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The Role of Financial Ratios in Bankruptcy Prediction: An Empirical Study Using Contemporary Financial Data

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Abstract
Corporate bankruptcy poses considerable risks to various stakeholders. This study investigated contemporary issues in predicting corporate bankruptcy in the non-financial public companies in the United States, using five key financial ratios: Cashflow to Total Liabilities (OANCFLT), Net Income to Total Sales (NIREVT), Total Liabilities to Total Assets (LTAT), Total Current Assets to Total Current Liabilities (ACTLCT), and Total Assets to Total Sales (ATREVT). Utilizing a multivariate logistic regression model and monthly data from 2017 to 2021, this research examined the predictive power of these ratios and their effectiveness in identifying early signs of corporate failure. The findings underscore the importance of certain financial ratios, particularly LTAT with 80% predictive power in the year before bankruptcy, and OANCFLT at 65% and statistically significant with t-values of -2.85, offering valuable insights for stakeholders aiming to mitigate financial risks.

Keywords: Corporate Bankruptcy, Financial Ratios, Bankruptcy Prediction, Financial Risk.

1. Introduction

Corporate bankruptcy has garnered considerable interest among various stakeholders in the financial sector. This attention is mirrored in academia, where numerous studies have been conducted to understand this phenomenon and develop strategies to prevent or minimize its occurrence. Corporate bankruptcy not only impacts companies and their employees but also has a deleterious multiplier effect on creditors, investors, and overall market confidence, affecting all stakeholders within the financial industry. Consequently, it is crucial to identify early signs of corporate bankruptcy so that stakeholders can proactively deploy measures to mitigate the associated risks. This study investigates contemporary issues in corporate bankruptcy prediction by utilizing five well-established financial ratios as predictive tools.

The importance of predicting corporate failure in the financial industry cannot be overstated. Bankruptcy can lead to massive unemployment, supply-chain disruptions, and erosion of market confidence. Major bankruptcies, such as those during the 2008 financial crisis and the recent COVID-19 disruptions, have underscored the need for robust mechanisms to predict corporate failure, prompting re-evaluation of existing models and the development of more reliable predictive measures. Financial statements provide raw data that offer insights into various aspects of a firm's financial position, such as profitability, liquidity, efficiency, and solvency. Financial ratios have been extensively studied and provide a useful basis for several bankruptcy prediction models.

Several approaches to detecting corporate failure have been proposed in the past, including statistical models by William Beaver and Edward Altman in the 1960s, later expanded by James Ohlson in the 1980s, machine learning approaches, qualitative analysis, the Altman Z-score, and market-based models.

Each approach has its strengths and weaknesses, and researchers often combine these methods to improve the predictive ability of their models. The choice of model typically depends on data availability, context, and the intended use of the analysis.

These models have various applications and are utilized by different interest groups within the financial industry, including banks and other financial institutions, investors, credit rating agencies, management, suppliers and creditors, regulatory institutions, labour unions, researchers, and insurance companies.

This study contributes to the existing body of literature by using the latest data to analyze the use of financial ratios in predicting corporate bankruptcy. Financial statements provide raw data that offer insights into various aspects of a firm's financial position, such as profitability, liquidity, efficiency, and solvency. Financial ratios have been extensively studied and provide a useful basis for several bankruptcy prediction models. Despite this extensive research on corporate bankruptcy, recent market disruptions, such as those caused by the pandemic, necessitate an updated analysis. This study leverages the most up-to-date data to examine corporate bankruptcy, aiming to offer fresh insights and enhance the predictive accuracy of existing models. By incorporating the latest data, this research seeks to provide a more robust understanding of corporate bankruptcy in the current economic context. To achieve this, the study examines companies that failed in 2022 due to economic disruptions caused by the COVID-19 pandemic in the United States. It uses five key financial ratios to study this phenomenon, aiming to provide insights into how these ratios can offer early warning signs of corporate failure.

The remainder of this paper is structured as follows: a review of existing literature related to corporate failure prediction, followed by a methodology section that explains the research design and techniques used in this study. Next, the analysis and result section analyze the data and discuss the key findings of the research. Finally, the paper concludes with a discussion of the implications, strengths, and weaknesses of this study, along with recommendations for future research.

