Insolvency Prediction of Georgian Construction Sector Companies

Tatuli Dushuashvili[1]

Abstract: Insolvency prediction is one of the critical issues for a company's financial health analysis. It allows revealing the factors affecting a company's financial state and foreseeing conditions threatening its financial health. Consequently, numerous research was done in bankruptcy/insolvency analysis. However, no unique model predicts the insolvency of any type of firm. Models differ according to industry-related features and country-specific characteristics. The paper aims to evaluate the financial health of construction companies operating in small and developing countries like Georgia and predict their future insolvency. The analysis of companies' individual financial statements was conducted to determine financial health, based on which the insolvency prediction model of construction companies was created. The model applied logistic regression and used key financial ratios to predict insolvency probability. According to the results, the model accuracy reached 90%, meaning that the model predicts insolvency by 90%. The study is one of the first attempts to predict the insolvency of Georgian companies by using financial ratios, as publicly accessible data on financial statements recently became available. The model developed in the paper will help researchers predict the insolvency of the construction sector in countries with similar characteristics to Georgia.

Keywords: Financial Health; Financial Ratios; Insolvency Analysis

1. Introduction

After the 2008 financial crisis, the level of corporate debt in the world continues to grow. In some countries, it has reached a historical maximum, which is a possible threat to the sustainability of any business. Almost half of the increased debt comes from emerging markets, of which a quarter is the debt of non-financial corporations (Abraham et. al, 2020). While increased debt in some cases implies increased access to global capital markets, history has shown that high debt-to-equity levels on corporate balance sheets can lead to losses, strengthen liquidity pressure, and increase debt service burden. This, in turn, can lead to credit deterioration and increased risks of corporate defaults, which can spill over into the financial system (Chow, 2015). Accordingly, the greater the sector's contribution to the economy, the more important its financial health and sustainability become.

The construction industry plays an important role in the growth of Georgia's economy. According to the National Statistics Office of Georgia (Geostat), the construction sector's average share in GDP

[1] Ilia State University, Faculty of Business, Georgia, E-mail: tatuli.dushuashvili@iliauni.edu.ge/.

during the period from 2010 to 2022 was 8%, with an average annual growth rate of 18% over the same period. Consequently, the real GDP of the construction sector in 2022 was 53% higher than in 2010.

According to the 2022 data, approximately 65,500 employees are employed in the construction sector, accounting for 9% of the total employment in the business sector. During the period from 2010 to 2022, the number of employees in the construction sector grew on average by 5%.

The average monthly wages in the construction sector also exceed those of the overall economy. In 2022, the average monthly wages for individuals employed in the construction sector stood at 2,040 GEL, whereas the average monthly salary across the country was 1,606 GEL.

Despite being one of the primary contributors to the country's economy, with a significant share and strong influence on other sectors' output, the construction sector faces a notable challenge regarding company survival rates. According to Geostat, only around 30% of construction sector companies survive after five years of operation.

An increasing trend characterizes the dynamic of loans granted to the construction sector. From 2010 to 2022, the volume of loans issued to construction companies annually grew, on average, by 22%. As a result, the amount of loans granted by commercial banks to the construction sector reached 3.6 billion GEL in 2022, compared to 0.4 billion GEL in 2010.

As can be observed, although the construction sector is one of the main contributors to Georgia's economy, the survival rate of construction sector companies is not high, and the loans of the construction sector are growing faster than the sector's output. This accentuates the further need for conducting a thorough assessment of the financial health and insolvency risks of construction sector companies.

The importance of stability assessment of the construction sector was also highlighted recently during the economic downturn caused by the COVID-19 pandemic. In response to the challenges faced by the construction industry, the Georgian government developed a support mechanism to help the sector mitigate the adverse effects caused by the pandemic. The more effectively a company assesses its risks, the more resilient it becomes to potential shocks, such as pandemics. According to Nuta et al. (2024), COVID-19 had a negative impact on Romanian companies' performance, and sectors like real estate and industrials were particularly inefficient due to their poor performance.

Chenghui and Dilanchiev (2023), observed bidirectional causality between domestic loans to the private sector and consumption expenditure in Georgia. This pattern of behavior can potentially contribute to bubble formation, especially in the aftermath of the military conflict between Russia and Ukraine. The effect of which is significantly increased demand for residential buildings in Georgia. This serves as an additional factor indicating the significance of the subject and the need for construction sector health analysis.

