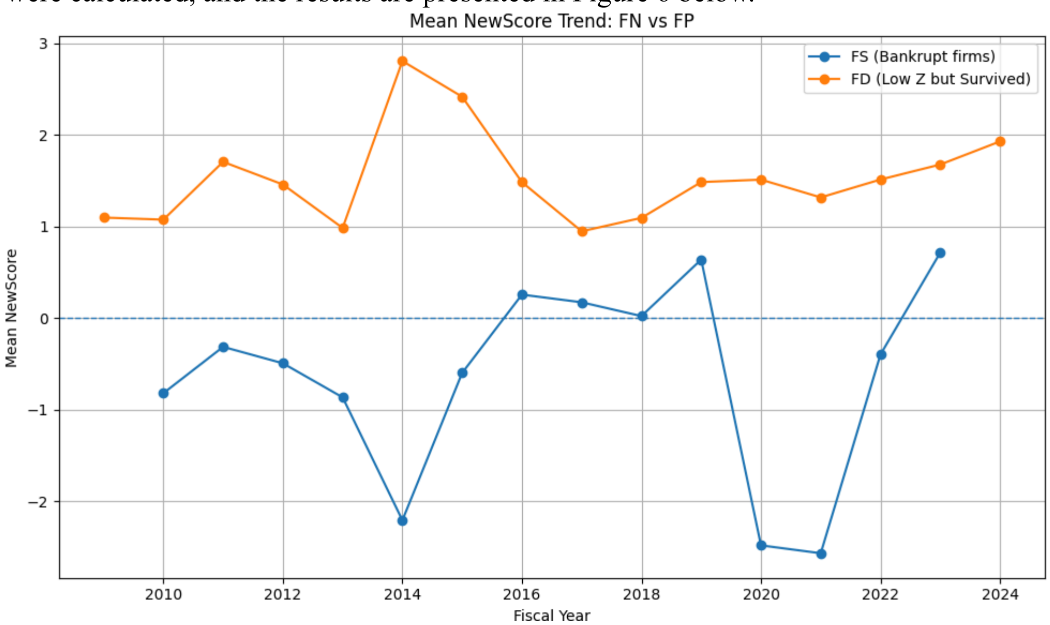

Figure 5. Mean NewScore Trend: FS vs FD

In the original Altman score, there were cases where FD firms showed lower scores than FS firms even though they did not actually go bankrupt. In contrast, in the newly constructed scoring function, the average score of the FD group was higher than that of the FS group for most of the observed periods.

In addition, since the FS group consists of firms that actually experienced bankruptcy, their scores tend to appear lower than those of the FD group at most points in time. These results suggest that the newly constructed scoring function may have greater discriminatory power than the original Altman score in distinguishing between the two groups.

CONCLUSION

The results of this study represent how the mathematical methods play a crucial role in economics and financial analysis. Specifically, the use of PCA for the selection of variables and coefficient estimation using Ridge regression demonstrates that financial differences among firms can be analyzed quantitatively and that differences between groups that were not clearly distinguished by existing models can be revealed more clearly. This suggests that corporate analysis can become more sophisticated through mathematical structural analysis beyond the simple interpretation of financial indicators. In addition, although the methods used in this study correspond to relatively basic techniques in linear algebra and statistics, meaningful insights could still be derived using these mathematical tools alone in the analysis of real data. This demonstrates that in the process of understanding and predicting economic problems, mathematical approaches function not merely as tools for calculation but also as analytical tools for understanding underlying structures. Moreover, the results of this study suggest that there are new potential for analysis when different academic fields are combined. When different academic fields–economics, statistics, mathematics, and data analysis–emerge and work together, more complex real-world problems can be understood more effectively, and such interdisciplinary approaches can also play an important role in solving practical social issues. For this reason, university education and academic research are important not only for delivering knowledge within a single field but also for creating new insights through connections between different disciplines.

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