ISSN 1611-1699 / eISSN 2029-4433

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2025
Volume 26
Issue 1
Pages 110–126
https://doi.org/10.3846/jbem.2025.22373

# HOW CAN DATA MANIPULATION MATTER IN PREDICTING THE FAILURE RISK? EVIDENCE FROM ROMANIAN COMPANIES

Isabella LUCUŢ CAPRAŞ [1], Monica Violeta ACHIM [2✉], Mihaela Stefan HINT [3], Lucian Vasile GĂBAN [4]

[1,2]Faculty of Economics and Business Administration, Babes-Bolyai University, Cluj-Napoca Romania
[3,4]Faculty of Economic Sciences, University of 1 December 1918 in Alba Iulia, Alba-Iulia, Romania

**Article History:**
- received 23 January 2024
- accepted 9 August 2024

**Abstract.** Recent fraud scandals have raised concerns about the reliability of financial data disclosed in financial statements. The main purpose of this article is to investigate how financial data manipulation affects company failure risk. The research sample comprises 63 non-financial Romanian companies listed on the Bucharest Stock Exchange between 2015 and 2020. Three types of statistical methods were used to determine and consolidate the results. The results partially support the strand in literature according to which there is a correlation between manipulated data and failure risk. More specifically, the findings indicate that there is no statistically significant correlation between the Beneish Model and the Altman Z-score. However, after a more in-depth investigation taking into account the specific elements that indicate the existence of customized data in financial data, it was discovered that, among the eight Beneish model component variables, days' sales in a receivable index, sales growth index, and total accruals to total assets have a significant impact on the measurement of bankruptcy risk. This study constitutes an important contribution to the body of knowledge because it focuses not only on the relationship between the risk of failure and financial statement manipulation, but it examines also the significance of financial manipulation indicators in predicting the likelihood of bankruptcy. Our findings are valuable to decision makers seeking a deeper understanding of the reality behind financial data presented in financial statements.

**Keywords:** data manipulation, Beneish score, failure risk, Altman score, performance, accruals.

**JEL Classification:** G32, G33, M41.

✉Corresponding author. E-mail: *monica.achim@econ.ubbcluj.ro*

## 1. Introduction

Considering major fraud scandals such as Enron, WorldCom, Xerox, and Lehman Brothers, corporate executives' concern about fraudulent business activities and corporate financial health has grown (Kassem & Higson, 2012; Mahama, 2015). Companies are required to adapt to evolving market conditions due to constantly changing market dynamics and intense competition, and corporate managers have the possibility to choose the best suitable approach for the organization (Valaskova et al., 2021).

Previous research on earnings management and failure risk showed inconsistent results. A number of studies found that the risk of failure is linked with the adoption of earnings management practices (Tarighi et al., 2022; Sincerre et al., 2016). On the other hand, other researchers have discovered that managers of high-debt businesses reduce their earnings to strengthen their ability to negotiate better financing agreements. Companies employ income-reducing financial manipulation tactics following a downgrade in their credit ratings (Koerniadi, 2023). Other opposing viewpoints argue that greater indebtedness corresponds with more limited earnings management practices because creditors and banks carefully supervise corporate operations, minimizing financial statement manipulation (Agrawal & Chatterjee, 2015; Zagers-Mamedova, 2009; Saleh & Ahmed, 2005). As a result, more clarity on this subject is required, and this study fills that gap by examining this link in Romanian organizations.

Investors can suffer significant losses as a consequence of fraudulent financial reporting procedures. Furthermore, earnings management techniques and the likelihood of bankruptcy can reduce public trust (Arshad et al., 2015). Therefore, it would be extremely beneficial if companies were able to identify the probability of failure or accounting fraud at an early stage by using predictive techniques. In this context, this study makes an important contribution by analyzing the relationship between the risk of financial distress and earnings management, as well as which accounting indicators of the Beneish model can improve the Altman Z-score model in predicting bankruptcy. For the purpose of our study, we use a sample of 63 non-financial Romanian listed companies for the period 2015–2020, using three types of statistical methods. Romania is considered significant for this study for two reasons. First, the decision to study Romania relates to the country's historical context; having been a country with a strong communist influence can serve as a model for many other countries with similar characteristics. Second, Romania has always attempted to develop, and its economic environment can be an example for many emerging countries and, hence, to firms in these countries.