The Law on Accounting, Reporting, and Auditing according to which enterprises should submit their financial statements to the Service for Accounting, Reporting and Auditing Supervision (SARAS) came into force in 2016. The data on enterprises' financial statements became available since 2017, and only the time series of 2017-2021 are available to date. Hence, analyzing companies' financial health using their financial statements have only recently become possible in Georgia. Therefore, this study is one of the first attempts to predict the insolvency of Georgian companies by using financial ratios.

The paper is structured as follows: Section 2 reviews the existing literature around insolvency prediction models and their evolution over time; Section 3 introduces the data used in the analysis and the methodology developed in the paper; Section 4 presents study results and raises a discussion.

2. Literature Review

The development of insolvency prediction models started with Beaver's (1966) univariate model and continues to date.

According to the univariate model, the dependent variable (company failure) was explained by one independent variable (financial ratio), and each indicator was studied separately. Beaver examined financial ratios to predict the insolvency of American companies. He conducted an analysis using Moody's Industrial Manual, examining 79 financially healthy companies and 79 bankrupt companies across 38 different industries from 1954 to 1964. He divided the possible financial ratios into six groups, from which 30 financial ratios were tested. Out of which, seven financial ratios showed a high degree of prediction. The results revealed that the individual financial ratio analysis could predict a company's failure for at least five years before bankruptcy. The study suggested that for further research, using multivariate analysis, where the dependent variable is explained by several independent ratios simultaneously, could yield a higher predictive ability.

Altman (1968) followed Beaver's research and used multiple discriminant analysis (MDA) for bankruptcy prediction, which later became known as the Z-score model. Altman analyzed 66 industrial sectors using MDA of 33 healthy and 33 bankrupt companies from 1946-1965. He constructed a model using five financial ratios. The study results showed that the model predicted a company's financial distress with 94% accuracy for insolvent companies and 97% accuracy for healthy companies one year prior to bankruptcy. However, the model loses its prediction accuracy over time. If the prediction accuracy stood at 95% one year before bankruptcy, it declined to 36% five years before bankruptcy.

A few years later, Altman, Haldeman, and Narayanan (1977) expanded Altman's model and constructed a new discriminating function for predicting a company's bankruptcy based on the seven financial ratios of 53 bankrupt and 58 healthy companies for 1969-1975. This model became known as the ZETA model. The study results showed that the model predicts a company's financial distress with 90% accuracy one year before insolvency and with 70% accuracy five years before insolvency.

After MDA, conditional probability models (such as logit and probit regression models) found prevalence. Ohlson (1980) was the first to use the logit regression model (LR) for bankruptcy prediction. Based on the nine financial ratios of 105 bankrupt and 2,058 healthy companies for the years 1970-1976, Ohlson examined the likelihood of bankruptcy. For this analysis, Ohlson used a logistic regression model, taking 0.38 as the critical point. The results showed that out of the nine explanatory variables used, company size, financial structure (total liabilities to total assets), company performance, and liquidity were significant determinants for the bankruptcy prediction of the company.

Zmijewski (1984) used a probit regression model and examined the probability of bankruptcy based on the financial ratios of 40 bankrupts and 800 healthy companies for 1972-1978. The results showed that three financial ratios: Return on Assets, Financial leverage (total debt to total assets), and liquidity (current assets to current liabilities) were significant determinants for the bankruptcy prediction of the company.

Later, for making predictions in business, researchers started using machine learning models such as Neural Networks (NN) and Support Vector Machines (SVM).

One of the first studies that used NNs for bankruptcy prediction was by Odom and Sharda (1990). They included Altman's financial ratios into NN and used both, their method and MDA, to compare the data of healthy and bankrupt US companies. The data was taken from the last financial statements before the companies declared bankruptcy. They reviewed 128 companies and conducted experiments by changing bankrupt/healthy firms' share in the training set. NN performed better than discriminant analysis in all but one sample combination for which the results were not statistically different (Adya & Collopy, 1998).

Regarding Support Vector Machines (SVM), Shin, Lee, and Kim (2005) applied SVM to forecast corporate bankruptcy and found that the model predicts bankruptcy with higher accuracy than NN in a small training data set size.

