# Insolvency Pattern Trends in Albanian Enterprises: An in-depth Investigation

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*Abstract:* - Predicting bankruptcy has become a significant focus for researchers, especially during periods of economic instability such as the COVID-19 pandemic and the ongoing Russian-Ukrainian conflict. Early detection of financial distress enables stakeholders to make more informed decisions, minimizing the adverse effects of business failures. In Albania, studies on bankruptcy prediction are scarce, particularly for economic entities such as limited liability companies and joint-stock companies, which dominate the market.
This paper aims to develop a bankruptcy prediction model tailored to the Albanian economic environment. By analyzing the financial data of 70 companies, we apply multivariate discriminant analysis to construct a stepwise Z-score model. This model incorporates 25 financial ratios, calculated using the SPSS software, to assess the probability of bankruptcy. Our findings indicate that liquidity, turnover, financial structure, and profitability ratios are significant predictors of bankruptcy. The model achieves an overall classification accuracy of 84.3%, with 91.4% accuracy in predicting bankrupt companies. These results suggest that the model is robust enough to forecast the likelihood of bankruptcy for Albanian economic entities with high accuracy.

*Key-Words:* - economic unit, bankruptcy prediction, financial ratio, multivariate discriminant analysis, Z score model, economic modeling, corporate governance, financial distress.

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## 1 Introduction

The economic environment in which entities operate is inherently uncertain, are characterized by rapid changes and unforeseen challenges, [1]. Evaluating an entity's financial health has become increasingly crucial, offering valuable insights to a wide range of stakeholders—including creditors, investors, government agencies, employees, and management. Despite efforts to maintain stability, many entities struggle to meet the escalating demands of their operational activities. This struggle often leads to financial distress and in severe cases, bankruptcy. Bankruptcy is not just a concern for individual companies; it is a significant economic phenomenon with far-reaching implications.

Bankruptcy carries substantial consequences for the economy, affecting employment rates, consumer confidence, public revenues, and the overall financial system. In smaller economies like Albania, which is transitioning to a capitalist market structure, the impact of bankruptcy can be even more pronounced. The ripple effects may hinder economic growth, destabilize financial markets, and reduce investor confidence. Understanding bankruptcy is therefore essential not only for preventing individual corporate failures but also for safeguarding economic stability and fostering sustainable development.

While extensive research has been conducted on bankruptcy prediction models in developed economies, there is a noticeable gap in the literature concerning emerging markets like Albania. Existing models often rely on financial indicators and economic conditions prevalent in more mature markets, which may not be directly applicable or fully effective in the Albanian context. The unique economic conditions, regulatory frameworks, and market dynamics in Albania necessitate a tailored approach to bankruptcy prediction. Moreover, there is limited empirical evidence on the specific factors leading to bankruptcy in Albanian companies, highlighting a critical need for localized research. More firms enter financial distress as a result of poor management rather than economic distress, [2].

This study aims to fill the identified research gap by developing a bankruptcy prediction model specifically tailored to Albanian economic entities. The objectives are threefold:

First, identify key factors leading to bankruptcy: By analyzing the financial statements of both bankrupt and non-bankrupt companies, the study seeks to uncover the financial ratios and indicators that most significantly influence a company's likelihood of bankruptcy in Albania.

Second, develop a predictive model: Utilizing multivariate discriminant analysis, the study will construct a model that accurately predicts bankruptcy based on the identified key financial ratios. This model aims to provide a reliable tool for early detection of financial distress among Albanian companies. The third objective is to contribute to stakeholder decision-making: The findings are intended to assist stakeholders—including investors, creditors, policymakers, and company management—in making informed decisions.

By understanding the bankruptcy predictors, stakeholders can take proactive measures to mitigate risks, allocate resources efficiently, and implement strategies to enhance financial stability.

The significance of this research extends beyond academic contribution; it has practical implications for the Albanian economy and its stakeholders. By providing a deeper understanding of the bankruptcy phenomenon in Albania, the study can enhance financial stability, inform policy and regulation, and support economic growth.

The remainder of this paper is organized as follows: Literature Review: This section will delve into existing definitions of bankruptcy, critical analysis of both univariate and multivariate bankruptcy prediction models used in prior research, bankruptcy in Albania. Methodology and Data: this outlines the data sources, sample selection, and the statistical methods employed, with a focus on variable selection procedures. Results and Discussion where we will present a detailed analysis of the financial data, compare key financial ratios between bankrupt and non-bankrupt companies, and discuss the findings from the multivariate discriminant analysis. The paper ends with a summary of key findings, implications for stakeholders, limitations, and suggestions for future research.

# 2 Literature Review

## 2.1 Bankruptcy Definition

Most used definitions present in studies refer to the legal definitions of respective countries [3], due to the ease and flexibility legal definitions offer.

In general, bankruptcy is defined as a situation when a company does not gain enough revenues from its operations to cover operational expenses. Usually when a company lacks ongoing liquidity, which means it fails to pay liabilities to third parties is the main cause of bankruptcy. When the liabilities are higher than the total assets the company goes bankrupt, [4]. Bankruptcy is to predict whether or not a company will fall into financial distress based on the current financial data, through mathematical, statistical, or intelligent models, [5].

In most countries, bankruptcy is a legal status of a company, given by county courts, often initiated by the company itself.

Bankruptcy is defined according to three aspects: financial, economic, and legal, [6].

According to the financial aspect, a company has gone bankrupt when it cannot pay its obligations in due time, showing financial weakness. One of the problems mostly observed from financial statements is the capital structure: high levels of short-run debts followed by high operational costs.

Economic bankruptcy refers to the situation when a company fails to gain any profit from its usual operations, [7].

As for the legal definition, bankruptcy is not defined as the inability to pay the debts in due time, but it refers to the situation where assets are not available enough to pay total liabilities, [8].

