Revisiting the Altman Z-score Model in the Modern Financial Environment

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Abstract

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Credit risk analysis is a cornerstone of financial research, involving the evaluation of a firm's ability to meet its financial obligations. Over time, a wide range of quantitative and qualitative approaches have been developed to model credit risk, among which the Altman Z-score remains one of the most widely used and influential frameworks. Introduced in 1968, the Z-score combines multiple accounting-based financial ratios into a single discriminant measure designed to signal the likelihood of bankruptcy and assess firms' financial health. Altman later developed extensions of the original model, such as the Z′ and Z″ scores, which were designed to broaden the applicability of the framework to privately held firms and firms operating in different sectors.

This dissertation revisits the Altman Z-score model by replicating its original framework using more recent firm-level data. The study evaluates whether the model's discriminating power and empirical properties persist in a modern economic and financial environment characterized by structural changes in capital markets, accounting practices, and corporate financing behavior. Following Altman (1968), the analysis reproduces a sequence of classification and validation tests, including in-sample accuracy, robustness tests, and bias-related evaluations using panel data on publicly listed U.S. manufacturing firms.

The results suggest that the Z-score continues to exhibit meaningful discriminatory power, although weaker than that reported in the original study. This indicates that signals of financial distress remain embedded in firms' financial statements prior to bankruptcy, even though classification accuracy declines as the time horizon from the bankruptcy event increases.

Keywords: Credit Risk Analysis, Bankruptcy Prediction, Altman Z-Score, Financial Ratios, Financial Distress.

Abstrato

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A análise do risco de crédito constitui um tema central no estudo das finanças, envolvendo a avaliação da capacidade de uma empresa cumprir as suas obrigações financeiras. Ao longo do tempo, foram desenvolvidas diversas abordagens quantitativas e qualitativas para modelar este risco, entre as quais o *Z-score* de *Altman* (1968) . Introduzido em 1968, o *Z-score* combina vários rácios financeiros baseados em informação contabilística numa única função discriminante, concebida para sinalizar a probabilidade de falência e avaliar a saúde financeira das empresas.

Esta dissertação tem como objetivo replicar o modelo *Z-score* de *Altman* (1968), mantendo o processo metodológico original, mas utilizando dados mais recentes ao nível das empresas. O estudo avalia o poder discriminatório do modelo e se as suas propriedades empíricas se mantêm num contexto económico e financeiro moderno, caracterizado por alterações nos mercados de capitais, nas práticas contabilísticas e nos padrões de financiamento empresarial.

Os resultados indicam que o *Z-score* continua a apresentar um poder discriminatório significativo, embora menos pronunciado do que no estudo original indicando que sinais de fragilidade financeira permanecem refletidos nos valores contabilísticos das empresas antes da ocorrência de falência, ainda que a precisão da classificação diminua à medida que se aumenta a distância temporal relativamente ao evento. Esta dissertação contribui para a avaliação contínua da relevância, robustez e interpretação dos modelos tradicionais de risco de crédito na análise financeira contemporânea, abrindo igualmente espaço para questionar se o modelo original continua a ser o mais eficiente ou se outros rácios financeiros poderão ser mais indicativos.

Palavras-chave: Análise de Risco de Crédito, Previsão de Falência, Modelo de *Altman* (*Z-Score*), Rácios Financeiros, Dificuldade Financeira.

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Introduction

Credit risk analysis is a foundational yet inherently complex problem in finance, reflecting the uncertainty surrounding a firm's ability to meet its contractual financial obligations. At its core, credit risk may be defined as the potential that a counterparty fails to honor agreed payments in full and on time. This concept is typically characterized by three interrelated dimensions: exposure to a potentially defaulting entity, the likelihood that default will occur, and the recovery rate in the event of default. Together, these dimensions shape the economic consequences of credit risk for lenders, investors, and the broader financial system.

Over time, a wide range of models has been developed to assess and quantify credit risk. Some approaches rely heavily on qualitative judgement, while others employ statistical and econometric techniques grounded in firm-level financial data. Among the latter, the Altman Z-score stands as one of the most influential and enduring models. Introduced by Altman (1968), the Z-score uses multiple discriminant analysis to combine a set of accounting-based financial ratios into a single measure designed to distinguish between bankrupt and non-bankrupt firms. Rather than estimating an explicit probability of default, the Z-score provides an ordinal measure of financial distress that reflects the overall financial soundness of a firm.

Despite its widespread adoption in academic research and professional practice, relatively limited attention has been devoted to reassessing the original empirical foundations of the Altman Z-score in a modern context. The economic environment in which the model was developed differs substantially from today's financial landscape. Changes in capital structure norms, the expansion of credit markets, evolving accounting standards, and the increased availability of external financing may all influence how financial ratios relate to bankruptcy risk. As a result, it remains an open empirical question whether the discriminating power and structural properties identified by Altman continue to hold when the model is applied to more recent data.

This dissertation addresses this gap by replicating the Altman (1968) methodology using contemporary firm-level data. The analysis follows the structure and logic of Altman (1968), reproducing a sequence of classification and validation tests designed to evaluate the model's performance at different horizons prior to bankruptcy. These tests include in-sample classification accuracy, out-of-time robustness using earlier financial statements, and additional procedures aimed at assessing potential bias in model performance. By adhering closely to the original methodological framework, the study isolates the effect of temporal and structural changes in the data environment from changes in model design.

The empirical analysis focuses on publicly listed U.S. manufacturing firms, using secondary data obtained from Compustat. This focus ensures comparability with Altman (1968) while allowing for a meaningful assessment of how the Z-score behaves in a modern setting. The findings provide insight into the persistence of financial distress signals across time and contribute to the broader discussion on the continued relevance of traditional accounting-based credit risk models.

From a managerial standpoint, the results are relevant for credit analysts, risk managers, and policymakers who continue to rely on Z-score-type measures in credit assessment, portfolio monitoring, and early warning systems. By clarifying the strengths and limitations of the Altman Z-score in today's environment, this research supports more informed and context-aware use of one of the most enduring tools in credit risk analysis.

Literature Review

Following the introduction of the original Z-score model in 1968, Altman later proposed modified versions of the model to address limitations related to data availability and differences across firm types. The original model was designed specifically for publicly traded manufacturing firms and relies on the market value of equity as one of its variables. However, for privately held firms, market values are often unavailable, making the direct application of the original Z-score impractical. To address this limitation, Altman developed the Z′-score, which replaces the market value of equity with the book value of equity, allowing the model to be applied to private firms Altman (1983).

Further on, Altman introduced the Z″-score to extend the applicability of the model to non-manufacturing firms and firms operating in emerging markets. In this version, the sales-to-assets ratio was removed from the model to account for structural differences in asset turnover across industries, particularly in service-based sectors where sales intensity may differ substantially from manufacturing firms. These adaptations were designed to preserve the predictive capacity of the original framework while improving its applicability across different institutional and industry contexts Altman (1995); Altman & Hotchkiss (2006).