Researchers have also done several studies comparing the results of traditional bankruptcy prediction models with the results of machine learning models. Tam and Kiang (1992) conducted a study of banking default prediction. They compared several methods: MDA, LR, K-nearest neighbor (KNN), Iterative Dichotomiser 3 (ID3) in decision tree learning, and single-layer and multi-layer neural networks. The multi-layer network model a year before bankruptcy and the LR model two years before bankruptcy predicted default with the highest accuracy.

At the same time, researchers began to think that the company's performance is influenced not only by internal factors but also by external (macroeconomic) factors. Some scholars (Zhou et. al, 2010) included macroeconomic variables in the neural network model, while others (Altman, 1971; Hol, 2007; Liu, 2004; Giriuniene et. al, 2019) analyzed the impact of macroeconomic variables on financial performance using statistical methods.

Altman (1971) was one of the first scholars who conducted empirical research analyzing the connection between macroeconomic variables and firms' bankruptcy. Altman examined data from 20 railroad companies that went bankrupt from 1939 to 1970. He developed a model that explored companies' failure using time series since World War II. Together with financial ratios, he applied macroeconomic variables, such as Gross National Product (GNP), Standard and Poor 500 Index, and money supply. The most relevant empirical results were obtained by a first-difference-multiple-regression. According to the results, the model showed high accuracy for two years before bankruptcy.

Zhou et al. (2010) included macroeconomic variables together with financial ratios in a neural network model. Based on the Compustat North America Dataset data, they tested two sets of data (S1 and S2). Within the model, Zhou et al. considered 12 financial ratios and the following macroeconomic variables: Gross Domestic Product (GDP), Personal Income Index, and M2 - Money Supply Index. The first data set was tested using the model that included only financial ratios. In contrast, the second set was tested using the model that included macroeconomic variables and financial ratios. The results of the research showed that the performance of the neural network model slightly improved by incorporating macroeconomic variables in it.

Giriuniene et. al. (2019) estimated the probability of bankruptcy of Lithuanian construction companies by using the data for 2013-2017. They constructed a model that used financial ratios on the one hand

and macroeconomic variables such as GDP, unemployment rate, inflation, changes in real estate prices, number of companies in the industry, volume of loans issued to the industry, and price index of construction materials on the other hand. According to the authors, the model combining macroeconomic variables and traditional financial ratios better predicts bankruptcy. As the results showed, the model predicted bankruptcy with 93.3% accuracy.

Environmental variables also gained significance in recent years. Liu et. al. (2022), surveyed small- and medium-sized enterprises within the Chinese restaurant industry and found that a commitment to environmental initiatives has a positive effect on supply chain risk management.

Several research studies were done comparing the methods discussed above. Aziz and Dar (2006) compared 89 empirical studies and 16 different insolvency prediction methodologies during such meta-analysis. Research showed that scholars most commonly use MDA and Logit models.

Bellovary et. al. (2007) reviewed bankruptcy prediction models for the period from 1930 to 2007. According to the authors, discriminant analysis was a prevalent method for the early stages of the development of bankruptcy prediction models; however, technological advances brought forward other ways, such as Logit analysis, Probit analysis, and Neural Networks. According to most studies, MDA and Neural Network models provided the highest forecasting accuracy.

Shi and Li (2019) reviewed 496 bankruptcy prediction studies published between 1968 and 2017. According to the authors, the logistic regression model is the most frequently used (out of 321 papers, 123 used the LR model, representing 38.3% of the total sample) within the studies using a statistical methodology. In contrast, neuronal networks are mainly used (relied on artificial intelligence method; 56 papers used NN, representing 17.5% of the total sample) within the studies using artificial intelligence methodology.

The reviewed literature shows the evaluation of bankruptcy prediction methodology and demonstrates that the logit regression analysis used in this paper while constructing the insolvency prediction model of Georgian construction sector companies, is one of the best methods to forecast corporate insolvency.

3. Data and Methodology

For constructing the model that would predict companies' future insolvency, the sector for research was selected. According to Geostat, the largest share of the construction industry in Georgia comes from the construction of residential and non-residential buildings (49%), followed by the construction of roads and railways (28%), while only a small share of the construction turnover is allocated to the remaining sectors. Consequently, this study focuses on the insolvency analysis of enterprises engaged in the construction of residential and non-residential buildings.