Financial stress is a situation when the cash flows are not large enough to pay short-run financial liabilities, [9].

[10] analyzed the difficulties that companies that have long–run debt face and how this can be used to prevent bankruptcy. They rely on the "Times interest earned ratio", to identify these difficulties. In practice, a company has financial difficulties, if earnings before interest, taxes, and amortization/ depreciation are lower than interest expenses for two subsequent years, or when EBITDA is less than 80% of interest expenses. [11] analyzed the early phases of financial difficulties and emphasized that the effects of these difficulties are not evident only in companies that fail to accomplish their liabilities.

## 2.2 Forecasting Models' Evolution

The first studies in the field of bankruptcy forecasting concluded the creation of one-variable models. These studies were based on the financial statements derived from the financial statements of bankrupt economic entities, comparing them to the same financial reports of economic entities that continued to operate normally. To classify an entity as bankrupt or not, the separation point is used, through which a higher ratio value of the report indicates a non-bankrupt entity, while a lower ratio value, a bankrupt entity.

Literature on bankruptcy forecasting dates back to the early 1930s when initial studies were done on the use of financial reports analysis to predict the bankruptcy of economic entities. Research until the mid-1960s focused on an analysis that used only one financial report. The most widely known study with a variable is [12]. [13] published the first multivariate study, which remains very popular in literature to this day. This model is a discriminatory analytical model with five variables, while the [14] model is a neural network with 14 factors.

There is a large variety in bankruptcy forecasting models from both the number of reports included in the models as well as the types of financial reports and methods used for the development of the model.

Discriminatory analysis was a very popular method for model development in the early stages of bankruptcy forecasting. However, advances and technology have made other methods (including logit analysis, probit analysis, and neural networks) more prominent.

Also, some models are more focused on entities belonging to a particular sector than other models. [15] developed a model specifically for predicting small business failure.

Multiple discriminatory analyses was used to develop a five-variable model or financial reports to predict the bankruptcy of manufacturing firms. "Z-score", as the model was called, predicted the bankruptcy of an entity if the result derived from the Z-score model falls within a certain range of results previously predicted by the model.

Z-score model had high predictive capability for the initial sample a year before bankruptcy (95% accuracy). However, the model's predictive capability dropped significantly from a year before bankruptcy to 72% accuracy two years before the bankruptcy, up to 48%, 29%, and 36% accuracy three, four, and five years before bankruptcy respectively. The predictive capability of the model when tested on a sample that contained more entities than were originally included in the first model study, turned out to have 79% accuracy.

Since the first Z-score model, the number and complexity of bankruptcy forecasting models has increased dramatically. There are about 165 bankruptcy forecast studies since that time. In the late 1960s there is published also [16]. The most well-known bankruptcy forecasting models that are being widely applied also named as the best bankruptcy forecasters were based on economic entities operating in the United States of America (USA).

In most cases, researchers seek to create new bankruptcy forecasting models for their countries using best practices with already-developed creation techniques. This is being followed by many researchers to adapt the bankruptcy forecast to the economic situation of a particular country and to get better forecast results.

[17] studied 76 entities operating in Japan from all industry sectors, except the financial sector, that went bankrupt from 1992-2005. The hazard regression technique has been used and the results of the generated models have been compared in parallel with the first Z-score models. It was found that the new model showed better results in terms of the accuracy of the bankruptcy forecast.

78 Croatian companies that went bankrupt in the period from January 2010 to June 2010 which operated in the manufacturing and trade industry were studied, [18]. The research was conducted using discriminatory analysis with many variables and logistical regression techniques. With the multi-variable discriminatory analysis method, 80% accuracy has been achieved, followed by logistical regression of 83%.

With the same approach, but broader financial data, a bankruptcy forecasting model has been created for Pakistan companies, [19]. 26 bankrupt and 26 still operating economic entities were selected as primary data from the 1996-2006 time period and it was estimated that the established model could achieve 77% accuracy. The model was created using multi-variable discriminatory analyses. The number of variables in the function is smaller comparing to Z-score model, consisting of EBIT and short-term actives, sales and assets, and cash flow reports.

The financial ratios selected for model construction are based on the financial statement data, mainly the statement of financial position and the statement of financial performance. In past studies, a very large number of variables were found to be important indicators of financial difficulties. Therefore, there werw compiled a list of 22 potentially important financial reports for evaluation and classified these variables into five categories of standard ratios: liquidity, profitability, financial leverage, solvency, and activity ratios. The reports were selected based on 1) their popularity in the literature and 2) their potential study affiliation. From the original list of 22 financial indicators, were selected five reports that yielded better results in predicting the bankruptcy of entities.

The results discovered that all entities with a Z level higher than 2.99 were non-bankrupt entities, while all entities with a Z lower than 1.81 were bankrupt economic entities. As for the companies with Z indicators between 1.81 and 2.99, it was impossible to give a categorically or almost certain result, this area was also called the area of indifference or "grey area", because it carried a high probability of possible classification errors. The Z-Score Model is a model for publicly traded entities and ad hoc adjustments are not scientifically valid. Therefore, he supported a complete revision of the model that replaced the market value with the value of the equity book in X4. Using the same data, the revised Z'-Score was derived.

From the above model, it resulted that all entities with a Z level higher than 2.90 were non-bankrupt entities, while all entities with a Z lower than 1.23 were bankrupt entities. As for the companies with Z indicators between 1.23 and 2.90, it was the "gray area", where a safe result could not be given.

In conclusion of the remarks, it is considered the overall applicability of his Z-Score model to be debatable. The model did not consider very large and very small entities, that the observation period was quite long (almost two decades), and that the analysis included only productive entities.