Project methodology and Data collection

As firm structures, accounting standards, and market dynamics have evolved considerably since the model was introduced, this replication aims to assess whether the Z-score continues to provide accurate classifications in a modern economic environment. Applying the model to more recent data therefore allows for a direct empirical evaluation of whether the relationships originally identified by Altman remain stable over time. Altman (1968) was developed for United States manufacturing companies and estimated a discriminant model using five accounting and market-based ratios: working capital to total assets (WC/TA), retained earnings to total assets (RE/TA), earnings before interest and taxes to total assets(EBIT/TA), market value of equity to book value of total debt (MVE/TD), and sales to total assets (Sales/TA).

To ensure comparability with the original design, the empirical dataset for this dissertation was extracted from WRDS Compustat North America, using the Fundamentals Annual database. The extraction window is defined by statement date and is referent to the time window from December 1984 through January 2025. The Observations for each firm reflect the latest complete financial statements available at the time of data collection.

The data extraction includes firm identifiers and descriptive fields. Each record is indexed by GVKEY, Compustat's stable firm identifier, alongside the fiscal-year end date (DATADATE) and fiscal year (FYEAR). Company name (CONM) is retained for traceability and manual validation when needed. To reproduce original model presented in Altman (1968) the dataset includes the variable FIC equal to "USA" to restrict to only U.S. firms. By filtering to FIC equal to "USA," the dissertation avoids mixing U.S. manufacturing sector with foreign firms that may be listed or reported in Compustat but operate under different institutional and reporting environments.

The dissertation further aligns the sample with Altman (1968) manufacturing focus by relying on the Standard Industrial Classification (SIC) code contained in Compustat. Manufacturing firms are identified using the conventional SIC interval from 2000 to 3999. The objective is not to argue that manufacturing is the only sector where distress prediction matters, but rather to preserve the comparability of the replication exercise by holding constant the industrial domain within which the Z-score was initially developed.

The final discriminant function used in Altman (1968) and used for the purpose of the dissertation is as follows:

$$\text{Z-score} = 1.2\frac{WC}{TA} + 1.4\frac{RE}{TA} + 3.3\frac{EBIT}{TA} + 0.6\frac{MVE}{TD} + 0.9\frac{Sales}{TA}$$

The extracted financial variables are chosen to permit direct construction of the five ratios used by Altman. To compute the respective ratios, all the direct variables were extracted, although for the fourth ratio, I opt to include both short-term debt (DLC) and long-term debt

(DLTT) to construct the book value of total debt, consistent with Altman (1968) definition of the denominator in the fourth ratio. This specific choice is critical, because total liabilities are broader than debt and would embed non-debt obligations that Altman (1968) did not intend to include.

After data extraction, I proceeded with the initial cleaning and filtering steps designed to improve the reliability of ratio computation while avoiding overly restrictive exclusions that would bias the sample. The first stage of cleaning addresses missing values. Because each Altman ratio depends on specific financial statement inputs, any firm-year observation with missing values in the required components cannot yield a valid ratio and therefore cannot be used in model estimation or evaluation. The second stage of cleaning focuses on zero values, but with a crucial distinction between economically meaningful zeros and zeros that mechanically break the ratios. In financial distress settings, it is common for firms to report zero profits, zero retained earnings, or even zero sales in a given year. These values are often informative signals of distress and are part of the economic phenomenon the model is meant to capture. Excluding all zero observations would therefore remove precisely the types of firm-years that discriminate bankrupt from non-bankrupt firms, introducing selection bias and weakening any subsequent inference about predictive accuracy. For this reason, I proceed to exclude only those zeros that render the ratio undefined, particularly when a denominator is equal to zero. This denominator-focused approach to zero handling preserves informative variation while ensuring that the calculated ratios remain mathematically valid. A third filtering step concerns the manufacturing restriction. Because the objective is a replication rather than a broad re-estimation across sectors, by applying the manufacturing filter at the early stage ensures that the dataset corresponds to the same industrial domain as the original study. The use of SIC codes allows this to be implemented consistently across the entire time range.

A key extension introduced at this stage is the inclusion of the variable STALT as Altman (1968) original work relied on a known set of bankrupt firms and a matched set of non-bankrupt firms. STALT is a categorical indicator that signals whether a company has undergone specific corporate status events, such as bankruptcy, liquidation, leveraged buyouts, or corporate reorganizations. Among the available status alert codes, the value “TL” indicates that a firm is in bankruptcy or liquidation, while a blank value indicates that no such event has been recorded for the firm in the dataset. In this dissertation, the STALT variable is used as a filtering mechanism to distinguish between bankrupt and non-bankrupt firms. Observations with STALT equal to TL are classified as bankrupt firms, whereas observations with blank STALT values are classified as non-bankrupt firms. Observations associated with other status alert codes, such as leveraged buyouts or corporate reorganizations, are excluded to avoid potential misclassification of financial distress events. Including STALT at the extraction stage ensures that subsequent steps, such as defining the bankruptcy year, selecting the pre-bankruptcy observation window, and matching control firms, are grounded in a variable that is available alongside the accounting and market data.

Following the data cleaning procedures, an additional restriction based on firm size was applied in the construction of the empirical sample. This step follows the same approach adopted by Altman (1968) and reflects important empirical characteristics of firm-level financial data. I decided to adopt a percentile-based approach to defining an economically meaningful asset-size range. Percentiles are computed using the full cleaned sample of U.S. manufacturing firms over the 1984–2024 period. Altman (1968) operates with a range between \$0.7 to \$25.9 million dollars, where this dispersion was substantial but not extreme, balancing representativeness against comparability. Based on these considerations, firms are restricted to those whose total assets lie between the 10^{th} and 60^{th} percentiles of the full-sample asset distribution. In the context of the present data, this corresponds to firms with total assets approximately between \$10.7 million and \$299 million (in nominal terms, as reported by Compustat). This range effectively preserves a wide range of medium-sized firms for which financial distress is both economically plausible and empirically observable. Although the percentile thresholds remain partly judgment-based, they were selected after inspecting the empirical asset distribution and evaluating where the concentration of extreme observations begins to affect comparability within the sample.

The decision to follow this approach reflects the fact that, even though financial ratios scale accounting variables and are intended to mitigate the influence of firm size, Altman (1968) argued that ratio normalization does not fully eliminate size-related effects. Firms located at the extreme ends of the size distribution may therefore exhibit systematically different financial characteristics that can distort the estimation and evaluation of bankruptcy prediction models. In particular, very small firms often display highly volatile financial ratios due to limited asset bases, irregular earnings, or incomplete accounting information, which reduces the reliability and comparability of their financial statements. On the other opposite end, very large firms typically have more stable financial structures and greater access to external financing, making bankruptcy events relatively rare. Including such firms could therefore increase the proportion of non-bankrupt observations without contributing meaningful information to the discrimination between bankrupt and non-bankrupt firms. Following this reasoning and with the procedure adopted in Altman (1968), firms located at the extreme ends of the asset size distribution were excluded from the sample to improve comparability across firms and enhance the reliability of the empirical analysis. In addition to firm specific characteristics that influence the asset size filtering, there is an additional layer of complexity to the analysis related to the difference in the distribution of total assets for U.S. manufacturing firms nowadays. Naturally currently firms exhibit a much stronger Positive skew than that observed at the time the paper was developed with total assets reaching several billions of dollars. Considering the general increase in the asset size reference, the chosen range to analyze should account for that shift to reflect properly a homologous data range to the original study. Rather than imposing absolute asset cutoffs, which would be difficult to justify given inflation and long-term structural growth in firm size.