According to the Accounting, Reporting, and Auditing Supervision databases, about 3,000 enterprises operate in the sector of construction of residential and non-residential buildings as of December 31, 2021. Out of these 3,000 enterprises, approximately 2,000 enterprises have reported financial statements for more than the last three consecutive years. For the Category III and IV firms, financial reporting was optional until 2019 according to the law on Accounting, Reporting, and Auditing. Hence, small companies that had not reported financial statements until 2019, were withdrawn from the analysis. In the next stage, individual financial statements of the remaining enterprises were analyzed. The companies with incomplete financial statements, lacking one of the three components

(Income Statement, Balance Sheet, Cash Flow Statement), were also excluded from the sample. Additionally, enterprises without any loans were also excluded from the sample for study purposes. Finally, 755 companies whose main activity was the construction of residential and non-residential buildings were included in the analysis.

The distribution of selected 755 companies according to size is as follows:

36 companies are large (category I and category II firms);

208 companies are medium (category III firms);

511 companies are small (category IV firms).

The sample was divided into financially distressed and financially healthy companies. The status was assigned according to the following criteria: If a company had negative net assets for the past three consecutive years, it was considered financially distressed and took status 1, while the companies that did not meet the mentioned criteria were considered financially healthy and were assigned status - 0. Finally, out of 755 companies in the sample, 119 were found to be financially distressed, while 636 companies were found to be financially healthy.

The analysis period focuses on the 2017-2021 financial data of companies functioning in the residential and non-residential building sector. For healthy companies, the data from 2021 was used, while for financially distressed companies, the data prior to distress, or the data before companies' net assets became negative was applied.

Approximately 30 financial ratios were calculated using the financial statements of 755 selected companies. Financial ratios covered the following categories: profitability ratios, liquidity ratios, cash flow ratios, and leverage ratios. Each ratio was individually tested using individual logit regression. Only the ratios significantly affecting the financial health status of the company were considered while constructing the model.

The Binomial Logistic Regression Model was applied within the study.

Equation 1. Formula for Binomial Logistic Regression

$$\text{Logistic Score} = P(\text{Score}) = P_i(Y) = \frac{e^{Y_i}}{1+e^{Y_i}} = \frac{1}{1+e^{-Y_i}}$$

Where, $Y_i = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + ... + \beta_k * X_k + \varepsilon_i$

In the regression $X_1,..., X_k$ are independent variables (financial ratios), while Y_i is a dependent variable (company status) that takes values 0/1 (depending on whether the enterprise is financially healthy or not). The logistic score ranges between 0 and 1, expressing the risk that the company will become insolvent.

4. Results

The model developed within this study contains six financial ratios and one non-financial ratio (company size). These six ratios are Net Profit Margin, ROCE (Return on Capital Employed), Quick Ratio, Debt Ratio, Net Working Capital Ratio, and Retained Earnings to Total Assets. Hence, the model took the form:

$$Y = F(NPM, ROCE, QR, DR, NWC, REtoTA, SIZE)$$

Equation 2 Formula for the probability of insolvency of a company

$$P_i(Y) = \frac{1}{1+e^{-(\beta_0+\beta_1 * NPM+\beta_2 * ROCE+\beta_3 * QR+\beta_4 * DR+\beta_5 * NWC+\beta_6 * REtoTA+\beta_6 * SIZE+\varepsilon_i)}}$$

Where P_i –is the probability of insolvency of the i^{th} company,

NPM is net profit margin = $\frac{Net\ Profit}{Total\ Revenue}$,

ROCE is the return on capital employed = $\frac{EBIT}{Capital\ Employed}$,

QR is quick ratio = $\frac{Cash\ and\ cash\ equivalents + Accounts\ recievables}{Current\ Liabilities}$,

DR is debt ratio = $\frac{Total\ debt}{Total\ Assets}$,

NWC is net working capital ratio = $\frac{Working\ Capital}{Total\ Assets}$,

REtoTA is Retained earnings to total assets = $\frac{Retained\ Earnings}{Total\ Assets}$.

A category is the measure of company size. Where 1 means category I firm, 2 means category II firm, 3 means category III firm, and 4 means category IV firm. Categories are determined according to the value of total assets, revenue amount, and number of employees. Category I firms are characterized by the highest value of total assets, the highest revenue amount, and the highest number of employees.