Our study found a negative correlation between failure risk and data manipulation risk, implying that firms in bankruptcy risk are unable to manipulate data because they are heavily supervised by banks and creditors while in the process of insolvency or seeking a new loan to survive. If predictive models had been applied in cases of financial scandals, the results would have indicated certain warning indicators for management to take essential preventative or remedial measures from the very beginning. Other than the organization's management, regulators, investors, and internal and external auditors can benefit from the use of these tools.

The paper is structured as follows. The next section provides a systematic literature review about the investigated topic and the research questions considered in this research. Section 3 provides the methodology and data. Following that, Section 4 provides the results that are further discussed in Section 5. The last section concludes the paper pointing out the main results, the limits and policy implications of the study.

## 2. Theoretical background and hypothesis development

In the analysis of corporate bankruptcy, researchers often consider also earnings management, as companies can manipulate their financial accounts to conceal critical financial situations (Séverin & Veganzones, 2021). Recent research has sparked interest in the occurrence of meeting or surpassing earnings thresholds. This phenomenon has become a focal point for researchers seeking to understand its implications and underlying mechanisms (Fang Li, 2010). This study relies on agency theory to explain the potential benefits of considering earnings management in predicting bankruptcy. Agency theory concerns the contractual relationship between one or more individuals and states that the agent, who is delegated by the principal to engage in business processes on his behalf, may not have the same interests

(Jensen & Meckling, 1976). Essentially, agency problems can occur when a contractual relationship is not adhered to due to asymmetric information, where one party possesses more information than the other (Agustia et al., 2020). In the context of this study, the agency problem arises from the fact that both parties seek to maximize their own interests, resulting in the management of a company (agent) not always acting in the best interest of the stakeholders (principal) by choosing not to disclose the true situation of the company. Managers use information asymmetries to hide unfavorable news and prioritize maximizing short-term wealth rather than benefitting shareholders (Srivastava et al., 2024).

## 2.1. The relationship between bankruptcy risk and earnings management

There is considerable literature on the relationship between the risk of bankruptcy and earnings management, but the results differ depending on the methods used, the type of financial statement manipulation practices considered, namely accrual-based earnings management and real earnings management, and the companies examined.

In literature, it is often argued that firms may choose to engage in earnings management practices based on the severity of their financial issues (Jaggi & Lee, 2002). When facing a high risk of bankruptcy, companies are more likely to be transparent about their financial situation because they are under closer scrutiny. Conversely, when the risk of bankruptcy is lower, firms may seek to conceal their debts. This is because providing misleading information during severe bankruptcy risk could have more negative consequences than positive ones. Li et al. (2021), who wanted to find out if and how earnings manipulation, one of the most frequent accountancy anomalies, might be employed to predict business distress, found that aggressive real earnings management implies a decreased likelihood of corporate failure. Firms with a higher Z-score that are not at risk of bankruptcy engage in more aggressive earnings management (Musanovic & Halilbegovic, 2021). Managers of firms at severe risk of bankruptcy chose to reflect their true money issues with the purpose of getting better conditions and terms from creditors and renegotiating debt covenants in the interests of obtaining government support (Agrawal & Chatterjee, 2015; Saleh & Ahmed, 2005; DeAngelo et al., 1994). Conservative accounting practices may have been chosen voluntarily by managers or as a result of pressure from lenders during the distress period. Managers risk losing credibility with lenders by trying to increase reported earnings, putting valuable financial resources at risk at critical times (Charitou et al., 2007a). Under audit opinion pressure, distressed firms are more likely to use conservative financial reporting procedures (Etemadi et al., 2013).

A little part of the literature found that companies that are financially distressed attempt to deceive other stakeholders about their true performance in order to attract more investors and lenders, which results in lower financial reporting quality; in other words, they employ manipulative strategies to maintain credibility, creditworthiness, and competitiveness (Tarighi et al., 2022; Valaskova et al., 2021). Real earnings management techniques are chosen over accruals when managers are under heavy pressure, such as when facing a bankruptcy proceeding, regardless of the long-term implications for the organization (Campa & Camacho-Minano, 2015). The primary incentive for bankrupt firms to engage in real earnings management is the issuance of new debt (Xu et al., 2021).

There are also some studies that found no relationship between bankruptcy and earnings management, such as the studies carried out by Campa and Camacho-Minano (2015), who found that companies that have made a reorganization decision do not manage their earnings more than their healthy counterpart and Aldahray and Alnori (2021), that found no significant link between accruals manipulation and the likelihood of failure prior to bankruptcy.