The main problem with Z-Score models is that they are influenced by the financial statements declared by the entities themselves, which are subject to false accounting practices. Among the reports most affected by these practices are retained earnings on total assets, which has deteriorated especially in entities that are operating normally, in addition to this ratio another item of financial statements is EBIT, which is subject to manipulation of financial statements. On the other hand, there are suggestions that since the characteristics of most firms change from year to year, forcasting models based only on financial data may be inconsistent to the time or sample selected, [20].

## 2.3 Bankruptcy in Albania

Considering our country, studies on predicting the bankruptcy of economic entities have been few. Mainly, they are focused on the reasons that lead Albanian economic entities to bankruptcy and are mainly done under research projects. The first study regarding bankruptcy forecasting was conducted by [21]. The focus of this study was only on entities with full or partial public capital because it is perceived that the quality of their financial statements is higher compared to other private economic entities. In this study, 139 state units were taken for the years 1999-2002 and the research methodology was discriminatory analysis with many variables because it best suited the profile of the selected database. The study singled out 6 financial reports as good predictors of bankruptcy. From the model, it resulted that all entities with a Z level higher than 1,723 were non-bankrupt entities, while all entities with a Z lower than -1,494 were bankrupt entities. As for the companies with Z indicators between -1,494 and 1,723, it was the "grey area", where a reliable result could not be given.

Regarding the variables identified as important by the model, it is noticed that three of them are common and are encountered as discriminatory variables even in studies conducted in other countries. These are Total Operating / Total Assets, Total Liabilities / Total Assets, and Logarithm of Long-Term Material Assets. In other countries, the most important liquidity variables are the current ratio, the rapid ratio, or the cash flow ratios, in the Albanian units with public capital, the only financial liquidity ratio is Sales / Accounts receivable. Combined together, the six financial ratios for Albanian entities differ from the ratious factors of bankruptcy of economic entities in developed Western countries.

Another study on the bankruptcy prediction of economic entities was undertaken [22], where the commercial economic units of the district of Elbasan were taken into study. For this study, the financial reports of 30 bankrupt entities and 30 non-bankrupt entities were obtained, and 22 financial ratios, included the ratios of liquidity, turnover, profitability, and financial structure. The study found that commercial entities with a Z greater than or equal to 0.15 are classified as bankrupt entities. Commercial entities with a Z less than 0.15 or equal are classified, by the above function, as non-bankrupt entities.

The latest study on the forecast of bankruptcy of Albanian economic entities based on discriminatory analysis with many variables, was carried out by [23]. The model was built on the financial statements of 100 bankrupt and non-bankrupt entities, which belonged to different sectors.

The number of economic units that develop their activity in Albania has increased, this is due to the facilities created in the procedures to start a business and also due to economic development. Albania is a relatively young country in terms of economy based on free market and the level of informality is high where economic entities conduct their activity without being registered by [24]. Along with the measures taken this phenomenon has been reduced and this is one of the reasons that the number of entities has increased significantly in recent years.

The Figure 1 presents the number of active Albanian economies from 2013 to 2020. The Figure 1 clearly shows almost the same number of active economic entities in the Republic of Albania.

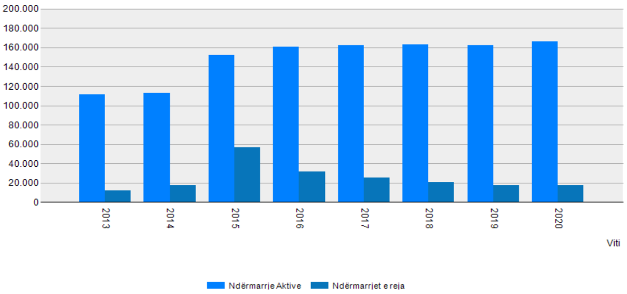


Fig. 1: Number of active operating entities, new entities
*Source: [25]*

There are no official statistics on the number of closed or bankrupt entities in Albania. That is why the data published by [25] in the enterprise register are used, which is a report that is published every year, such as the number of economic units at the end of each year and the number of new economic entities created during each year of the period taken into study. 2016 accounts with the largest number of entities closed about 22,986 units, in 2015 about 17,038 units closed, and in 2014 15,923 units closed. This high number of closed entities may have also come as a result of the increase of the income tax rate in 2014 from 10% to 15%. As mentioned above the action towards informality has given its contribution to the closure of economic units. But the closure of economic units may have come for other reasons as well, for example by decision of the entity partners, merger with other economic units, or even acquisition by other units, etc. During 2019-2020 due to the pandemic situation, many businesses faced difficulties, though they were subject to government fiscal policies adapted to this situation.

## 3 Methodology

It is clear that to analyze the status of an entity, the best results are achieved using financial data, from which one can assess the previous and current position of the entity including financial status, assets, and liabilities, capital trends, income and losses, changes, etc. [26] asserts that most researchers link bankruptcy forecast assessment to the methodology of financial analysis. Using financial analysis, the bankruptcy forecast can be calculated with financial reports, which is precisely a quantitative assessment of the financial condition of the economic entity, negative tendencies, and probability of bankruptcy, [27]. It is recognized that financial ratios can be used as a faithful warning system in order to anticipate corporate bankruptcy, [28]. Quantitative assessment and its parameters are the main component of the whole financial analysis because it can quickly and sufficiently show the financial situation and the interaction between different balance sheet accounts.

However, financial reports can be interpreted differently depending on which economic entity is underrating, so it is important to know what kind of economic entities are focused on the bankruptcy forecast model. In this case, the question may arise as to whether the models applied globally are appropriate to predict bankruptcy for certain economic entities. It should also be noted that most such models were not created by taking data from different economic entities but on now-out-of-date financial data. The first Z-score model was created using financial data from the period 1946-1965. In addition, different countries have different economic realities, taxes, competition, and other external factors that influence economic entities and differ compared to other countries. This means that bankruptcy forecasting models created using financial data of entities operating in other countries distort the forecast.