β_0 is an intercept value; $\beta_1,\ldots,\beta_6$ are parameters of estimates and ε_i is an error term.

According to the results (Table 1), four variables (NPM, DR, NWC, REtoTA) are significant at the 5% level, two variables (ROCE and size) are significant at the 10% level, while quick ratio did not appear to be significantly different from the population value.

The signs of the ratios are logical: higher Net Profit Margin, ROCE, Quick Ratio, Net Working Capital, and Retained Earnings to Total Assets decrease the probability of insolvency. In contrast, a higher Debt Ratio and smaller company size increase the probability of insolvency.

Table 5. The results of the Logistic Regression

	coefficient	S.E.	Wald	p-value	exp(b)	lower	upper
Intercept	-4.267	0.927	21.18	$4.199E^{-06}$	0.014		
NPM	-0.020	0.009	4.686	0.030	0.981	0.963	0.998
ROCE	-0.012	0.006	3.679	0.055	0.989	0.977	1.000
QR	-0.007	0.005	1.565	0.211	0.993	0.983	1.004
DR	2.545	0.470	29.30	$6.204E^{-08}$	12.74	5.070	32.02
Category	0.465	0.241	3.725	0.054	1.592	0.993	2.553
NWC	-1.345	0.361	13.88	0.0002	0.261	0.129	0.529
REtoTA	-3.393	0.544	38.99	$4.269E^{-10}$	0.034	0.012	0.098

According to the model, the coefficient of Retained Earnings to Total Assets and Debt Ratio has the most significant impact on the probability of construction company insolvency. An increase in the Debt Ratio by one unit increases the probability of insolvency by more than 2.5 times. The higher the Debt Ratio is, the more the company's assets are financed through debt. While an increase in the Retained Earnings to Total Assets ratio by one unit decreases the probability of insolvency by 3.4 times. The higher the retained earnings are, the more assets are funded by accumulated earnings, and the less the company relies on debt or shareholder's capital.

Net Working Capital ratio and company size also highly impact the probability of construction company insolvency. An increase in the working capital to total assets by one unit decreases the probability of insolvency by 1.34 times. The higher the net working capital, the more additional funds a company has to refund its current liabilities. Regarding company size, the results show that the bigger the company is, the lower its probability of becoming insolvent. According to the model, one category change in a company's size (becoming smaller by one category) increases its probability of insolvency by 47%.

The rest of the ratios have a lower impact on the probability of company insolvency. However, their impact is still significant. An increase in Net Profit Margin and Return on Capital Employed by one unit decreases the probability of insolvency by 2% and 1.2%, respectively. The more profitable the company is and the more return it generates on capital employed, the higher its probability of being financially healthy.

According to the results, the proposed model predicts the insolvency of Georgian construction companies by 57% for financially distressed companies and by 96% for healthy companies. The total accuracy of the model is 90%, meaning that the model predicts insolvency by 90%. The achieved results (accuracy rate of 90%) were shown by using the cut-off point of 0.35. This implies that if a company's logit score is more than 0.35, the company is expected to become insolvent, and if a company's logit score is less than 0.35, the company is expected to stay financially healthy (solvent).