Sample Group Composition

After the data is extracted and all cleaning and filtering procedures are employed as described in the previous section, the construction of the empirical samples followed a two-stage procedure designed to replicate as closely as possible the original methodology proposed by Altman (1968).

The first step consisted in the formation of Group 1, composed of firms that filed for bankruptcy. For each firm classified as bankrupt, two observations were retained: the financial statement prior to bankruptcy (denoted as $t-1$) and the bankruptcy year observation (t).[1]Bankruptcy status was identified using the status variable provided in the dataset, ensuring that the $(t-1)$ observation corresponded to a period in which the firm was still operating normally. This approach mirrors Altman (1968) use of the last available accounting information prior to failure and allows the analysis to focus on predictive performance rather than contemporaneous distress signals.

Following the construction of Group 1, Group 2 was formed as a matched sample of non-bankrupt firms. The matching procedure was conducted ensuring comparability between

[1] Altman (1968) reports that the financial statements used in his analysis had an average lead time of approximately seven and one-half months prior to bankruptcy. This implies that the timing of pre-bankruptcy financial information varied across firms and was not constrained to a fixed calendar-year offset. Consistent with this design, the present study defines the pre-bankruptcy observation $(t-1)$ as the last available annual financial statement preceding the bankruptcy event, thereby preserving the variability in reporting lead times documented in the original study.

the two Groups along key structural dimensions. Firms in Group 2 were selected from the same industry and asset size range as those in Group 1 and were required to exhibit no bankruptcy indication over the relevant period. The Groups have the same number of observations composed of 25 firms each. Additionally, the temporal dimension was preserved by matching observations in Group 2 to the same fiscal years used for the corresponding bankrupt firms. This matching strategy ensured that differences observed between the two Groups could be more plausibly attributed to financial characteristics rather than size, industry composition, or macroeconomic conditions.

Once both Groups were fully constructed, the five financial ratios originally proposed by Altman were computed and combined using the estimated discriminant coefficients to obtain a Z-score for each firm-year observation. These discriminant scores form the basis for all subsequent statistical testing and classification analysis.

During this stage, an exploratory examination of the computed Z-score distributions revealed the presence of a small number of extreme observations. Several observations exhibited disproportionately large discriminant scores, driven by unusually high values in one or more underlying financial ratios. The ratio that exhibits more dispersion in terms of extreme values was MVE/TD, which signals some important aspects in respect to current firms' debt structure and lending behavior. Given that the Z-score is a linear combination of accounting ratios, many of which are known to display heavy-tailed behavior, such extreme values are not unexpected in large, heterogeneous financial datasets. Nevertheless, their magnitude raised concerns regarding their potential to influence directly the results of the subsequent test and inflate results, not being representative of the actual sample. To address this issue and to enhance the interpretability and statistical reliability of the results, a systematic outlier assessment was conducted at the Z-score level. A secondary dataset was then constructed in which these extreme observations were removed symmetrically across Groups, while preserving the matched-pair structure between bankrupt and non-bankrupt firms. This procedure ensured that any subsequent differences in results could be attributed to the presence or absence of extreme values, rather than to changes in sample composition. Outliers were identified using a non-parametric criterion based on the interquartile range of the Z-score distribution, applied separately to bankrupt and non-bankrupt firms. Observations falling outside 1.5 times the interquartile range from the first and third quartiles were flagged as extreme, for example, in Group 1, the first and third quartiles of the Z-score distribution are 0.243 and 3.515, respectively, resulting in an interquartile range of 3.272. Applying the

1.5×IQR rule produces lower and upper bound of −4.665 and 8.423. Observations outside this interval were classified as extreme values, leading to the removal of 12 observations from the sample. As for Group 2, the first and third quartiles of the Z-score distribution are 2.866 and 5.258, respectively, resulting in an interquartile range of 2.392 with a lower and upper thresholds of −0.722 and 8.846, leading to the removal of 11 observations.

Empirical evidence

The first set of empirical tests focused on assessing the individual discriminating power of each financial ratio. This was achieved by performing univariate F-tests comparing the mean values of each ratio between bankrupt and non-bankrupt firms using $t-1$ observations. These tests evaluate whether each ratio, taken in isolation, is capable of distinguishing between the two Groups. The results provided an initial indication of which variables exhibited statistically meaningful differences between the Groups and therefore potential predictive relevance.

Considering the subsample excluding extreme values, the results indicate that variables WC/TA, RE/TA, and EBIT/TA display statistically significant differences between the two Groups. Specifically, WC/TA is significant at the 0.001 level, while RE/TA and EBIT/TA are significant at the 0.01 level. These findings suggest that measures related to liquidity, profitability, and operating performance retain strong individual explanatory power in distinguishing between bankrupt and non-bankrupt firms in the contemporary sample. In contrast, variables MVE/TD and SALES/TA do not exhibit statistically significant differences between Groups at conventional significance levels when considered in isolation and therefore do not yet appear to contribute meaningfully to Group separation on a purely univariate basis.

Table 1 - Univariate analysis of Altman financial ratios

Variable	Mean Group 1 (%)	Mean Group 2 (%)	F-ratio	p-value	Significance
WC/TA	2.927	31.711	20.327	<0.001	***
RE/TA	-31.552	17.548	10.838	0.002	**
EBIT/TA	-6.326	5.621	8.455	0.005	**
MVE/TD	99.561	204.714	3.894	0.054	
Sales/TA	121.124	133.882	0.754	0.389	

Table 1: Group 1 includes 28 Bankrut firms and Group 2 includes 24 non-bankrupt firms. F-tests are based on df(1,50). ***, ** indicate significance at the 1% and 5% levels respectively.

Table 1 presents the univariate analysis of the five financial ratios originally proposed by Altman (1968). The table compares the mean values of each ratio between Group 1 (bankrupt firms) and Group 2 (non-bankrupt firms) to assess whether the variables differ significantly across the two groups.

On a strict univariate level, the mean values of all five ratios are higher for the non-bankrupt Group than for the bankrupt Group. This pattern is fully consistent with the results reported in Altman (1968) and aligns with economic intuition. Firms that remain solvent exhibit stronger liquidity positions, higher retained earnings relative to assets, superior operating profitability, greater market capitalization relative to debt, and higher asset turnover than firms that subsequently fail. Moreover, the signs of the discriminant coefficients associated with each variable are positive, implying that higher ratio values contribute positively to the discriminant score. Consequently, firms exhibiting weaker financial characteristics tend to receive lower Z-scores, while financially healthier firms receive higher scores. This confirms the interpretation originally advanced by Altman (1968): the greater a firm's bankruptcy potential, the lower its discriminant score. Taken together, these findings suggest that while several ratios already exhibit strong individual discriminating ability, a complete assessment of the model's performance requires a multivariate framework. Variables that appear weak or insignificant on a univariate basis may nonetheless contribute materially to Group separation once interactions among ratios are taken into account, an issue explored in the subsequent analysis.