For the reasons listed above, it can be suggested that the bankruptcy forecasting model should be based on carefully classified financial data. This includes the sector of the industry in which the entity operates, the size of the entity, etc.

In the Table 1, we can see what kinds of categories of financial reports have been used by various researchers who have already created a bankruptcy forecasting model. These ratios are met in different studies during the literature review. Here are summarized the most met ratios that are being used for bankruptcy evaluation in a timely or country-based context.

[29] has estimated 190 bankruptcy forecast models and concluded that the most well-known reports presented in the model's functions are financial reports and they are used in 93% of cases analyzed.

It is clear that the main purpose of bankruptcy forecasting models is to predict the probability of bankruptcy as accurately as possible using the best financial reports that have the greatest potential to estimate the bankruptcy of an entity in the future. The predictive potential of the model is precisely the key factor to consider. It is clear that the forecasting potential is the result of a model created because it depends on how the primary sample of financial data is used, analyzed, and selected. It also relies on selected ratios and their potential and accuracy to reflect the probability of an economic entity going bankrupt. Studies show that the accuracy and potential of the model are calculated by taking the financial data of the sampled companies and checking the number of entities so that the models are able to properly classify the entities, in bankruptcy or not.

[30] assessed the predictive potential of bankruptcy forecasting models to correctly classify entities by studying the various techniques used to construct the forecasting model.

Table 1. Comparison of financial reports used by various authors

| [28] | [18] |
|---|---|
| • Solvency ratio<br>• Liquidity ratio<br>• Financial leverage ratio<br>• Profitability reports<br>• Asset turnover ratio | • Liquidity ratio<br>• Assets ratio<br>• Financial structure reports<br>• Profitability reports<br>• Cash flow statement |
| **[19]** | **[17]** |
| • Financial leverage ratio<br>• Liquidity ratio<br>• Profitability reports<br>• Asset turnover ratio | • Liquidity ratio<br>• Profitability reports<br>• Financial leverage ratio<br>• Solvency ratio<br>• Activity reports |

*Source: Author's work*

## 3.1 Data

Data published by Albanian athorities shows that the majority of economic entities in Albania are organized entities in the form of limited liability companies and anonymous companies. These economic entities chosen for this study had an annual turnover of over 8 million dollars. So, they are considered big enterprises based on fiscal classification in Albania and are subject to a 15% tax on profit.

The financial statements of the bankrupt entities in the period 2008 - 2016 have been reviewed. The reason why this period is selected is that the companies were bankrupted and after that, there was no data for them. Second, after 2014 Albania switched from a proportional tax system to a progressive tax system. Since 2014 the law for Income Tax was amended continuously changing the classification of enterprises and making impossible comparisons between enterprises that operate in these two periods.

Due to the earthquake that happened in 2019 and the COVID-19 pandemic, there were continuous tax exemptions for these enterprises which will continue till 2029. And lastly, it takes 5-7 years for an enterprise to fully liquidate.

To provide data related to the bankrupt entities, the list of bankrupt entities published by [31], has been used and historical extracts of entities have also been reviewed. From there a champion of 70 entities was selected, of which 35 bankrupt and 35 non-bankrupt. Their selection was made based on the following conditions:

1. Economic entities to which the bankruptcy procedure has been opened in the court of the judicial district.
2. Economic entities that in the historical extract have the status of bankruptcy.
3. Economic entities that have reported losses for at least three consecutive years.
4. Prohibition of single economic activity, as the latter has resulted in losses for several consecutive periods.

Of the economic entities taken in the study, as is the tendency of all economic entities in Albania, most of them are concentrated in the trade sector.

Table 2. Business enterprises according to industry

| | Frequency | % |
|---|---|---|
| Trade | 46 | 67% |
| Industry | 8 | 12% |
| Construction | 12 | 17% |
| Services | 4 | 4% |
| Total | 70 | 100% |

Table 2 shows the composition of the entities selected accordig to the industry they operate. Also, most of the economic entities selected in the study are concentrated in Albania's major cities, specifically in Tirana, Durres, Shkoder, Elbasan, and Fier.

## 3.2 Selection of Variables

As mentioned above, the most commonly used explanatory variables in forecasting models are financial ratios, which represent relationships between different voices of financial statements. The financial ratios analyzed should be selected on some theoretical basis, coupled with demonstrated empirical evidence of their usefulness The selection of financial ratios to be included in the study was made based on previous studies and it turns out that liquidity financial ratios are included in almost all studies, as well as profitability ratios, activity ratios, and financial structure. At most, 25 financial reports are included in this study. The financial ratios are grouped into liquidity, turnover, structure, and profitability ratios.

Liquidity refers to the entity's ability to repay short-term liabilities when they mature. The importance of liquidity and its analysis is evident when we consider the consequences that the inability of the entity to repay short-term liabilities brings. The most extreme liquidity problems reflect the inability of the entity to cover short-term liabilities, a situation which may lead to the forced sale of its investments and assets, and in the latter case to bankruptcy and liquidation, [32]. Part of the liquidity analysis is also the turnover reports, which are calculated by counting the net sales figure and showing how effectively the entity is managing its assets. The structure's financial statements refer to the financial resources used by the entity and focus primarily on the entity's ability to settle long-term obligations. Profitability can be defined as the ultimate measure of the economic success achieved by a company to the capital invested in it. This economic success is determined by the size of the net accounting profit, [33].

In this case, the financial reports for the entities were calculated one year before the beginning of the bankruptcy proceedings.

### 3.3 Building the Model for Bankruptcy Forecasting

To forecast the bankruptcy of Albanian economic entities, we will employ Multiple Discriminant Analysis (MDA). MDA and neural network analysis are among the most effective techniques for modeling bankruptcy prediction, [30]. Before conducting the analysis, several key assumptions must be satisfied to ensure the validity and reliability of the MDA model.