2. Literature Review

Bankruptcy prediction remains a vital area of research due to its significant economic consequences. The most accepted definition of corporate failure views it as bankruptcy, defined legally as the inability of a debtor to meet its financial obligations (Veganzones & Severin, 2021). According to Joos, De Bourdeaudhuij, and Ooghe (1995), bankruptcy is often caused by severe liquidity and solvency issues, which can lead to the dissolution of a corporation. Altman's Z-score model, developed in 1968 by Edward I. Altman, remains one of the most well-known tools for predicting bankruptcy by using five financial ratios to achieve an accuracy rate of 94%, initially for manufacturing firms but now adapted to other sectors (Altman, 1968; Agarwal & Taffler, 2007).

Beaver (1966) demonstrated that individual financial ratios, such as the cash flow-to-total debt ratio, the current ratio, the net income-to-total assets ratio, the working capital-to-total assets ratio, and the debt-to-equity ratio, could predict corporate failure up to five years before it occurs. However, univariate models have since been replaced by more complex multivariate models, such as Ohlson's (1980) logistic regression, which combines multiple financial ratios along with factors like company size and performance.

Jackson and Wood (2013) contributed to the field by critically reviewing various insolvency prediction models and methodologies within the UK context. They found that newer approaches, such as the contingent claims method and neural network techniques, performed better than traditional accounting-based models like those of Altman and Ohlson. Their research highlights the importance of exploring advanced methodologies, particularly in regional settings.

Recent studies have also incorporated macroeconomic factors. Braga and Cunha (2022) demonstrated that combining microeconomic factors with macroeconomic indicators such as GDP and enterprise birth rates significantly enhances bankruptcy prediction models in the Portuguese construction sector, achieving 90% accuracy up to three years before bankruptcy. Similarly, Giannopoulos and Sigbjørnsen (2019) evaluated six models, including Altman's and Taffler's, and found Taffler's model had the highest accuracy in predicting bankruptcy in Greece, further emphasizing the need for regional model adaptations.

Ncube (2014) applied Altman's Z-score to Zimbabwe's financial sector and found that 83.33% of financial institutions were distressed, supporting the model's applicability in developing economies. Similarly, Ajayi et al. (2021) explored the Nigerian oil and gas sector using multivariate discriminant analysis, highlighting key financial ratios, such as EBIT and working capital, as critical indicators with an 88.2% accuracy rate.

Tian and Yu (2017) expanded the application of financial ratios in international markets, using adaptive LASSO to improve predictive accuracy across different market structures. They found that different financial ratios showed varying predictive power depending on the regional context, with Japan's market favouring ratios like retained earnings to total assets.

In summary, financial ratios remain a crucial tool in bankruptcy prediction, with Altman's Z-score model widely validated across sectors and regions. However, studies such as those by Jackson and Wood (2013) suggest that newer methods, including neural networks and region-specific adaptations, offer enhanced predictive accuracy, particularly when combined with macroeconomic variables.

3. Methodology

Hypotheses

Null Hypothesis (H_0): The financial ratios do not significantly predict bankruptcy for non-financial public companies.

Alternative Hypothesis (H_1): The financial ratios significantly predict bankruptcy for non-financial public companies.

To test these hypotheses, a series of t-tests and logistic regression models were used to compare the means of the five financial ratios for failing and non-failing companies across different years.

The following financial ratios were used as independent variables in the test:

i. Cash Flow to Total Liabilities (OANCFLT).
ii. Net Income to Total Sales (NIREVT).
iii. Total Liabilities to Total Assets (LTAT).
iv. Total Current Assets to Total Current Liabilities (ACTLCT).
v. Total Assets to Total Sales (ATREVT)

Research design

This study applies a logistic regression (*logit*) model to predict corporate failure using five key financial ratios as independent variables. The *logit* model is preferred for its straightforward and intuitive approach, which Ohlson (1980) described by posing the question: "What is the probability that a firm, belonging to a specified population, will fail within a specified time frame?"