To get a more precise analysis of the effect of the ratios on the final Z-score, the relative contribution of each financial ratio was examined. Following Altman (1968), the objective of this analysis is to assess not only the individual importance of each variable, but also its effective contribution within the multivariate discriminant framework, where interactions between variables are considered. In a discriminant model, the coefficients obtained from the estimation indicate the direction and weight of each ratio in the classification rule. However, these coefficients cannot be interpreted directly as measures of relative importance because the financial ratios are measured on different scales and may exhibit different levels of variability. To address this issue, Altman proposed the use of scaled discriminant coefficients, which adjust the original coefficients by the dispersion of each variable. This adjustment is obtained by multiplying each discriminant coefficient by the square root of the corresponding diagonal element of the variance–covariance matrix. Since these diagonal elements represent the variances of the individual ratios, their square roots correspond to the standard deviations of each variable. By incorporating this adjustment, the resulting statistic reflects the contribution of each ratio to Group separation while accounting for differences in variability across variables. In practical terms, this means that the relative contribution of each financial ratio depends not only on the magnitude of its coefficient but also on how dispersed the variable is within the sample. For example, a ratio may have a large discriminant coefficient but exhibit very little variation across firms. In such a case, its effective contribution to distinguishing bankrupt from non-bankrupt firms would be limited. On the other hand, a variable with a smaller coefficient but greater variability may play a more important role in separating the two Groups. The scaled coefficients therefore provide a dispersion-adjusted measure of the importance of each variable in the discriminant function, allowing for a more meaningful comparison of their relative contributions.

Table 2 - Relative contribution and ranking of Altman ratio variables

Variable	Scaled Vector	Rank
MVE/TD	1.182	1
RE/TA	0.820	2
Sales/TA	0.527	3
EBIT/TA	0.522	4
WC/TA	0.323	5

Table 2: The scaled vector measures the relative contribution of each financial ratio to the discriminant function. It is obtained by multiplying the estimated discriminant coefficient of each variable by the square root of the corresponding diagonal element of the variance–covariance matrix of the variables. This transformation standardizes the variables, allowing their importance in separating bankrupt and non-bankrupt firms to be compared on a common scale. The rank orders the variables according to the magnitude of their scaled vectors, with higher values indicating a greater contribution to the model's discriminatory power

As showed on Table 2 the results of this analysis indicate that the largest contribution towards the difference between the two Groups is provided by MVE/TD, followed by RE/TA and SALES/TA. Variables EBIT/TA and WC/TA exhibit smaller relative contributions once dispersion is taken into account. These rankings differ notably from the ordering implied by the univariate tests, underscoring the importance of a multivariate perspective when assessing the informational content of financial ratios. In particular, the rank of SALES/TA is notorious considering the individual discriminating test previously computed. Although this ratio did not display statistically significant differences between Groups on a univariate basis, its scaled contribution ranks third in the multivariate setting. This finding closely resembles Altman (1968) original results and highlights a key insight of multiple discriminant analysis: variables that appear weak or insignificant when examined in isolation may nonetheless play an important role once their interactions with other variables are considered. The multivariate context therefore illuminates information that is not apparent from univariate testing alone.

The next step in the analysis involves evaluating the overall discriminating power of the model by examining the separation between the Group means, or centroids, of the discriminant scores. In the context of multiple discriminant analysis, the centroid of each Group is defined as the mean Z-score of all observations belonging to that Group. The objective of the estimation procedure is to maximize the distance between these centroids while simultaneously minimizing the dispersion of individual firm scores around their respective Group means. Formally, the centroid of Group g is computed as the average of the discriminant scores of the firms belonging to that Group. This measure provides a summary of the typical financial profile associated with bankrupt and non-bankrupt firms, respectively. A large separation between centroids indicates strong difference of the overall average between the two Groups. For the sample analyzed, the estimated Group centroids are as follows. The mean Z-score for non-bankrupt firms is 3.38, while the corresponding value for bankrupt firms is 1.19. The positive ordering of these centroids is fully consistent with the theoretical interpretation of the Z-score: firms with stronger financial conditions exhibit higher discriminant scores, whereas firms closer to financial distress display lower scores.

To assess whether this observed separation is statistically meaningful, I employed an F-test. This test evaluates the ratio of the between-Group sum of squares to the within-Group sum of squares, thereby assessing whether the observed Group means are significantly different from one another. The logic of this test aligns directly with the primary objective of multiple discriminant analysis, which is to identify variables, and combinations of variables, that maximize differences between Groups while preserving homogeneity within Groups. The corresponding F-statistic is 17.57 with degrees of freedom (1, 50), yielding a p-value of 0.00011. The null hypothesis that the discriminant scores of bankrupt and non-bankrupt firms are drawn from the same population is therefore rejected. This result indicates that prior Group classifications are statistically distinct when evaluated one year prior to bankruptcy and confirms that the discriminant function possesses meaningful separating power at this horizon. Consequently, classification analysis based on the relative proximity of individual firm Z-scores to the Group centroids is justified and builds the basis for the subsequent evaluation.

Given that the discriminant function demonstrates statistically significant separation between bankrupt and non-bankrupt firms at the t−1 horizon, the next step consists in evaluating the model's classification accuracy. Following Altman (1968), classification performance is displayed through a matrix, which compares each firm's actual Group membership with its predicted group assignment based on the discriminant score. Classification is performed by assigning each firm-year observation to the group whose centroid is closest in terms of the discriminant score. Specifically, a cutoff value is defined as the midpoint between the two group centroids. Firms with Z-scores below this cutoff are classified as bankrupt, while firms with Z-scores above the cutoff are classified as non-bankrupt. This procedure operationalizes the principle that firms should be assigned to the Group they most closely resemble in the discriminant space.

The accuracy matrix presented in Table 3 is structured with actual Group membership represented along one dimension and predicted Group membership along the other. Correct classifications, referred to as "hits" (H), occur when the predicted Group coincides with the firm's actual status. Misclassifications, or "misses" (M), arise when these classifications differ.

Table 3 - Prediction Matrix and Error Types

Actual Group Membership	**Predicted Group Membership**	
	Bankrupt	Non-Bankrupt
Bankrupt	H	M_1
Non-Bankrupt	M_2	H

Table 3: The table presents the classification results of the discriminant model. Hits (H) occur when the predicted classification coincides with the firm's actual status. Misses (M) represent misclassifications. A Type I error (M_1) occurs when a bankrupt firm is incorrectly classified as non-bankrupt, while a Type II error (M_2) occurs when a non-bankrupt firm is incorrectly classified as bankrupt.