First, the independent variables included in the model must be normally distributed. This can be tested using statistical methods such as the Kolmogorov-Smirnov test or the Shapiro-Wilk test. Ensuring normality allows the discriminant function to accurately reflect the relationships between variables.

Second, the independent variables should not be highly correlated with each other. Multicollinearity can lead to unreliable coefficient estimates and affect the interpretability of the model. A correlation matrix or variance inflation factors (VIF) can be used to detect multicollinearity.

Third, the variance-covariance structure of the independent variables must be the same across all groups of the dependent variable. This assumption ensures that the discriminant function applies equally to all groups. Box's M Test can be used to assess this assumption.

Fourth, the groups of the dependent variable (e.g., bankrupt and non-bankrupt entities) must be mutually exclusive, meaning an entity belongs to only one group. Additionally, each group should have a similar number of observations to prevent biased results due to unequal group sizes.

To enhance the model's predictive accuracy while maintaining simplicity, we use the stepwise method for variable selection. This process involves: adding variables, which are added one at a time based on their statistical significance and contribution to the model; removing variables that no longer contribute significantly as new variables are added; and criteria for inclusion/exclusion using statistical tests like the F-test with a common significance level set at 0.05.
This method ensures that only variables with a significant impact on the model's accuracy are included, optimizing the model's performance.

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots \beta_n X_n \qquad (1)$$

where Z is the dependent variable:
$\beta_0$ is the constant $\beta_1$ .... $\beta_n$ are the coefficients of the model
$X_1$....$X_n$ are the dependent variables included in the model

After constructing the discriminant function, we assess its effectiveness using the following statistical indicators: Canonical Correlation Coefficient and Wilks' Lambda.

The first measures the strength of the relationship between the discriminant scores and the groups.

A higher value (closer to 1) indicates a stronger association and better discriminative power.

The second test indicates the proportion of total variance in the discriminant scores not explained by differences among groups. A smaller value suggests that the model effectively discriminates between groups. The associated p-value should be less than 0.05 for the model to be considered statistically significant.

If the model meets these criteria, we can conclude that it reliably differentiates between bankrupt and non-bankrupt entities.

To classify entities into the appropriate groups, we calculate a cutoff discriminant score using the group centroids obtained from SPSS:

$$Z = \frac{N_A Z_B + N_B Z_A}{N_A + N_B} \quad (2)$$

where: Z is the starting point
$N_A$ is the number of observations of group A, in this case, the group of bankrupt entities.
$N_B$is the number of observations of group B, in this case, the group of non-bankrupt entities.
$Z_A$ are the values of centroids, data obtained from SPSS
$Z_B$ are the values of the centroids, data obtained from SPSS.

This method ensures that entities are classified based on their proximity to group centroids, accounting for group sizes.

## 4 Data Analyses and Result Interpretation

To build the bankruptcy forecasting model, the financial ratios of bankrupt and non-bankrupt entities need to be calculated. The data used for the calculation of the ratios are taken from financial statements. Table 3 shows descriptive statistics related to financial ratios, where the average, minimum, and maximum values for each report are given, for the bankrupt entities.

It can be noticed that bankrupt entities are characterized by long periods of collection of customers, there is also a large distribution of values as there are entities in their financial statements the values of accounts receivable, inventories, and accounts payable have zero values that in the Table 3, are presented in the minimum values of the ratios. Also, the total debt ratio has a high average value, as a large number of entities have accumulated losses and share capital is presented with negative values. While the profitability ratios, which in the numerator have the net invitation are presented in negative values, this is normal for bankrupt entities. Table 4 shows descriptive statistics related to financial ratios, where the average, minimum, and maximum values for each report are given, for the non-bankrupt entities.

Table 3. Descriptive statistics on financial reports of bankrupt entities

| | Average | MAX | MIN |
|---|---|---|---|
| Current ratio | 2.43 | 42.12 | 0.16 |
| Quick ratio | 2.19 | 42.12 | 0.13 |
| C. Assets / C. Liab | 0.16 | 2.18 | 0.00 |
| Adequacy of NWC | 1.46 | 41.12 | -0.84 |
| Ability to generate money | -0.36 | 0.89 | -12.68 |
| Ability to pay debts | -0.37 | 0.64 | -12.67 |
| Turnover of total assets | 0.49 | 2.96 | -0.23 |
| Turnover of acc. rec | 2.35 | 27.73 | 0.00 |
| PMA | 2289.65 | 36500 | 0.00 |
| Inv. turnover | 5.79 | 62.99 | 0.00 |
| PMI | 816.38 | 9865 | 0.00 |
| Turnover of accounts payable | 2.02 | 34.42 | 0.00 |
| PMSHF | 1748.37 | 15869.57 | 0.00 |
| Turnover of Current Assets | 0.72 | 5.87 | 0.01 |
| Turnover of Fixed Assets | 120.63 | 3678.15 | 0.01 |
| Turnover of WNC | 5.62 | 191.54 | -7.68 |
| Total debt ratio | 1.03 | 3.18 | 0.22 |
| Total debts/Share capital | 13.89 | 357.68 | -20.89 |
| Share capital/Total assets | -0.03 | 0.78 | -2.18 |
| Long term Debt/Total assets | 0.33 | 2.88 | 0.00 |
| Current liabilities/Total debt | 0.72 | 1.00 | 0.00 |
| Net profit/Sale | -0.70 | 0.31 | -6.53 |
| ROA | -0.07 | 0.16 | -0.80 |
| ROE | -0.44 | 2.02 | -16.37 |
| ROE/ROA | 14.02 | 204.00 | -19.98 |

*Source: Author's work*

The financial ratios of non-bankrupt units are more favorable, characterized by high turnover ratios, the debt ratio fluctuating on average to 0.56, and positive profitability ratios.

But a common thing for the entities under consideration, both bankrupt and non-bankrupt entities, a large part of them do not have long-term liabilities in the statement of position. So entities prefer short-term financing over long-term one.