Ohlson (1980) highlights several advantages of the *logi*t model over other models like the Multi-discriminant Analysis Model (MDA). Firstly, the *logit* model does not require the predictor variables to follow a normal distribution, making it more adaptable to financial data which often lacks this normality. Secondly, the probabilities of bankruptcy generated by the *logit* model provide more nuanced insights than the binary classifications of MDA. Lastly, logistic regression can handle non-linear relationships between variables more effectively than the linear approach of MDA (Hassan et al., 2017). The analysis was performed using STATA; chosen for its robust statistical capabilities and effectiveness in handling complex econometric models. The data set was sourced from the Wharton Research Data Services (WRDS) database, which provided comprehensive and reliable financial data from five-year annual financial reports of all public companies in the United States.

Data Collection

The dataset includes pooled financial data from non-financial public companies from 2017 to 2021, specifically selected to evaluate the chosen ratios' ability to predict company failures that occurred in 2022. Financial firms were excluded to maintain consistency and comparability. The data comprises both companies that filed for Chapter 11 bankruptcy in 2022 and those that did not, thus offering a balanced analysis perspective.

Data consisting of 47,945 records from 37,089 US public companies over five years was obtained from WRDS. This dataset was merged with the list of failed companies, sourced from the SEC filings in the US. Sectors without any bankrupt companies were excluded to maintain uniformity in the sample. Given the correlation between company size and failure risk (Ohlson, 1980), companies outside the size range of the largest and smallest failed companies were excluded. This refined dataset includes 129 failed and 25,191 non-failed companies, maintaining an approximate ratio of 200 non-failed to every failed firm, suitable for analysis. Table 1 below shows the distribution of failed and non-failed companies by year. The dummy variables 0 and 1 represents the non-failed and failed companies respectively.

Table 1: Distribution of failed and non-failed companies

	Failed		
Year	0	1	**Total**
2017	4,906	25	4,931
2018	4,904	24	4,928
2019	5,011	26	5,037
2020	5,189	29	5,218
2021	5,181	25	5,206
Total	25,191	129	25,320

Source: Data derive from CSRP/Compustat merged Database (Wharton Research Data Services, 2024.

During the data preparation phase, a crucial step involved was the winsorization of variables, aimed at minimizing the impact of outliers that could skew results and lead to inaccurate conclusions. Winsorization was conducted at the 5% level for both the upper and lower tails of each variable's distribution.

Specifically, for each variable or ratio, values in the top 5% were replaced with the value at the 95th percentile, and values in the bottom 5% were replaced with the value at the 5th percentile. This method helps maintain the data's originality while reducing the influence of extreme values (Chen et al., 2021). For instance, if a company's debt-to-equity ratio is in the top 5% of all observed values, it is adjusted to match the 95th percentile value of this ratio across all companies. Similarly, if a company's current ratio is among the lowest 5%, it is adjusted to the 5th percentile. This winsorization process was applied to all five variables used in this study, enhancing the robustness and reliability of the logistic regression model used for predicting corporate bankruptcy.

Financial Ratios and Formation of Variables

The selection of financial ratios follows Beaver's (1966) methodology, where one ratio was chosen from five different Beaver's groupings. Beaver (1966) provides justification for selecting these ratios to include, their ubiquity in literature, proven performance in past studies, and their calculation from metrics related to cash flow. The selected ratios are as follows:

- Cash flow to total liabilities
- Net income to total revenue
- Total liabilities to total assets
- Current assets to current liabilities
- Total assets to total revenue

These ratios form the variables used in our analysis.

Table 2: List of financial ratios

	Variable	**Interpretation**
1.	*OANCFLT = OANCF/LT*	Cashflow to total liabilities
2.	*NIREVT = NI/REVT*	Net income to total sales
3.	*LTAT = LT/AT*	Total liabilities to total assets
4.	*ACTLCT = ACT/LCT*	Total current to total current liabilities
5.	*ATREVT = AT/REVT*	Total asset to total sales

Source: Author's Compilation.

A dummy variable named "failed" was created, taking on binary values where 1 represents failed firms and 0 represents non-failed firms. Table 3 below shows the summary statistics of our independent variables while table 4 shows the statistical distribution by failed and non-failed firms.

Table 3: statistical distribution of the variables

Variable	N	Mean	SD	p25	p50	p75
OANCFLT	25056	-0.218	2.245	-0.183	0.027	0.159
NIREVT	23029	-13.731	322.697	-0.218	0.021	0.113
LTAT	25272	0.601	0.775	0.299	0.556	0.780
ACTLCT	21036	3.744	6.191	1.278	1.927	3.741
ATREVT	23030	38.303	740.491	1.102	1.968	6.766

Source: Data derive from CSRP/Compustat merged Database (Wharton Research Data Services, 2024.