Applying this classification procedure to the (t−1) sample yields the following results. The estimated centroids are 1.19 for bankrupt firms and 3.38 for non-bankrupt firms, resulting in a cutoff value of 2.29. Out of a total of 52 firm-year observations, 41 are correctly classified, corresponding to an overall classification accuracy of 78.85 percent. The remaining 11 observations are misclassified, consisting of 7 Type I errors and 4 Type II errors as presented in Table 3 below.

Table 4 - Classification Matrix of bankruptcy prediction model (t-1)

Actual / Predicted	**Bankrupt**	**Non-Bankrupt**
Bankrut	20	4
Non-Bankrupt	7	21

Table 4 : The table presents the classification results of the bankruptcy prediction model using financial information from one year prior to bankruptcy (t-1). Rows indicate the actual firm status, while columns report the predicted classification produced by the model. Correct classifications occur along the diagonal of the matrix: 20 bankrupt firms and 21 non-bankrupt firms are correctly identified. Off-diagonal observations represent misclassifications, where 4 bankrupt firms are incorrectly predicted as non-bankrupt (Type I error) and 7 non-bankrupt firms are incorrectly predicted as bankrupt (Type II error).

This accuracy assessment indicates that the discriminant model correctly classifies a substantial part of firms one year prior to bankruptcy. As emphasized by Altman (1968), this percentage is analogous to the coefficient of determination in regression analysis, in that it measures the proportion of observations whose Group membership is correctly explained by the model. While some degree of upward bias is expected in the initial classification test, given that the same observations are used to estimate the discriminant coefficients and to assess classification performance, the results nonetheless provide encouraging evidence of the model's explanatory power at the one-year horizon.

Importantly, the distribution of misclassification errors highlights the inherent trade-off faced by bankruptcy prediction models. Type I errors represent failures to identify firms that subsequently become bankrupt, while Type II errors reflect false distress signals for firms that remain solvent. The relative magnitudes of these errors will be examined further in subsequent robustness and validation tests, which aim to assess the stability of the model's predictive performance beyond the initial sample.

The second set of empirical tests examines the discriminating ability of the model when financial data from two years prior to bankruptcy ($t-2$) are employed. This horizon represents a more demanding prediction setting, as financial distress signals are typically less pronounced further away from the failure event. Considering this sample, the average lead time was analyzed showing an average of 16 months prior to bankruptcy. Applying the discriminant function to the $t-2$ observations yields Group centroids of 2.39 for bankrupt firms and 3.45 for non-bankrupt firms. While the ordering of the centroids remains consistent with economic intuition, non-bankrupt firms exhibiting higher Z-scores, the distance between the two-Group means is notably smaller than that observed at the ($t-1$) horizon. This compression of centroids reflects the reduced clarity of financial distress signals at longer forecasting horizons. The statistical significance of this separation is tested using an F-test on the discriminant scores. The estimated F-statistic is 3.03 with degrees of freedom (1, 50), corresponding to a p-value of 0.088. At significance levels of $\alpha = 0.05$, the null hypothesis that the discriminant scores of bankrupt and non-bankrupt firms are drawn from the same population cannot be rejected. This result indicates that, two years prior to bankruptcy, the discriminant function no longer achieves statistically significant separation between the two Groups. Classification performance at the $t-2$ horizon also deteriorates relative to the one-year-ahead results. Out of 52 observations, 38 firms are correctly classified, yielding an overall accuracy of 73.08 percent. Considering the overall rate of misclassifications, type I error, bankrupt firms incorrectly classified as non-bankrupt showed an error rate of 25 percent, and Type II, non-bankrupt firms incorrectly classified as bankrupt an error rate of 29.17 percent. Both error rates increase substantially relative to the $t-1$ test as presented in table 5.

Table 5 - Classification matrix of bankruptcy prediction model (t-1)

Actual / Predicted	Bankrupt	Non-Bankrupt
Bankrut	17	7
Non-Bankrupt	7	21

Table 5 : The table reports the classification results of the bankruptcy prediction model using financial information from two years prior to bankruptcy (t-1). Rows represent the actual status of the firms, while columns indicate the predicted classification generated by the model. Correct classifications appear along the diagonal: 17 bankrupt firms and 21 non-bankrupt firms are correctly identified. Off-diagonal values represent misclassifications, where 7 bankrupt firms are incorrectly classified as non-bankrupt (Type I error) and 7 non-bankrupt firms are incorrectly classified as bankrupt (Type II error).

This reduction in classification accuracy is consistent with Altman (1968) original findings and is economically intuitive. As bankruptcy becomes more remote, firms that will ultimately fail may still exhibit relatively stable financial profiles, while solvent firms may temporarily experience weaker performance. Nevertheless, the model retains a semi-strong level of predictive ability two years prior to failure, correctly classifying more than seventy percent of observations.

While classification accuracy within the estimation sample is informative, it may be biased upward due to sampling error and variable selection (search bias). As noted by Altman (1968), such bias arises because the same observations are used both to estimate the discriminant coefficients and to evaluate classification performance. Under these circumstances, high in-sample accuracy does not necessarily imply that the discriminant function will perform equally well when applied to new observations. To address this concern, a validation procedure analogous to that proposed by Frank et al. (1965) and later adopted by Altman (1968) was implemented. The purpose of this procedure is to assess whether the discriminant model maintains its predictive ability when applied to observations that were not used to estimate the model parameters.

The validation procedure consists of repeatedly dividing the original sample into two parts: a training subsample, used to estimate the discriminant function, and a holdout subsample, used exclusively for evaluating the model's classification performance. This procedure was repeated five independent times, each time drawing a new random subset of firms for coefficient estimation. By varying the composition of the training sample across replications, the test provides a direct assessment of the stability of the discriminant function and its sensitivity to the specific firms used to estimate the model parameters. In each replication, 12 firms from the bankrupt Group and 12 firms from the non-bankrupt Group were randomly selected from the initial sample, resulting in a training subsample of 24 firms. The discriminant coefficients and the corresponding Group centroids were then estimated using only this subsample. The remaining firms, which were not involved in the estimation of the discriminant function, constituted the holdout sample. In this case, this resulted in 26 firms. These observations were subsequently classified using the discriminant function obtained from the training subsample, based on the proximity of their Z-scores to the estimated Group centroids. By comparing the predicted classifications with the actual Group membership of these firms I aimed to evaluate the model's predictive performance on previously untreated observations. The results from the 5 replications are presented in Table 6.

Table 6 - Accuracy of Classifying the Secondary Sample

Replication	**Percent Correct Classifications (%)**	**Value of t**
1	75	3.05
2	82.14	4.44
3	75	3.06
4	82.14	4.44
5	78.57	3.69
Average	78.57	3.74

Table 6: The table reports the classification accuracy of the bankruptcy prediction model when applied to the secondary (validation) sample across five replications of the analysis. Percent Correct Classifications indicates the proportion of firms correctly classified by the model in each replication. The t-value tests whether the discriminant function significantly differentiates between bankrupt and non-bankrupt firms in the sample. The final row reports the average classification accuracy and mean t-value across all replications.