Therefore, the following hypothesis is proposed:

*H1: A decrease in the risk of company failure is linked to an increase in earnings management.*

### 2.2. The prediction of bankruptcy and earnings management

Regarding earnings management ratios and the prediction of bankruptcy in companies, a comprehensive and accurate examination of a firm's financial information can highlight early indicators of financial instability and the employment of misleading strategies, helping the business and its stakeholders avoid negative consequences.

Many studies have been conducted to determine whether the quality of financial information is important in the prediction of the risk of bankruptcy. These studies show that Altman's Z-score model (1968) is overstated (or understated) for earnings-management data sets with increasing (or decreasing) income (Cho et al., 2012). Furthermore, the inclusion of earnings management indicator variables significantly improves the predictive power of the Z-score for companies' bankruptcy risk (Lin et al., 2016). Leverage, liquidity, size, profitability, efficiency, and cash flow are additional variables that help separate default and compliant firms (Costa et al., 2022; Du Jardin et al., 2019). Li et al. (2021) argued that, regarding the prediction of financial distress risks, liquidity ratios outperform other traditional financial ratios, such as profitability and leverage. Furthermore, high financial manipulation indicates a low probability of failure. However, Serrano-Cinca et al. (2019) developed an index to detect bankruptcy based on accounting distortions, but only the private firm sample resulted in slightly better forecast accuracy.

Consequently, the following research question was established:

*RQ: How may financial data manipulation accounting ratios be used to improve the distinction between companies that face the risk of failure and those that do not?*

## 3. Methodology and data

### 3.1. Data and sample

The sample of the present study consists of 63 non-financial Romanian firms listed on the Bucharest Stock Exchange in the standard and premium category. All the data were manually gathered from the annual reports and financial statements of the companies on the BSE website (www.bvb.ro). The study's time frame covers the period from 2015 to 2020.

### 3.2. Variables

The dependent variable is represented by failure risk. Because the Z score models of Altman are widely used for measuring the bankruptcy score (Saji, 2018; Goh et al., 2022; Singh et al., 2023; Bandyopadhyay, 2006), we decided also to use it for the purpose of our study. The "Z" model for company bankruptcy prediction first appeared in the United States and was developed by Altman (1968). A description of the Altman Z-score is presented in Appendix 1. In our study, we used the 1.8 threshold to distinguish between companies that are at risk of bankruptcy and those that are not. We assigned a value of 1 to companies that are facing bankruptcy risk and a value of 0 to those that are not.

The independent variable is represented by the risk of manipulation and was measured using the Beneish (1999) model, which is a valuable tool for identifying companies with possible manipulations of their financial statements (Sujeewa & Kawshalya, 2020; Shakouri et al., 2021; Nyakarimi, 2022). This approach uses eight variables to determine whether a company has manipulated its earnings. We assigned a value of 1 to companies that engage in earnings management and a value of 0 to those that do not. The description of the M-score, according to Beneish (1999), is presented in Appendix 2.

The control variables considered in the research are represented by the quality of corporate governance (Achim et al., 2016; Süsi & Lukason, 2019), and the five financial indicators included in the Z score. In determining of corporate governance quality, we calculate a corporate governance score, following the methodology proposed by Achim and Borlea (2013). The value of a company's governance score ranges from 0 to 41.

A summary of variables description is presented in Table 1.

**Table 1.** Description of the variables considered in the study (source: own representation)

| Variable | Measurement method | Sources |
|---|---|---|
| Dependent variable | | |
| Failure risk | Altman Z-score (Zscore) (detailed in Appendix 1) | Own calculations |
| Independent variables | | |
| Earnings Management | Beneish M-Score (M score) (detailed in Appendix 2) | Own calculations |
| | DSRI: Days' sales in a receivable index | Own calculations |
| | GMI: Gross margin index | Own calculations |
| | AQI: Asset quality index | Own calculations |
| | SGI: Sales growth index | Own calculations |
| | DEPI: Depreciation index | Own calculations |
| | SGAI: Sales and general and administrative expenses index | Own calculations |
| | LVGI: Leverage index | Own calculations |
| | TATA: Total accruals to total assets | Own calculations |
| Control variables | | |
| Corporate governance | The corporate governance score (CG) | Own calculations |
| Indicators in the Altman risk model | Ratio of working capital to total assets (RWC) | Own calculations |
| | Ratio of retained earnings to total assets (RRE) | Own calculations |
| | Ratio of earnings before interest and taxes to total assets (REBI) | Own calculations |
| | Ratio of market value of equity to book value of total liabilities (RMVE) | Own calculations |
| | Ratio of sales to total assets (RSTA) | Own calculations |