Table 4: statistical distribution by failed and non-failed firms

failed	N	Mean	SD	Min	p25	p50	p75	Max
	24928	-0.218	2.250	-19.945	-0.181	0.027	0.160	170.500
	22921	-13.733	323.413	-33974.670	-0.215	0.022	0.114	1542.565
0	25143	0.599	0.776	0.000	0.298	0.554	0.778	66.431
	20921	3.751	6.205	0.006	1.279	1.929	3.748	198.344
	22922	38.411	742.222	0.037	1.101	1.967	6.774	73223.990
	128	-0.365	0.853	-6.335	-0.340	-0.043	0.028	0.387
	108	-13.317	76.999	-728.615	-1.080	-0.126	-0.054	1.172
1	129	0.881	0.543	0.009	0.587	0.785	1.056	3.695
	115	2.504	2.744	0.146	1.165	1.625	2.612	16.506
	108	15.227	54.541	0.392	1.171	2.171	5.545	437.423
	25056	-0.218	2.245	-19.9448	-0.183	0.027	0.159	170.500
	23029	-13.731	322.69	-33974.670	-0.218	0.021	0.113	1542.565
Total	25272	0.601	0.7755	0.000	0.299	0.555	0.780	66.431
	21036	3.744	6.1915	0.006	1.278	1.927	3.741	198.344
	23030	38.303	740.4905	0.037	1.102	1.968	6.766	73223.990

Source: Data derive from CSRP/Compustat merged Database (Wharton Research Data Services, 2024.

4. Results and Discussion

Financial Ratios and Stability Assessment

To evaluate the financial stability of failing and non-failing companies, we examined typical differences in our key financial ratios:

Cash Flow to Total Liabilities Ratio: Typically, this ratio tends to be lower in failing companies, which often face challenges in generating adequate cash flow to cover their liabilities. In contrast, non-failing companies generally produce sufficient cash flow to comfortably meet their liabilities.

Net Income to Total Revenue Ratio: Failing companies usually report a lower ratio due to reduced profitability, which diminishes the proportion of net income to total revenue. Conversely, non-failing companies often exhibit a higher ratio, reflecting better profitability and financial health.

Total Liabilities to Total Assets Ratio: This ratio is generally higher in failing companies and lower in non-failing companies.

Current Assets to Current Liabilities Ratio (Current Ratio): This ratio is often smaller in failing companies and larger in non-failing companies, indicating their respective financial strengths and weaknesses.

Total Asset to Total Revenue Ratio: The relationship between total assets and total revenue can vary and is not conclusively larger or smaller. It depends on the company's efficiency in using its assets to generate revenue.

The figures 1-5 graphically illustrates the behaviour of these ratios over five-year period