To better see the differences between financial reports between bankrupt and non-bankrupt entities, we will rely on comparative analysis through financial reports.

Table 4. Descriptive statistics on financial reports of non-bankrupt entities

| | Average | MAX | MIN |
|---|---|---|---|
| Current ratio | 2.56 | 12.94 | 0.64 |
| Quick ratio | 1.66 | 10.01 | 0.07 |
| Curr. Ass. /Curr. Lia | 0.29 | 2.55 | 0.00 |
| Adequacy of NWC | 1.56 | 11.94 | -0.36 |
| Ability to generate money | 0.28 | 1.60 | -0.22 |
| Ability to pay debts | 0.19 | 1.33 | -0.22 |
| Turnover TA | 2.10 | 6.48 | 0.19 |
| Turnover Acc.Reic | 23.00 | 179.84 | 0.96 |
| PMA | 90.22 | 378.63 | 2.03 |
| Inv. turnover | 17.07 | 101.30 | 0.00 |
| PMI | 125.26 | 1871.80 | 0.00 |
| Turnover of Acc.Pay | 22.99 | 220.68 | 0.00 |
| PMSHF | 99.40 | 523.67 | 0.00 |
| Turnover of Current Assets | 2.61 | 5.57 | 0.36 |
| Turnover of Long run assets | 58.68 | 510.58 | 0.42 |
| Turnover of WC | 5.49 | 24.12 | -29.87 |
| Total debt ratio | 0.56 | 0.93 | 0.08 |
| Total liabilities/Shared capital | 2.28 | 12.71 | 0.08 |
| Share capital/Total assets | 0.44 | 0.92 | 0.07 |
| LR liabilities/Total assets | 0.13 | 0.62 | 0.00 |
| Current liabilities/Total debt | 0.81 | 1.00 | 0.21 |
| Net profit/Sales | 0.06 | 0.52 | -0.15 |
| ROA | 0.10 | 0.49 | -0.05 |
| ROE | 0.24 | 1.19 | -0.26 |
| ROE/ROA | 3.24 | 13.73 | 1.08 |

*Source: Author's work*

Initially, we have the liquidity ratios, where it is noticed that the current ratio fluctuates at the same values for both bankrupt and non-bankrupt units. It is also seen that the fast ratio is higher for non-bankrupt entities. The biggest changes are in the ratios that have in the counter the cash flow from the operating activity, respectively in the ratios of the ability of the entity to generate money and pay debts. This is because the values of operating flow for bankrupt entities are negative, while for non-bankrupt entities are positive and these are expected values for entities that are on the verge of bankruptcy.

While the comparison of turnover ratios shows that bankrupt entities have lower values than non-bankrupt units, except the turnover ratio of long-term assets, this is because the values of long-term assets in bankrupt entities occupy a small part of the total assets of the entity. The low turnover of receivable accounts in non-bankrupt entities also indicates the problems with liquidity that these entities face.

In the reports of the financial structure, it is noticed that the highest difference between the units taken in the study is in the ratio of Total Liabilities / Share Capital report, where bankrupt entities are financed with debt higher than non-bankrupt entities and accumulated losses year after year also reduce the share capital of the unit, leading to an increase in this ratio. Also, the total debt ratio of bankrupt entities is higher than non-bankrupt entities.

In terms of profitability ratios, bankrupt entities have negative indicators and the largest difference is seen in the ratio of the financial leverage index, whereas as mentioned above, bankrupt entities have high values of liabilities, which affects this ratio.

## 4.1 Multiple Discriminatory Analysis

For the construction of the bankruptcy forecast model, multiple discriminatory analyses have been used, as mentioned above, tests must initially be carried out to see if analysis assumptions are met.

The first assumption for the normal distribution of independent variables, from the Kolmogorov – Smirnov test and the Shapiro – Wilk test, shows that the variables involved do not have a normal distribution. This is a problem also encountered in previous studies but does not pose a problem in the case where the number of observations is large.

The second assumption requires that the variables included in the model are not correlated with each other and variables that have high correlation values between them are excluded from the model.

The third assumption requires that the variance-covariance structure of the independent variables must be similar within the same set of dependent variables. The latter is tested by Box M, in which the hypothesis is tested that the covariance matrix between bankrupt and non-bankrupt groups does not change. When the value of this indicator has sig. $<0.05$, indicates that there are differences in the covariance matrix between groups.

Table 5. Box M

| | | |
|---|---|---|
| Box's M | | 110.372 |
| F | Approx | 10.342 |
| | df1 | 10 |
| | df2 | 21106.703 |
| | Sig. | .000 |

*Source: Authors' work*

As noted in the Table 5, it turns out that there are differences between the structure variance-covariance, but this also comes as a result of not fulfilling the above assumption for normal distribution. But as mentioned above in the case in which the number of observations is high and the number of observations is the same in both groups, the strength of the discriminatory model is not affected by the latter.

M Box is very sensitive, so ignore if p <.001 and the sample size are equal. However, if it is significant and you have an unequal sample size, the test is not robust, [34].

As for the last assumption, it can be said that it is fulfilled because the groups are mutually exclusive and this is based on the defined conditions, which divide the entities into bankrupt or not. The number of observations is the same in both groups, 35 bankrupt and 35 non-bankrupt.

After performing the tests to meet the assumptions, we proceeded with the construction of the model, which resulted in the following model:

$$Z = -1.571+0.224\, X_1+ 0.683\, X_2+ 2.645\, X_3- 3.208\, X_4 \quad (3)$$

where:

$X_1$ ➔ Ability to generate money ratio
$X_2$ ➔ Short-term assets turnover
$X_3$ ➔ Share capital / TotalAssets
$X_4$ ➔ ROA

The ratio of ability to generate money is the fourth most important variable from the above model, which shows the relationship between monetary means and resources accomplished by the operating activity of the entity with short-term liabilities. This ratio shows the entity's ability to reach sufficient cash to settle short-term liabilities.