### 3.3. Methods

Three alternative statistical approaches were utilized for the purpose of this study: multivariate analysis of variance, linear discriminant analysis, and binary choice model. Multivariate analysis of variance (MANOVA) was performed to determine the variable combinations with the best-discriminating power among all possible combinations (Johnson & Wichmen, 2020).

Linear Discriminant Analysis (LDA) seeks to construct a linear combination of factors that maximize the separation between two groups, as indicated by the Z score variable (Greene, 2008). Binary choice models, such as the logistic model and the probit model, are econometric models in which the dependent variable is qualitative and has just two values (0/1) (Cameron & Trivedi, 2022). Companies with or without a bankruptcy risk will be set to 1 and 0 in this scenario, respectively. We will then examine six models with varied combinations of significant variables. Finally, using the binary models, we will analyze the robustness of the obtained results.

## 4. Results

### 4.1. Descriptive statistics of the variables

Table 2 summarizes the descriptive statistics for the variables studied: mean, maximum, minimum, standard deviation, Skewness, and Kurtosis. The values for the Altman Z-Score and the Beneish M-score range from 0 to 1, and their mean values are 0.6058 and 0.3545, respectively. For both variables, Skewness and Kurtosis indicate that the distribution shape is normal. Regarding the other variables SGI, CG, and RSTA have a normal distribution. For DSRI, GMI, AQI, DEPI, SGAI, LVGI, TATA, RWC, RRE, REBI, and RMVE the presence of a positive Kurtosis indicates a peaked distribution. In addition, the results displayed in the table indicate that a total of 378 observations were considered.

**Table 2.** Descriptive statistics of the variables (source: own processing)

| Variable | Mean | Median | Max. | Min. | Std. Dev. | Skewness | Kurtosis | Obs. |
|---|---|---|---|---|---|---|---|---|
| Zscore | 0.61 | 1.00 | 1.00 | 0.00 | 0.49 | –0.43 | 1.19 | 378 |
| Mscore | 0.35 | 0.00 | 1.00 | 0.00 | 0.48 | 0.61 | 1.37 | 378 |
| DSRI | 1.72 | 1.01 | 103.60 | 0.23 | 6.69 | 13.25 | 186.25 | 378 |
| GMI | 1.05 | 0.86 | 235.61 | –105.09 | 14.37 | 10.44 | 197.95 | 378 |
| AQI | 1.74 | 0.99 | 51.26 | 0.06 | 4.69 | 7.95 | 71.46 | 378 |
| SGI | 1.04 | 1.05 | 2.17 | 0.03 | 0.33 | 0.24 | 4.64 | 378 |
| DEPI | 1.24 | 0.99 | 33.42 | 0.01 | 2.05 | 12.11 | 173.52 | 378 |
| SGAI | 1.22 | 1.01 | 33.95 | 0.15 | 1.91 | 14.40 | 235.94 | 378 |
| LVGI | 1.08 | 1.03 | 5.25 | 0.13 | 0.44 | 4.53 | 36.63 | 378 |
| TATA | –0.05 | –0.04 | 2.07 | –1.20 | 0.18 | 4.17 | 58.60 | 378 |
| CG | 25.67 | 29.00 | 41.00 | 0.00 | 11.85 | –0.60 | 2.21 | 378 |
| RWC | 0.12 | 0.16 | 0.81 | –5.13 | 0.56 | –4.80 | 35.25 | 378 |
| RRE | 0.01 | 0.01 | 2.10 | –1.13 | 0.17 | 4.76 | 74.33 | 378 |
| REBI | 0.04 | 0.03 | 2.09 | –1.11 | 0.18 | 4.12 | 63.85 | 378 |
| RMVE | 2.65 | 0.48 | 176.49 | 0.01 | 13.34 | 11.13 | 138.07 | 378 |
| RSTA | 0.62 | 0.57 | 2.31 | 6.63 | 0.43 | 1.01 | 4.44 | 378 |

## 4.2. Main results

The first step consisted of conducting the multivariate analysis of variance (MANOVA), and the results are presented in Table 3. A one-way MANOVA model is obtained by specifying fifteen dependent variables followed by one categorical variable defining two groups. It can be observed that the p-value (≤ 0.05) for TATA, RWC, RRE, REBI, RMVE, and RSTA are statistically significant. In this regard, we can conclude that not every accounting ratio can be utilized as a discriminator to identify enterprises at risk of bankruptcy.