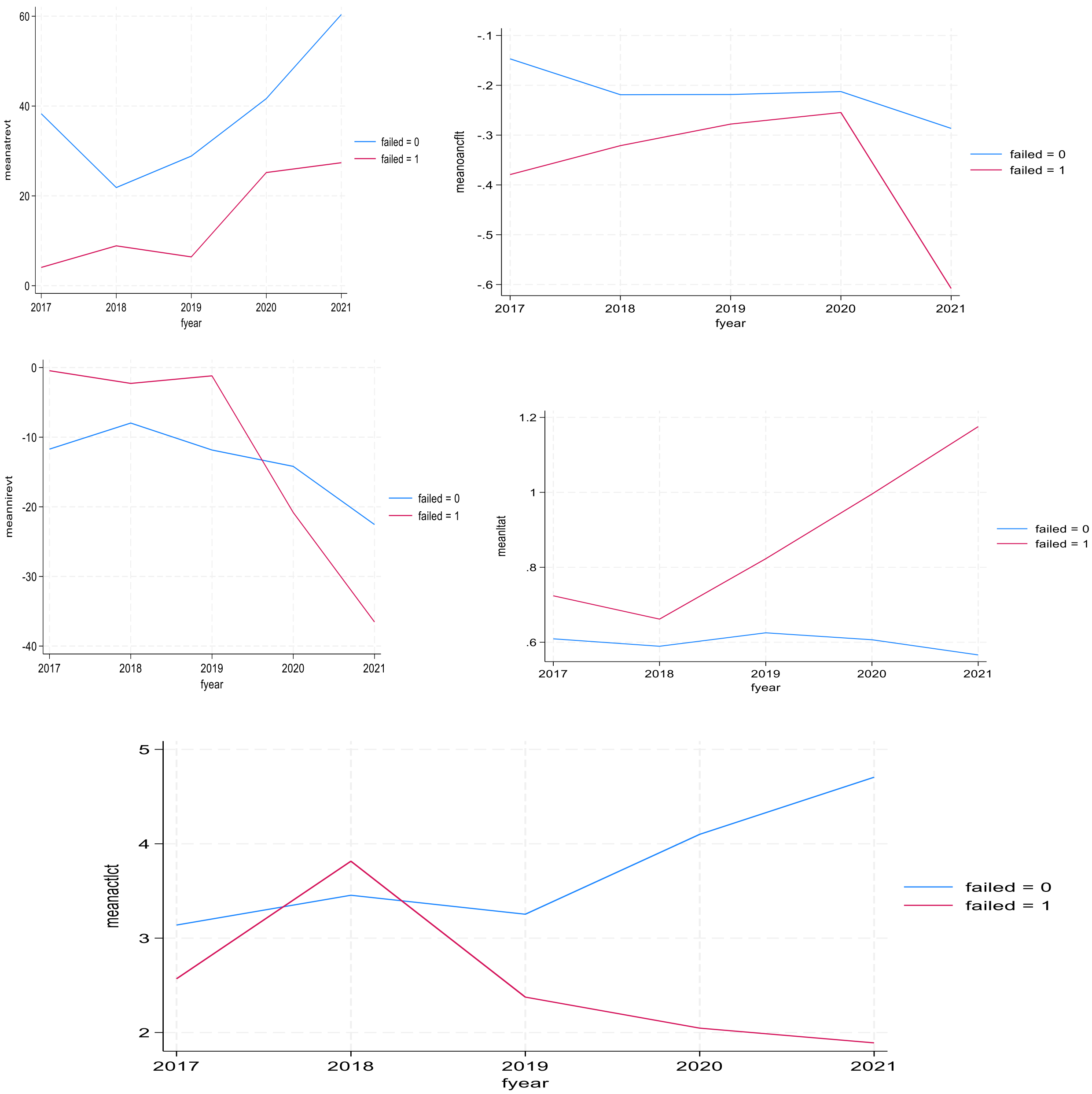

Figure 1-5: Graph of mean of variables against time periods

From the graph. the average values for the variables *OANCFLT*, *NIREVT*, and *ACTLCT* for the failed companies tend to decrease considerably as we approach 2021, the year before bankruptcy. Additionally, as predicted, the mean value for *LTAT* increases for failed companies as the bankruptcy year approaches, highlighting the usefulness of this ratio in bankruptcy prediction. The mean values for the variable *ATREVT* also performed well in prediction. Although the values for failed companies are lower than those for non-failed companies and increase as the bankruptcy year approaches, they increase at a slower rate compared to non-failed companies.

While these are general trends, there can be exceptions due to company-specific circumstances, industry norms, and other external factors. To explore this further, a statistical test of significance is conducted.

Univariate Analysis

Statistical Significance Test

Table 5 summarizes the results of our test of significance performed. It compares the means of our five financial ratios between failed and non-failed companies over a five-year period.

Table 5: t-test statistical results

Ratios	Failed (Means)					Non-failed (Means)					T-test					p-values				
	2021	2020	2019	2018	2017	2021	2020	2019	2018	2017	2021	2020	2019	2018	2017	2021	2020	2019	2018	2017
OANCFLT	-0.61	-0.255	-0.28	-0.32	-0.38	-0.29	-0.21	-0.22	-0.22	-0.15	1.16	0.422	0.46	0.751	1.31	0.13	0.338	0.325	0.23	0.1
NIREVT	-36.5	-20.82	-1.19	-2.28	-0.45	-22.6	-14.2	-11.8	-7.97	-11.7	0.43	0.481	-3.78	-2.12	-2.03	0.34	0.317	1E-04	0.019	0.02
LTAT	1.175	0.995	0.823	0.662	0.724	0.57	0.607	0.63	0.59	0.61	-3.9	-3.61	-2.58	-1.04	-1.5	0	6E-04	0.008	0.155	0.07
ACTLCT	1.891	2.088	2.375	3.816	2.57	4.71	4.1	3.25	3.45	3.14	9.82	5.178	1.86	-0.37	0.93	0	0	0.038	0.358	0.18
ATREVT	27.38	25.19	6.415	8.878	4.07	60.4	41.65	28.9	21.9	38.3	1.4	1.054	3.59	1.762	2.03	0.08	0.149	2E-04	0.041	0.02