Short-term asset turnover ratio is ranked second in importance, from the analysis performed. This report shows the number of times that short-term assets are converted into monetary means for an exercise period.

The Share capital / Total Asset Ratio ratio is the most important variable in the model built by discriminatory analysis. This report shows what is the part of share capital in total assets.

The ROA ratio is the ratio of returns on total assets, from discriminatory analysis as the third most important variable. In this model, there is a negative relationship with the dependent variable, the higher the value of this ratio, the lower the possibility of the entity going bankrupt.

Variables that have multi-colinearity are removed from the model. Table 6 provides the multi-colinearity analysis between the dependent variables in the constructed model.

Table 6. Correlation between dependent variables

| | AGI | TSH-TA | Capital/TA | ROA |
|---|---|---|---|---|
| AGI | 1 | 0.051 | -0.229 | -0.014 |
| TSH-TA | 0.071 | 1 | -0.003 | 0.067 |
| Capital/TA | -0.239 | -0.013 | 1 | 0.048 |
| ROA | -0.014 | 0.081 | 0.048 | 1 |

*Source: Authors work*

The function constructed by the discriminant analysis is called the canonical function and to test the statistical significance of this model two indicators are used the canonical correlation coefficient and the Lambda value.

The canonical correlation coefficient indicates the importance of the built function and its ability to distinguish which group belongs to a given economic entity. The higher this indicator the more explanatory the function built.

The Lambda value shows that the part of the total variance, which can not be explained by the function for the difference between the groups taken into study, in our case bankrupt and non-bankrupt entities. This indicator is intended to be as small as possible. The results of model testing are shown in Table 7.

Table 7. Model testing

| Funct. | E.V | % Var. | Cum % | Canonical Corr. |
|---|---|---|---|---|
| 1 | 1.271 | 100.0 | 100 | .749 |
| Test of Function(s) | Wilks' Lambda | Chi-square | df | Sig. |
| 1 | .428 | 52.41 | 4 | .000 |

*Source: Author's work*

From the Table 7 it can be seen that the value of the canonical correlation coefficient is 74.9%, so it can be said that it is a high value.

The Lambda indicator is at the value of 0.428 with a magnitude of 0.000, which is smaller than the magnitude 0.05, which means that the constructed function is statistically significant.

Thus accepting the alternative hypothesis thrown at the beginning of this paper, that the model built for bankruptcy forecasting is statistically significant.

The final step in building the bankruptcy forecast model is to determine the breakpoint, which is calculated as follows. Table 8 shows that there is not a “gray area” between the two groups of entities and the center values for the study groups are as follows.

Table 8. Centres Indicators

| Status | Function |
|---|---|
| Bankrupt economic entities | -1.115 |
| Non-bankrupt economic entities | 1.115 |

*Source: Author's work*

The breakpoint between groups is calculated from the following formula:

$$Z = \frac{\text{NA ZB} + \text{NB ZA}}{\text{NA} + \text{NB}} = \frac{35 * 1.115 + 35 * (-1.115)}{35 + 35} = 0 \tag{4}$$

According to the discriminatory function, entities with a value of Z greater than 0 are considered bankrupt entities, while entities with a Z lower than 0 are considered non-bankrupt entities.

The final test of the discriminatory function is that of the evaluation of the classification results by the constructed function. Table 9 shows how accurate the model is for entity classification according to the sample.

Table 9. Forecast Model Classification Results

| Status | Prediction by model | | Total |
|---|---|---|---|
| | Bankrupt | Non-bankrupt | |
| Bankrupt | 32 | 3 | 35 |
| Non-bankrupt | 8 | 27 | 35 |
| Bankrupt | 91.4 % | 8.6 % | 100 |
| Non-bankrupt | 22.9% | 77.1% | 100 |

*Source: Author's work*

Table 9 shows that the discriminatory function manages to classify 91.4% of bankrupt economic entities and 77.1% of non-bankrupt economic entities.

The constructed model can correctly classify 84.3% of the initially sampled entities. These results differ from other studies performed in other countries.

Those models often rely on financial ratios and indicators that may not fully capture the nuances of a specific country's economic landscape. For instance, differences in accounting standards, legal frameworks, market maturity, and industry structures can affect the relevance and predictive power of certain variables. Therefore, applying international models directly to Albanian entities may result in less accurate predictions due to these contextual discrepancies.

That's why the best way was to create a specific model for a given country, in this case, Albania. Country-specific models can achieve much better results than popular models used globally to evaluate domestic states.

## 4.2 Discussion

The model developed for forecasting bankruptcy among Albanian enterprises demonstrated a high classification accuracy, correctly identifying 91.4% of bankrupt entities and 77.1% of non-bankrupt entities. The overall accuracy of 84.3% suggests that the model is robust enough to predict insolvency within the studied economic context. This classification success is an important contribution to improving early bankruptcy detection, allowing enterprises, investors, and policymakers to take proactive measures to mitigate risks.

The study identifies several financial ratios as significant predictors of bankruptcy. The most critical variable is the ratio of *share capital to total assets*, followed by *short-term assets turnover*, *ability to generate money* and *return on assets (ROA)*. These indicators highlight the importance of liquidity management and the capital structure of enterprises in predicting financial distress. Notably, the ability of firms to convert short-term assets into cash and manage their financial structure plays a vital role in distinguishing bankrupt from non-bankrupt firms. The negative relationship between ROA and bankruptcy risk underscores the direct impact of profitability on financial stability.