After that, we examine if the fifteen-dimensional mean vectors of the two groups, as determined by the Z score variable, differ. The null hypothesis states that the mean vectors for the two groups are the same. All four multivariate tests (W, P, L, R) reject the null hypothesis, indicating some kind of difference between the fifteen-dimensional mean vectors of the two groups. Only the result of the W test is included in the table MANOVA. All multivariate tests show a p-value small enough (p-value = 0.000). For all tests, the final column indicates whether the F statistic is exactly F distributed (e). This is true, and we can move on.

**Table 3.** Multivariate analysis of variance (MANOVA) (source: own processing)

| Variables | Coefficients | p-value | No. obs. | W test (p-value) | F distribution |
|---|---|---|---|---|---|
| Mscore | –0.057 | 0.255 | 378 | 0.000 | E |
| DSRI | –1.363 | 0.053 | 378 | 0.000 | E |
| GMI | 0.310 | 0.837 | 378 | 0.000 | E |
| AQI | –0.661 | 0.180 | 378 | 0.000 | E |
| SGI | –0.068 | 0.051 | 378 | 0.000 | E |
| DEPI | –0.104 | 0.629 | 378 | 0.000 | E |
| SGAI | – 0.306 | 0.127 | 378 | 0.000 | E |
| LVGI | 0. 045 | 0.325 | 378 | 0.000 | E |
| TATA | –0.043 | 0.025 | 378 | 0.000 | E |
| CG | –1.649 | 0.186 | 378 | 0.000 | E |
| RWC | –0.391 | 0.000 | 378 | 0.000 | E |
| RRE | –0.090 | 0.000 | 378 | 0.000 | E |
| REBI | –0.106 | 0.000 | 378 | 0.000 | E |
| RMVE | –5.520 | 0.000 | 378 | 0.000 | E |
| RSTA | –0.093 | 0.040 | 378 | 0.000 | E |

*Note*: e – exact, a – approximate, u – upper bound on F distribution.

As a consequence, the results show that only the accounting ratios TATA, RWC, RRE, REBI, RMVE, and RSTA can act as discriminators to identify companies with possible bankruptcy risk. The sign of the regression coefficients of the variables TATA, RWC, RMVE, and RSTA are negative, which was to be expected. Higher levels of TATA reflect a higher level of accruals, meaning a way to manipulate profit. The negative coefficient of TATA in relation to the Z score reflects that a higher level of accruals is associated with a lower level of risk failure. The coefficient is statistically significant at 5% level of significance. DSRI and SGI are also indicators that reflect manipulating data. Even if they have negative coefficients, they are significant only at a 10% level of significance. Therefore, we let them out in our further analysis. The rest of the significant variables reflect the ratio of working capital management (RWC), rate of assets efficiency (RRE, REBI, and RSTA), and rate of equity financing (RMVE). Higher the management of working capital, the efficiency of using assets and equity financing, and lower the bankruptcy risk of the companies.

We may observe that M score has a negative, statistically insignificant relationship with the Z score. This means that manipulated data is not the only way to discriminate between companies with high failure risks and companies with low levels of risk. There are many other factors that contribute to the success of the companies.

In the second step, a linear discriminant analysis was conducted in order to find a linear combination of variables that maximizes the separation between two groups and six groups of variables were analyzed. Each group of variables includes the variable TATA and the other variables were introduced in an order defined by the power of discrimination. Each group of variables is associated with a statistical model (1–6) presented in the Linear Discriminant Analysis (Table 4).

From Table 4, it can be concluded that model 5, which involves the variables TATA, RWC, RMVE, and RSTA, ensures the linear combination of discriminating variables that are the most important or helpful in discriminating between the groups. The variables RWC and RMVE are farther from the origin (–0.613 and –0.635) with greater discriminating power, and variables TATA and RSTA are closer to the origin (–0.195 and –0.179), which means a lower discriminating power. The discriminatory power between the two groups, formed by the Z score variable provided by model 5, is significant because the classification percentage is 86%.