Source: Data derive from CSRP/Compustat merged Database (Wharton Research Data Services, 2024.

From the table 5, distinct differences in mean values emerge between failed and non-failed companies, highlighting considerable variations in company performance and stability. For the *OANCFLT* ratio, failed companies consistently show lower mean values than non-failed ones across all years, although these differences are not statistically significant (p-values > 0.05). Conversely, the *NIREVT* and *LTAT* ratios reveal statistically significant lower mean values for failed companies in 2019, 2018, and 2017 (p-values < 0.05), but no significant differences in 2021 and 2020 for *NIREVT*, and in 2018 and 2017 for *LTAT*. Similarly, the *ACTLCT* ratio shows significantly lower mean values for failed companies in 2021, 2020, and 2019 (p-values < 0.05), with no significant differences in 2018 and 2017. The *ATREVT* ratio also indicates significantly lower means for failed companies in 2019, 2018, and 2017 (p-values < 0.05), but not in 2021 and 2020. These varying levels of statistical significance across different years and ratios underscore the need for a multifaceted approach in predicting company failure. The consistent significance of some ratios, like *NIREVT* and *LTAT* in specific years, suggests their potential predictive value. However, the lack of significance in other ratios, such as *OANCFLT*, despite their visual performance, indicates the necessity for further research to understand their effectiveness in predicting company failure across different periods.

4.2.2 The Logit Model

Our study utilized a *logit* regression model to predict the likelihood of bankruptcy based on five financial ratios. This model analyses how these ratios influence a company's probability of facing bankruptcy. Formally, the model is specified as follows:

$$log\left(\frac{p(bankruptcy = 1)}{1 - p(bankruptcy)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5$$

Where, p(bankruptcy) represents the probability of a firm going bankrupt, while X_1, X_2,…X_5 represent the financial ratios: *OANCFLT, NIREVT, LTAT, ACTLCT,* and *ATREVT.* β_0 is the intercept term, providing a baseline value for our model, and β_1, β_2, β_3, β_4 *and* β_5 are the coefficients associated with each financial ratio.

Before running the logit model, the financial ratios were tested for multicollinearity to eliminate any redundancy among the variables.

Table 6: Logit model results

Variables	**Area Under ROC Curve**				
	2021	**2020**	**2019**	**2018**	**2017**
OANCFLT	0.669	0.651	0.627	0.660	0.661
NIREVT	0.752	0.700	0.356	0.312	0.307
LTAT	0.802	0.743	0.682	0.682	0.621
ACTLCT	0.656	0.626	0.544	0.511	0.556
ATREVT	0.428	0.480	0.529	0.460	0.521

Source: Data derive from CSRP/Compustat merged Database (Wharton Research Data Services, 2024.

Table 6 presents the logit model results indicating the predictive power of various financial ratios (*OANCFLT, NIREVT, LTAT, ACTLCT, and ATREVT*) in forecasting bankruptcy over five years (2017-2021). The Area Under the ROC Curve (AUC) is used as a measure of this predictive power, with values closer to 1 indicating better predictive accuracy. For the ratio *OANCFLT* (Operating Cash Flow/Total Liabilities), the AUC values are consistent, ranging from 0.627 to 0.669, suggesting that *OANCFLT* has a moderate and relatively stable predictive power for bankruptcy across the years, with its highest predictive power in 2021 (AUC = 0.669).

The ratio *NIREVT* (Net Income/Revenue) shows a considerable variation in AUC values, starting low in 2017 (0.307) and increasing substantially, indicating that *NIREVT* has become a much better predictor of bankruptcy in recent years, whereas its predictive power was very poor in 2017 and 2018.