A comparative analysis of the financial ratios between bankrupt and non-bankrupt entities reveals significant differences in liquidity and profitability ratios. Non-bankrupt entities tend to exhibit stronger liquidity positions and more favorable profitability ratios, while bankrupt entities are often characterized by negative profitability and higher leverage. For instance, bankrupt entities demonstrated higher debt ratios and a more precarious capital structure, with accumulated losses depleting their share capital. These findings align with previous research that emphasizes the importance of liquidity and capital management in preventing bankruptcy.

Another issue, relating to the industry, there are observed no differences in industry classification.

# 5 Conclusion

This study also focused on several statistics related to active economic entities in Albania, where the number of entities has increased for the period taken in the study. Also, the Albanian economic entities are organized mainly in the form of limited liability companies and mainly operate in the commercial and construction sectors. For this reason, limited liability entities and joint stock companies have been selected in this study, where most of the selected entities operate in the commercial and construction sectors.

The results of this study align with the global trend toward using multivariate models for bankruptcy prediction, reflecting similar themes found in models like Z-Score and Ohlson's logit model. However, the Albanian model diverges in its emphasis on certain financial ratios—especially *share capital/total assets*—and its adaptation to local economic conditions. When compared with other country-specific models, the Albanian model demonstrates strong predictive power, highlighting the importance of tailoring bankruptcy prediction tools to the unique regulatory, market, and financial environments of the country being studied. So, the main conclusion listed below, are:

-High predictive accuracy of the bankruptcy model: The study successfully developed a bankruptcy prediction model for Albanian enterprises using multivariate discriminant analysis which indicates that the model is a reliable tool for identifying firms in financial distress in Albania.

- Key predictors of bankruptcy: The study identified several critical financial ratios that serve as strong predictors of bankruptcy for Albanian enterprises. The most significant variable was the *share capital to total assets ratio*, followed by *short-term assets turnover*, *ability to generate money* and *return on assets (ROA)*. These ratios highlight the importance of liquidity, efficient asset management, and profitability in preventing financial distress.

- Importance of liquidity and financial structure: The analysis revealed that liquidity ratios, particularly the *ability to generate money* and *short-term asset turnover*, play a crucial role in distinguishing between bankrupt and non-bankrupt firms. Additionally, bankrupt firms were found to have a more fragile capital structure, characterized by higher debt levels relative to their share capital, which underscores the importance of managing financial leverage.

- Local economic context and bankruptcy trends: The findings underscore the unique economic context of Albania, where many firms rely on short-term financing and operate in sectors with high exposure to external shocks (e.g., construction, trade).

-Sector-Specific Insights: The research found that the majority of bankruptcies occurred in the trade and construction sectors, which dominate the Albanian economy. This sector-specific focus suggests that industries with high fixed costs and lower liquidity buffers are particularly vulnerable to financial distress.

Based on the conclusions we draw some suggestions on how can we improve the situation:

Strengthening financial management practices through improving liquidity management and ensuring that their financial structures are more resilient. This can be achieved by maintaining healthier ratios of share capital to total assets and reducing reliance on short-term debt. Better cash flow management and optimizing the turnover of short-term assets will help companies avoid liquidity crunches that could lead to insolvency.

Use of the bankruptcy prediction model for early intervention from stakeholders, including investors, creditors, and policymakers, to adopt the bankruptcy prediction model as a tool for early identification of financial distress.

Given that the trade and construction sectors are particularly vulnerable to bankruptcy, Albanian policymakers should consider targeted interventions for these sectors. This could include offering tax relief, providing access to low-interest loans, or encouraging diversification of revenue streams to reduce sectoral risks.

-Encouraging long-term financing over short-term liabilities was noted as a common issue among both bankrupt and non-bankrupt firms. To reduce the risk of insolvency, companies should be encouraged to seek more sustainable, long-term financing solutions. -Financial institutions can play a role by offering favorable terms for long-term loans to reduce the dependence on short-term borrowing.

Improving transparency and accuracy in financial reporting: which is crucial for the accuracy of bankruptcy predictions. Efforts should be made to improve the transparency and accuracy of financial reporting among Albanian enterprises, particularly in sectors with high levels of informality.

Future studies should consider incorporating non-financial factors that may influence bankruptcy, such as governance structures, market competition, and macroeconomic conditions.

The study highlights the prolonged nature of bankruptcy proceedings in Albania. To expedite the resolution of bankruptcy cases and reduce economic uncertainty, judicial reforms aimed at streamlining bankruptcy processes should be considered. In 2016 there was issued a new bankruptcy law which included clear provisions regarding the publication of court decisions, aiming to increase transparency in the procedures. Furthermore, changes were made concerning the monitoring entities involved in bankruptcy procedures. Besides the Bankruptcy Supervision Agency (AMF), the roles of the Prosecutor's Office and the High State Audit were enhanced. This was done to prevent abuses and fraud related to bankruptcy proceedings. Law No. 110/2016 offers economic units the opportunity to restructure their obligations. The law stipulates that the debtor has the right to present a reorganization plan to the bankruptcy court. Additionally, this right is also granted to the bankruptcy administrator and to creditors who hold more than 20% of the total claims. An important point to mention is that bankruptcy procedures were followed for economic units that were already in bankruptcy proceedings at the time Law No. 110/2016 was enacted. The procedures for these units would continue according to the repealed law's procedures. For economic units that submit their requests after the effective date of the new law, the procedures of this new law will be followed. This practice resulted in the simultaneous application of two laws after 2016.

In conclusion, the study provides valuable insights into the bankruptcy dynamics of Albanian enterprises, offering a reliable predictive tool that can guide stakeholders in mitigating financial risks. However, future research should aim to refine this model by considering a broader range of factors and economic contexts.

**Declaration of Generative AI and AI-assisted Technologies in the Writing Process**

During the preparation of this work the authors used Grammarly and Quillbot in order to improve the readability and language of the research paper. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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**Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)**

The authors equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

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**Conflict of Interest**

The authors have no conflicts of interest to declare.