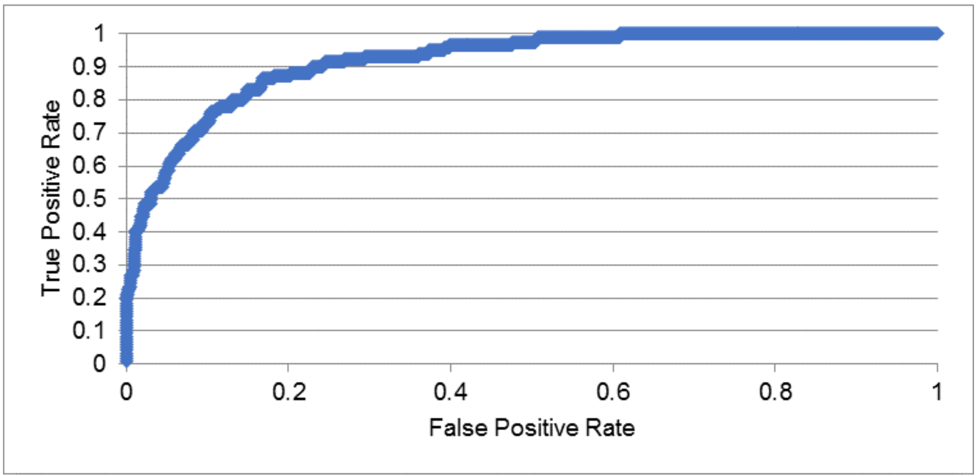

Figure 1. Receiver Operating Characteristic (ROC) Curve

As the dependent variable is binary (takes value 0 if a company is healthy and 1 if a company is financially distressed), a Receiver Operating Characteristic (ROC) analysis was conducted (Graph 1). The area under the ROC curve is shown by the Area Under the Curve (AUC) indicator. The closer the AUC value is to 1, the better the model's ability to correctly predict classes (healthy/financially distressed). According to the results, the AUC value of the model is 0.9, which is close to 1, showing that the model predicts 90% of companies' status correctly.

The model constructed for Georgian construction sector firms showed particular similarity with Ohlsen's O-score model. Among the ratios used in the Ohlson model, several coincide with or are similar to those used for Georgian construction companies (Table 2).

Table 2. The results obtained by the Ohlson Model and those obtained by the Model developed for Georgian construction companies

Ohlson Model		Model for Georgian Companies	
Variables	**Coefficient**	**Variables**	**Coefficient**
Size	-0.407	Category	0.465
Total Liabilities/Total Assets	6.03	Total Debt/Total Assets	2.545
Net Working Capital	-1.43	Net Working Capital	-1.345
CL/Current Assets	0.076	Liquid Assets/CL	-0.007
ROA	-2.37	ROCE	-0.012
Funds from operations/Total Liabilities	-1.83	Retained Earnings/Total Assets	-3.393
Change in net income	-0.521	Net Profit Margin	-0.020
Debt/Asset Ratio dummy	-1.72		
Net income dummy	0.285		
Cut-off point	0.38	Cut-off point	0.35

In the case of the Ohlson model, the change in Working Capital to Total Assets ratio by one unit decreases the probability of insolvency by 1.43 times and in the case of the proposed model, one unit change of the same ratio reduces the probability of insolvency by 1.34 times. According to Ohlson, the bigger the firm is, the smaller its probability of insolvency (one unit change leads to a reduction of probability by 41%). Almost the same figure we get in the case of Georgian companies, as the bigger the company's category is (i.e., the smaller a company's size is), the higher its probability of insolvency. Ohlson uses Return on Assets (ROA) to measure the effect of profitability ratios and concludes that one unit change in ROA decreases the probability of insolvency by 2.4 times. While the proposed methodology uses ROCE and finds that one unit change in the ratio reduces the probability of insolvency by 1.2%.

The cut-off point that minimizes Type I and Type II errors in the Ohlosn model is 0.38, while the cut-off point minimizing the sum of errors in the case of the model constructed for Georgian construction firms is 0.35.

5. Conclusion and Policy Recommendations

The paper develops an insolvency prediction model for Georgian construction companies. As the financial statements of Georgian companies became publicly available since 2017 (after the law on Accounting, Reporting, and Auditing came into force), the study is one of the first research forecasting insolvency using individual financial statements. The period is the study's main limitation, as only the data for 2017-2021 was available during the research period. Another limitation is the completeness and continuity of the data, as in some cases, the data for some years are missing, and in other cases, financial statements are incomplete, and some components are absent. However, the remaining sample size stays sufficient, despite the mentioned limitation. The study recommends the following:

(1) Additional measures are needed to regulate the quality and completeness of the financial statements publicly submitted by enterprises;

(2) Regulators should assess the financial health of sectors of significance, overseeing their performance, and ensuring their readiness in case of an economic shock.

An insolvency prediction model developed within the study will help researchers to further advance insolvency analysis and spread the model to other countries with similar characteristics to Georgia, or other economic sectors, which will be easier as more time series data will be available over time. The study findings will also help company managers analyze their company's financial health further and forecast possible financial distress.

According to the findings, from the analyzed 30 financial ratios, only six appeared significant while predicting the probability of the company's insolvency. These six ratios are Net Profit Margin, ROCE (Return on Capital Employed), Quick Ratio, Debt Ratio, Net Working Capital Ratio, and Retained Earnings to Total Assets.