Across the five replications, the percentage of correct classifications in the holdout samples ranged from 75 percent to 82.1 percent, with an average accuracy of 78.57 percent. To assess whether this level of performance exceeds what would be expected by random assignment, a one-sample t-test was applied to the proportion of correct classifications in each replication, testing the null hypothesis that classification accuracy equals 50%. The resulting t-statistics ranged from 3.06 to 4.44, with an average value of 3.74, indicating statistically significant discrimination in every replication. These results reject the hypothesis that the observed classification accuracy is attributable to chance alone and provide strong evidence that the discriminant function retains substantial explanatory and predictive power when applied to observations not used in its estimation. Consistent with Altman (1968) conclusions, the findings suggest that any upward bias arising from intensive variable search or in-sample evaluation is limited, and that the model's performance is not driven by a small subset of influential firms. Overall, the replication exercise supports the robustness of the discriminant model and reinforces its validity as a tool for distinguishing between bankrupt and non-bankrupt firms.

The following empirical test performed aims to evaluate the propensity of the discriminant model to generate false bankruptcy signals when applied to firms that experience significant earnings difficulties but do not, in fact, fail. In Altman (1968) framework, this constitutes a more relative assessment of Type II errors, that is, cases in which economically distressed yet viable firms are incorrectly classified as bankrupt. From a practical perspective, this test is particularly relevant, as excessive false alarms may undermine the usefulness of bankruptcy prediction models for credit assessment and investment decision-making. Consistent with Altman (1968), the firms included in this secondary sample were selected solely on the basis of negative net income in the base year corresponding to periods of adverse macroeconomic conditions. Importantly, bankruptcy status was not used as a selection criterion beyond ensuring that all firms remained non-bankrupt, and no restrictions were imposed on asset size. The discriminant analysis itself was conducted using financial data from the base year only, while the persistence of earnings difficulties over the preceding three-year window was examined descriptively to characterize the degree of financial distress within the sample. Classification was performed using the fixed discriminant coefficients and group centroids obtained from the original sample, thereby preserving the out-of-sample nature of the test. Two distinct moments of macroeconomic adverse conditions were used to conduct the following test. These two moments are the Global financial crisis of 2008-2009, and the more recent Covid-19 shock.

Results for the Global Financial Crisis (2008–2009)

The first implementation of the test focuses on the Global Financial Crisis, using fiscal years 2008 and 2009 as base years. For each year, a random sample of 33 manufacturing firms with negative net income was selected. The results indicate a pronounced tendency of the model to classify these distressed firms as bankrupt. The value of t to test the significance of the results was calculated as follows:

$$t = \frac{Proportion\ Correct - 0.5}{\sqrt{\frac{0.5(1-0.5)}{n}}}$$

Table 7 below presents the results obtained when testing the model for the 2008 sample. A presented only 7 out of 33 firms (21.2%) were correctly classified as non-bankrupt, while 26 firms (78.8%) were incorrectly classified as bankrupt. The corresponding Altman-style t-statistic of −4.05 strongly rejects the null hypothesis of random classification, indicating that the model performs significantly worse than a 50 percent benchmark in this environment. This result reflects the exceptional severity of the financial conditions prevailing in 2008, during which even firms that ultimately survived exhibited financial profiles closely resembling those of bankrupt firms.

Table 7 - Classification Results for Distressed Firms – 2008

Outcome	Number of Firms	Percent
Correctly classified as Non-Bankrupt	7	21.2
Misclassified as Bankrupt	26	78.8
Total	33	100
t-statistic	-4.05	

Table 7: The table reports the classification outcomes of the bankruptcy prediction model when applied to a sample of financially distressed firms in 2008. The Outcome column indicates whether the firms were correctly identified as non-bankrupt or misclassified as bankrupt by the model. Number of Firms reports the count of observations in each category, while Percent shows their relative proportion in the sample. The t-statistics measure the statistical significance of the difference between the groups based on the discriminant function.

Table 8 shows the results obtained when testing the model for the 2009 sample. The classification performance improves modestly. Fifteen firms (45.5%) were correctly classified as non-bankrupt, while 18 firms (54.5%) were misclassified. The associated t-statistic of −0.52 suggests that classification accuracy is not statistically distinguishable from random assignment. This improvement relative to 2008 is consistent with the partial stabilization of financial markets and corporate earnings following the peak of the crisis, though the model still exhibits a substantial false-alarm rate.

Table 8 - Classification Results for Distressed Firms – 2009

Outcome	Number of Firms	Percent
Correctly classified as Non-Bankrupt	15	45.5
Misclassified as Bankrupt	18	54.5
Total	33	100
t-statistic	-0.52	

Table 8: The table reports the classification outcomes of the bankruptcy prediction model when applied to a sample of financially distressed firms in 200 The Outcome column indicates whether the firms were correctly identified as non-bankrupt or misclassified as bankrupt by the model. Number of Firms reports the count of observations in each category, while Percent shows their relative proportion in the sample. The t-statistics measure the statistical significance of the difference between the groups based on the discriminant function.

When the two years are pooled as presented in Table 9, the overall accuracy falls to 33.3 percent, with two-thirds of firms incorrectly classified as bankrupt. The pooled t-statistic of −2.87 indicates that the model's performance remains significantly below random classification. Taken together, the Global Financial Crisis results highlight a clear limitation of the discriminant model: during periods of extreme macroeconomic stress, the financial characteristics of distressed but surviving firms converge toward those typically associated with bankruptcy, leading to a high incidence of Type II errors.

Table 9 - Classification Results for Distressed Firms – Pooled 2008–2009

Outcome	Number of Firms	Percent
Correctly classified as Non-Bankrupt	22	33.3
Misclassified as Bankrupt	44	66.7
Total	66	100
t-statistic	-2.87	

Table 8: The table reports the classification outcomes of the bankruptcy prediction model when applied to the pooled sample of financially distressed firms from 2008 and 2009. The Outcome column indicates whether firms were correctly classified as non-bankrupt or misclassified as bankrupt by the model. Number of Firms shows the count of observations in each category, while Percent reports their proportion in the total sample. The t-statistic evaluates the statistical significance of the discriminant score relative to the model's classification threshold, indicating whether the distressed firms are statistically distinguishable from the non-bankrupt group.

Results for the COVID-19 Shock (2020)

The second implementation examines fiscal year 2020, capturing the economic disruption caused by the COVID-19 pandemic. Owing to the broader availability of data in this period, the sample comprises 374 non-bankrupt manufacturing firms with negative net income. In contrast to the Global Financial Crisis results, as presented on the Table 10 below, the classification accuracy in 2020 is markedly closer to random. Approximately 49.2 percent of firms are correctly classified as non-bankrupt, while 50.8 percent are misclassified as bankrupt. The corresponding t-statistic of −0.31 indicates no statistically significant deviation from random assignment.

Table 10 - Classification Results for Distressed Firms – COVID-19 Period (2020)

Outcome	Number of Firms	Percent
Correctly classified as Non-Bankrupt	184	49.2
Misclassified as Bankrupt	190	50.8
Total	374	100.0
t-statistic	-0.31	

Table 10: The table presents the classification outcomes of the bankruptcy prediction model when applied to a sample of financially distressed firms during the COVID-19 period in 2020. The Outcome column indicates whether firms were correctly classified as non-bankrupt or misclassified as bankrupt by the model. Number of Firms reports the number of observations in each category, while Percent indicates their proportion in the sample. The t-statistics evaluate the statistical significance of the discriminant score relative to the model's classification threshold, providing an indication of whether distressed firms are statistically distinguishable from the non-bankrupt group.