For *LTAT* (Total liabilities to total assets), the AUC values are consistently high compared to other ratios, ranging from 0.621 to 0.802, indicating that *LTAT* has strong and stable predictive power for bankruptcy, with its peak in 2021 (AUC = 0.802).

The ratio *ACTLCT* (Current Assets/Current Liabilities) has AUC values ranging from 0.511 to 0.656, suggesting that *ACTLCT* has a moderate predictive power, though it has been increasing over the years, peaking in 2021 (AUC = 0.656).

Finally, *ATREVT* (Total Assets/Revenue) has generally low AUC values, ranging from 0.428 to 0.529, indicating that *ATREVT* has relatively poor predictive power for bankruptcy, with some slight improvement over the years but still not reaching high levels of accuracy.

In summary, *LTAT* has consistently strong predictive power for bankruptcy across all years, followed by *NIREVT*, which has improved greatly in recent years. *OANCFLT* and *ACTLCT* show moderate predictive power, with *OANCFLT* being more stable and ACTLCT showing improvement over time. *ATREVT* has generally poor predictive power for bankruptcy across the years. These insights can help prioritize which financial ratios to focus on when assessing the risk of bankruptcy.

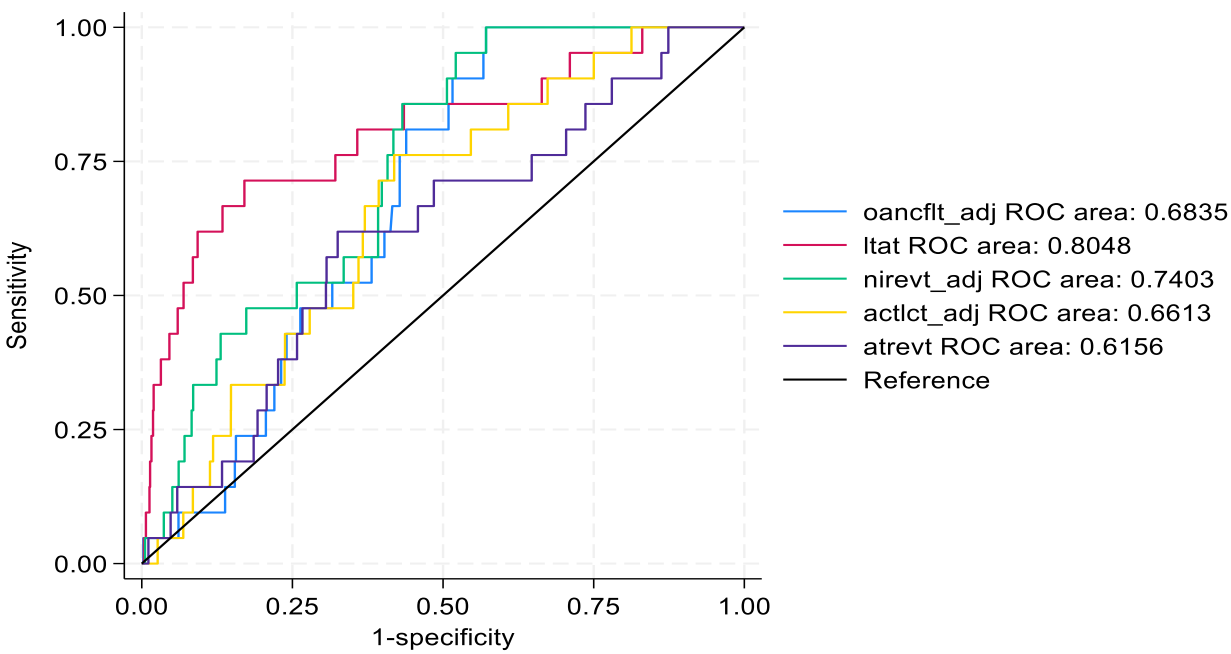

Figure 6: Combined ROC curves

The logit regression model demonstrated strong performance over the combined five-year period, with all ratios achieving over 60% accuracy in predicting failures, as depicted in Figure 6.

Multivariate Analysis

Table 7 presents the findings of the multivariate logistic regression analysis for our five ratios across the five-year span from 2017 to 2021.