Retained Earnings to Total Assets and Debt Ratio appeared to be most significant. An increase in the Debt Ratio by one unit increases the probability of insolvency by 2.5 times, while an increase in the Retained Earnings to Total Assets ratio by one unit decreases the probability of construction company insolvency by 3.4 times.

The results state that for financially distressed companies, the model predicts insolvency by 57% and for healthy companies by 96%. The model's total accuracy is 90%, indicating that it predicts insolvency by 90%.

6. Acknowledgement

The research (PHDF-21-895) has been supported by Shota Rustaveli National Science Foundation of Georgia (SRNSFG).

References

Abraham, F.; Cortina J.J. & Schmukler, S.L. (2020). Growth of Global Corporate Debt: Main Facts and Policy Challenges. *World Bank Policy Research Working Paper*, No. 9394.

Adya, M. & Collopy, F. (1998). How effective are neural networks at forecasting and prediction? A review and evaluation. *Journal of Forecasting*, 17(5-6), pp. 481-495.

Altman, E. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, 23(4), pp. 589-609.

Altman, E. (1971). Railroad Bankruptcy Propensity. *The Journal of Finance*, 26(2), pp. 333-345.

Altman, E.; Haldeman, R. & Narayanan, P. (1977). Zeta analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, 1, pp. 29-54.

Aziz, M. & Dar, H. (2006). Predicting corporate bankruptcy: where we stand. *Corporate Governance*, 6(1), pp. 18-33.

Beaver, W. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, pp. 71-111.

Bellovary, J.L; Giacomino, D.E. & Akers, M.D. (2007). A Review of Bankruptcy Prediction Studies: 1930 to Present. *Journal of Financial Education*, 33, pp. 1-42.

Chenghui, L. & Dilanchiev, A. (2023). The Nexus of Financial Deepening and Poverty: the Case of Black Sea Region Economies. *The Singapore Economic Review*, 68(4), pp. 1183-1205.

Chow, T.S.J. (2015). Stress Testing Corporate Balance Sheets in Emerging Economies. *International Monetary Fund Working Paper*, No. WP/15/216.

Giriūniene, G.; Giriūnas, L.; Morkunas, M. & Brucaite, L. (2019). A Comparison on Leading Methodologies for Bankruptcy Prediction: The Case of the Construction Sector in Lithuania. *Economies*, 7, p. 82.

Hol, S. (2007). The influence of the business cycle on bankruptcy probability. *International Transactions in Operational Research*, 14(1), pp. 75-90.

Liu, J. (2004). Macroeconomic determinants of corporate failures: evidence from the UK. *Applied Economics*, 36(9), pp. 939-945.

Liu, Y.; Dilanchiev, A.; Kaifei, X. & Hajiyeva, A.M. (2022). Financing SMEs and business development as new post Covid-19 economic recovery determinants. *Economic Analysis and Policy*, 76, pp. 554-567.

Nuta, A.C.; Habib, A.M; Neslihanoglu, S.; Dalwai, T. & Rangu, C.M. (2024). Analyzing the market performance of Romanian firms: do the COVID-19 crisis and classification type matter? *International Journal of Emerging Markets*.

Odom, M. & Sharda, R. (1990, June 17-21). A neural network model for bankruptcy prediction. *International Joint Conference on Neural Networks (IJCNN)*, San Diego, CA, United States.

Ohlson, J. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research*, 18(1), pp. 109-131.

Shi, Y. & Li, X. (2019). An overview of bankruptcy prediction models for corporate firms: a systematic literature review. *Intangible Capital*, 15(2), pp. 114-127.

Shin, K.S.; Lee, T.S. & Kim, H.J. (2005). An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications*, 28(1), pp. 127-135.

Tam, K.Y. & Kiang, M.Y. (1992). Managerial Applications of Neural Networks: The Case of Bank Failure Predictions. *Management Science*, 38(7), pp. 913-1065.

Zhou, L.; Lai, K.K. & Yen, J. (2010, November 18-20). Bankruptcy Prediction Incorporating Macroeconomic Variables Using Neural Network. *15th Conference on Technologies and Applications of Artificial Intelligence, (TAAI)*, Hsinchu, Taiwan.

Zmijewski, M. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research*, 22, pp. 59-82.