This outcome suggests that, while the model continues to generate a substantial number of false bankruptcy signals, it does not systematically overclassify distressed firms as bankrupt during the COVID shock to the same extent observed in 2008. This difference is economically intuitive. Although the COVID-19 shock led to sharp earnings declines across many firms, it was widely perceived as a temporary and exogenous disruption, often accompanied by extraordinary policy support. As a result, the financial profiles of distressed firms in 2020 appear less persistently “bankruptcy-like” than those observed during the systemic collapse of credit markets in 2008.

In comparison with Altman (1968) original findings, which reported a correct classification rate of approximately 79 percent for a similar secondary sample, the present results indicate a deterioration in performance in modern crisis episodes, particularly during 2008–2009. This divergence likely reflects changes in financial structure, market dynamics, and the nature of economic shocks over time. Nevertheless, the COVID-19 results demonstrate that the model’s tendency toward false alarms is not uniform across crises, reinforcing the importance of contextual interpretation when applying traditional bankruptcy prediction models to contemporary data.

Overall, the results of the test underscore an important trade-off inherent in the Altman Z-score framework. While the model demonstrates strong discriminatory power in distinguishing bankrupt from non-bankrupt firms under normal conditions, it exhibits a pronounced tendency to overpredict bankruptcy during periods of widespread economic distress. This behavior is particularly evident during the Global Financial Crisis, where the model systematically classifies surviving but distressed firms as bankrupt, resulting in elevated Type II error rates. From a methodological standpoint, these findings do not invalidate the discriminant model but rather mark its domain of applicability. The results suggest that the Z-score captures structural indicators of financial vulnerability that become prevalent among many firms during severe downturns, thereby reducing its ability to distinguish between temporary distress and irreversible failure. Consequently, the model’s output should be interpreted with caution when applied in environments characterized by broad economic shocks.

Practical Application of the Model: Determination of the Optimal Z-score

The following section extends the empirical results obtained in the previous tests by applying the model in a more practical context. The objective is to determine a classification range that allows firms to be categorized according to their respective Z-scores and to identify an optimal Z-score threshold that enables bankruptcy prediction without the need for computer-based discriminant analysis.

The procedure used to determine the optimal Z-score threshold is conducted in two phases. In Altman (1968), this procedure begins by identifying firms whose Z-scores fall within the overlapping region between bankrupt and non-bankrupt firms in the initial sample. This region is referred to as the "gray area" or "zone of ignorance", as it represents the range of values in which the discriminant model is less capable of clearly distinguishing between the two Groups. The gray area is defined as the interval bounded by the lowest Z-score among non-bankrupt firms and the highest Z-score among bankrupt firms. In the present sample, this interval ranges from 0.36 to 5.47, whereas in the original Altman study the corresponding interval was substantially narrower, lying approximately between 1.81 and 2.99. The bigger interval overlap observed in the present sample indicates a greater dispersion of Z-scores across the two Groups and suggests that the model's may be weaker when applied to more recent data. This result is consistent with the findings obtained in the previous validation tests, which showed that although the model retains predictive ability, its classification accuracy is lower than that reported in the original study.

Figure 1- Initial Sample Gray Area

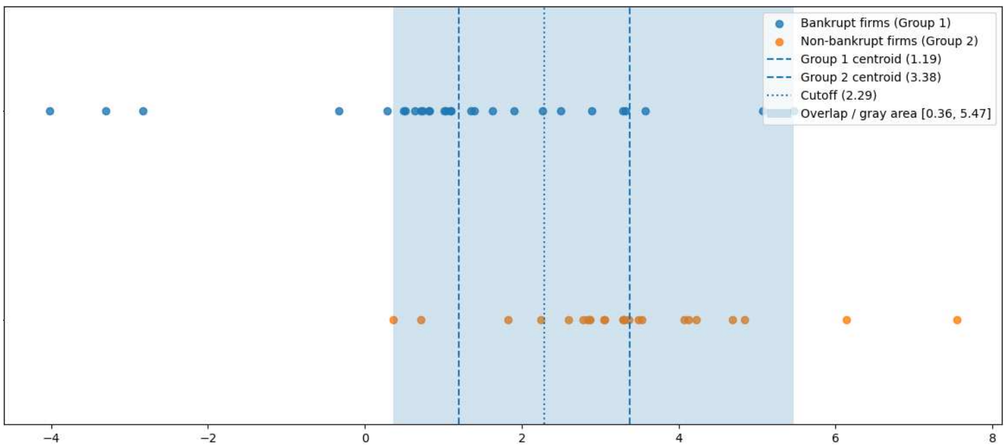

Figure 1: illustrates the distribution of the initial sample of firms along the discriminant score, highlighting the separation between bankrupt firms (Group 1) and non-bankrupt firms (Group 2), as well as the gray area in the distribution of Z-scores for the initial sample. The gray area represents the intermediate zone in which firms cannot be clearly classified as either bankrupt or non-bankrupt according to the model's cutoff values (centroids).

All firms whose Z-scores fall within the gray area are listed in Table 11, ordered in ascending order of their Z-scores. The second phase evaluates alternative Z-score thresholds within this overlapping interval. As the original study I formed consecutive intervals using the Z-scores ordered from the gray area. As described in Altman (1968), the analysis considers Z-scores between, but not including, the indicated values, and the number of misclassifications associated with each interval is then calculated. The results of this procedure are presented in Table 12.

The optimal classification threshold was determined by identifying the interval that minimizes the number of misclassifications. In the present analysis, the lowest number of misclassifications occurred in the interval 2.49–2.59, which showed in 10 misclassified firms. Following the approach suggested by Altman (1968), the midpoint of this interval is taken as the operational Z-score cutoff. From this I assumed the midpoint of the interval 2.54 to be the value that discriminates best between bankrupt and non-bankrupt firms. This value is very close to the optimal cutoff found in Altman (1968), where the discriminant analysis yielded a critical Z-score of approximately 2.68. Despite the greater dispersion observed in the present dataset, the proximity between the two thresholds suggests that the general structure of the model remains consistent with the original findings.