Table7: Multivariate Logistic Regression Results

	2021	2020	2019	2018	2017
failed					
OANCFLT	-0.458***	-0.082	-0.010	-0.255	-0.458***
	(-2.85)	(-0.27)	(-0.04)	(-0.66)	(-2.85)
NIREVT	-0.001	0.006	0.006	0.069	-0.001
	(-0.55)	(0.14)	(0.33)	(0.77)	(-0.55)
LTAT	0.283**	0.284	0.326	0.401	0.283**
	(2.11)	(1.39)	(1.25)	(1.19)	(2.11)
ACTLCT	-0.458**	-0.040	-0.002	-0.103	-0.458**
	(-2.47)	(-0.37)	(-0.03)	(-0.70)	(-2.47)
ATREVT	-0.001	-0.009	0.001	-0.031	-0.001
	(-0.30)	(-0.29)	(0.09)	(-0.71)	(-0.30)
Constant	-4.442***	-4.405***	-4.651***	-4.433***	-4.442***
	(-5.86)	(-7.70)	(-8.25)	(-6.81)	(-5.86)
INDUSTRY FE	YES	YES	YES	YES	YES
ROC AUC	0.8115	0.7760	0.7161	0.7029	0.7224
MAX VIF	2.42	2.75	2.78	4.95	1.96
Observations	3197	3040	2712	3281	3281

Source: Data derive from CSRP/Compustat merged Database (Wharton Research Data Services, 2024.

The multivariate logistic regression results for the five financial ratios over the period from 2017 to 2021 show that the *OANCFLT* (Cashflow to Total Liabilities) ratio has a significant negative effect on bankruptcy in 2021 and 2017 (coefficients of -0.458 with t-values of -2.85), indicating that higher cash flow relative to total liabilities reduces the likelihood of bankruptcy in these years.

The *NIREVT* (Net Income to Total Sales) ratio is not statistically significant in any year, suggesting it does not have a strong predictive power for bankruptcy in this multivariate context.

The *LTAT* (Total Liabilities to Total Assets) ratio is positively significant in 2021 and 2017 (coefficients of 0.283 with t-values of 2.11), implying that higher total liabilities relative to total assets increase the probability of bankruptcy in these years.

The *ACTLCT* (Total Current Assets to Total Current Liabilities) ratio is significantly negative in 2021 and 2017 (coefficients of -0.458 with t-values of -2.47), suggesting that better liquidity decreases the likelihood of bankruptcy.

The *ATREVT* (Total Assets to Total Sales) ratio do not show any significant effect across the years.

The industry fixed effects (INDUSTRY FE) are included in all models, accounting for industry-specific variations. The ROC AUC values range from 0.7029 to 0.8115, showing good model performance in predicting bankruptcy, with the highest predictive power in 2021. The Variance Inflation Factor (VIF) values are below 5, suggesting no severe multicollinearity among the predictors.

Overall, the results highlight the significant and consistent roles of *OANCFLT*, *LTAT*, and *ACTLCT* ratios in predicting bankruptcy, particularly in the years 2021 and 2017.

5. Conclusion and Recommendations

This study demonstrates the varying predictive power of five key financial ratios in forecasting corporate bankruptcy over the period from 2017 to 2021. The LTAT, NIREVT and OANCFLT performed well in the univariate analysis while OANCFLT, LTAT and ACTLCT demonstrate higher performance in the multivariate regression. The consistent significance of OANCFLT, LTAT, ratios, highlights their relevance in bankruptcy prediction. These findings provide critical insights for stakeholders in the financial industry, aiding in the development of strategies to identify and mitigate the risk of corporate failure. Additionally, while financial ratios can predict bankruptcy up to five years before it occurs, the prediction is more precise in the last 2 years leading to the bankruptcy year.

Finally, subsequent research would utilize the insights learned in this work and apply it to the Nigerian context to study the applicability and effectiveness of these financial ratios in predicting corporate bankruptcy within the unique economic and regulatory environment of Nigeria. This could involve analyzing the financial statements of Nigerian companies to assess whether the same ratios hold predictive power and exploring any additional local factors that might influence bankruptcy outcomes. Such research could provide a deeper guidance for stakeholders in Nigeria, including investors, financial institutions, and policymakers, to better understand and mitigate the risks associated with corporate failure in the country.

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