Table 11- Distribution of Z-scores for Bankrupt and Non-Bankrupt Firms

Non-bankrupt firm (Group 2)	Z-score	Bankrupt firm (Group 1)
13412	0.356779	
	0.490352	2078
	0.517877	8964
	0.633030	10915
	0.713766	8523
1533	0.715808	
	0.738221	10284
	0.810462	10633
	0.819330	6716
	1.014985	8207
	1.035419	31479
	1.091123	11679
	1.100409	3693
	1.351048	25932
	1.393044	14038
	1.631637	4195
12497	1.821310	
	1.900238	14296
14794	2.239218	
	2.260592	1475
	2.494534	9382
1970	2.593537	
7326	2.778741	
1971	2.839100	

9285	2.863278	
2289	2.875289	
	2.896306	12674
13354	3.051761	
11748	3.053199	
	3.284423	14380
8150	3.287799	
10202	3.303946	
11588	3.305702	
	3.323556	7185
4803	3.369109	
6044	3.486459	
2130	3.530853	
	3.574968	5608
13608	4.069743	
3524	4.123385	
1560	4.221258	
3840	4.681039	
2802	4.839176	
	5.071593	6240
	5.466252	30340

Table 11: The table presents the ordered distribution of Z-scores for firms in the sample, separating non-bankrupt firms (Group 2) and bankrupt firms (Group 1). Each observation corresponds to a firm identified by its database identifier and the associated Z-score calculated using the bankruptcy prediction model. The values are arranged in ascending order of the Z-score to facilitate comparison between the two groups. This presentation allows the identification of overlapping score ranges between bankrupt and non-bankrupt firms, highlighting the gray area where classification becomes less clear and the probability of misclassification increases.

Table 12 - Misclassified Firms Across Z-Score Intervals

Range of Z	**Number Misclassified**	**Firms**
0.36-0.49	24	13412, 2078, 8964, 10915, 8523, 10284, 10633, 6716, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
0.49-0.52	23	13412, 8964, 10915, 8523, 10284, 10633, 6716, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
0.52-0.63	22	13412, 10915, 8523, 10284, 10633, 6716, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
0.63-0.71	21	13412, 8523, 10284, 10633, 6716, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
0.71-0.72	20	13412, 10284, 10633, 6716, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296,

		1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
0.72-0.74	21	13412, 1533, 10284, 10633, 6716, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
0.74-0.81	20	13412, 1533, 10633, 6716, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
0.81-0.82	19	13412, 1533, 6716, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
0.82-1.01	18	13412, 1533, 8207, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.01-1.04	17	13412, 1533, 31479, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.04-1.09	16	13412, 1533, 11679, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.09-1.10	15	13412, 1533, 3693, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.10-1.35	14	13412, 1533, 25932, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.35-1.39	13	13412, 1533, 14038, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.39-1.63	12	13412, 1533, 4195, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.63-1.82	11	13412, 1533, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.82-1.90	12	13412, 1533, 12497, 14296, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
1.90-2.24	11	13412, 1533, 12497, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
2.24-2.26	12	13412, 1533, 12497, 14794, 1475, 9382, 12674, 14380, 7185, 5608, 6240, 30340
2.26-2.49	11	13412, 1533, 12497, 14794, 9382, 12674, 14380, 7185, 5608, 6240, 30340
2.49-2.59	10	13412, 1533, 12497, 14794, 12674, 14380, 7185, 5608, 6240, 30340
2.59-2.78	11	13412, 1533, 12497, 14794, 1970, 12674, 14380, 7185, 5608, 6240, 30340

2.78-2.84	12	13412, 1533, 12497, 14794, 1970, 7326, 12674, 14380, 7185, 5608, 6240, 30340
2.84-2.86	13	13412, 1533, 12497, 14794, 1970, 7326, 1971, 12674, 14380, 7185, 5608, 6240, 30340
2.86-2.88	14	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 12674, 14380, 7185, 5608, 6240, 30340
2.88-2.90	15	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 12674, 14380, 7185, 5608, 6240, 30340
2.90-3.05	14	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 14380, 7185, 5608, 6240, 30340
3.05-3.05	15	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 14380, 7185, 5608, 6240, 30340
3.05-3.28	16	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 14380, 7185, 5608, 6240, 30340
3.28-3.29	15	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 7185, 5608, 6240, 30340
3.29-3.30	16	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 7185, 5608, 6240, 30340
3.30-3.31	17	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 7185, 5608, 6240, 30340
3.31-3.32	18	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 7185, 5608, 6240, 30340
3.32-3.37	17	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 5608, 6240, 30340
3.37-3.49	18	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 5608, 6240, 30340
3.49-3.53	19	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 5608, 6240, 30340
3.53-3.57	20	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 2130, 5608, 6240, 30340
3.57-4.07	19	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 2130, 6240, 30340

4.07-4.12	20	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 2130, 13608, 6240, 30340
4.12-4.22	21	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 2130, 13608, 3524, 6240, 30340
4.22-4.68	22	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 2130, 13608, 3524, 1560, 6240, 30340
4.68-4.84	23	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 2130, 13608, 3524, 1560, 3840, 6240, 30340
4.84-5.07	24	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 2130, 13608, 3524, 1560, 3840, 2802, 6240, 30340
5.07-5.47	23	13412, 1533, 12497, 14794, 1970, 7326, 1971, 9285, 2289, 13354, 11748, 8150, 10202, 11588, 4803, 6044, 2130, 13608, 3524, 1560, 3840, 2802, 30340

Table 12: The table presents the distribution of misclassified firms across different Z-score intervals. The Range of Z column represents successive intervals of the Z-score produced by the bankruptcy prediction model. Number Misclassified indicates the number of firms whose predicted classification does not correspond to their actual status within each Z-score interval. The Firms column lists the identifiers of the firms associated with these misclassifications.

Conclusion and Recommendations

This dissertation seeks to analyze the accuracy of the previously developed model by Altman (1968). Economical, sociological changes that happened from the time the model was developed until nowadays really shaped firm compositions and changed its behavior.

Accessing the continuous validity of the model and continuous improvement of the same according to the current reality shows relevant academic and financial evolution. Keeping up with the sector changes is important and credit risk analysis is one of the cornerstones of the entire financial system. At the time, Altman (1968) introduced a practical and intuitive way of accessing risk and as shown from the test and evaluation conducted throughout my dissertation it was possible to conclude that the model still shows predictive capacity although some parameters changed substantially when we consider the initial study. The model still guarantees a 78.85 percent accuracy when predicting bankruptcy one year prior to the event. Against the model at the time, it was developed this yield an accuracy score of 94 percent of its initial sample.

An interesting remark of the study is the effect of systematic shocks and the effects of such in firms credit risk analysis. As previously tested, the effect of the global financial crisis (2008-2009) and Covid-19, it exhibits a pattern to overpredict bankruptcy during periods of economic distress. Considering the methodology applied, these findings do not invalidate the discriminant model but rather establish its domain of applicability as the results suggest that the Z-score captures structural indicators of financial vulnerability that show more prominence among many firms during severe downturns, thereby reducing its ability to distinguish between temporary distress and irreversible failure.

Out of 22 ratios, at the time, Altman (1968) selected the combination of 5 which showed the best result when considering the separation of groups between bankrupt and non-bankrupt, a strong recommendation would be to further analyze the possibility of new and modified ratio and a different combination that better highlights the effects of the current financial system. As the methodological approach of the dissertation followed strictly what was made previously, some of the limitations of the study still apply. The present dissertation limitations are that the firms examined were all publicly held manufacturing corporations for which comprehensive financial data were possible to collect. In addition, the sample size of the present dissertation was smaller than the one where the study was previously conducted, although the results showed statistically significant findings.

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