**Table 4.** Linear Discriminant Analysis (LDA) (source: own processing)

| Variables | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| TATA | 1 | 0.747 | 0.291 | –0.249 | –0.195 | –0.157 |
| RWC | | | | | –0.613 | –0.493 |
| RRE | | | | | | –0.365 |
| REBI | | | | | | –0.424 |
| RMVE | | | 0.948 | –0.545 | –0.635 | –0.511 |
| RSTA | | 0.686 | | –0.228 | –0.179 | –0.144 |
| N | 378 | 378 | 378 | 378 | 378 | 378 |
| % | 50 | 54 | 76 | 74 | 86 | 84 |

*Note*: N – the number of observations % – the classification percentage

In order to answer the formulated research questions and achieve the goal of this research, the other models will also be analyzed based on the results of Table 4. Model 1 contains only the TATA variable. The power of discrimination is the lowest (50%). Consequently, the TATA variable cannot act as a single discriminator used to identify companies with bankruptcy risk. Model 2 additionally includes the RSTA variable. The discrimination power increases to 54%, and their coefficients are 0.747 and 0.686, far enough from the origin. The separation percentage is not significant enough, and for this reason, there is the need to introduce other variables. Model 3 also includes the RMVE variable. It is a variable with a significant impact on the power of discrimination, with a coefficient of 0.948. This model ensures a classification percentage of 76%. Model 4 includes the TATA, RMVE, and RSTA variables. From the point of view of the classification percentage, this model is weaker than model 3. The classification percentage is 74%, which means that this combination of variables does not ensure a sufficiently high discrimination power. Model 5, as described above, offers the highest discrimination power found so far. Model 6 includes all the six significant variables found using MANOVA. This does not ensure a higher classification percentage than was found in Model 5. We have a lower percentage, equal to 84%.

Consequently, we conclude that the accounting ratios from model 5, form the linear combination that maximizes the separation between two groups. Therefore, the TATA, RWC, RRE, REBI, RMVE and RSTA represent the best predicting variables for the failure risk.

## 4.3. Robustness checks

The last step was represented by the robustness checks of the results that were performed through the application of the Probit models. Table 5 shows the results of the probit estimations for each of the six models.

The sign of the regression coefficients of the variables from models 1–5 are negative, as expected. The p-value for the regression coefficients is, at most, 0.034. This means that these variables have a negative impact on the risk of bankruptcy; in other words, their increase leads to a decrease in the risk of bankruptcy. The significant impact (89%) of the four variables on the risk of bankruptcy is consistent with the results obtained in the two previous tables. The impact of the independent variables in the five models is statistically significant. The chi-square p-value for the five models is between 0.000 and 0.014. The percentage of correct classification (%) is increasing, from 61 to 89. This underlines the high level of robustness of the results obtained in the MANOVA and LDA (Table 3 and Table 4).

**Table 5.** PROBIT estimations for models 1–6 (source: own processing)

| Variables | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| TATA | –0.935 | –0.523 | –1.019 | –0.892 | –2.830 | –8.841 |
| | (0.014) | (0.000) | (0.018) | (0.034) | (0.009) | (0.000) |
| RWC | | | | | –4.762 | –2.447 |
| | | | | | (0.000) | (0.000) |
| RRE (iv) | | | | | | Iv |
| REBI (iv) | | | | | | Iv |
| RMVE | | | –0.964 | –1.266 | –1.501 | –1.005 |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| RSTA | | –0.154 | | –1.323 | –2.155 | –1.362 |
| | | (0.010) | | (0.000) | (0.000) | (0.000) |
| CONST | 0.218 | 0.720 | 1.055 | 2.215 | 3.905 | 2.007 |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 378 | 378 | 378 | 378 | 378 | 378 |
| $\chi 2$ p-value | 0.014 | 0.007 | 0.000 | 0.000 | 0.000 | 0.000 |
| Pseudo R2 | 0.01 | 0.018 | 0.274 | 0.369 | 0.603 | 0.59 |
| % | 61 | 63 | 78 | 79 | 89 | 93 |

*Note*: The p-values are in parentheses. iv – instrumental variables, % – the classification percentage.

It was not by chance that we left the model 6 at the end. The behavior of the six independent variables included in the model presents some particularities. The correlation matrix from Table 6 shows us that there is a high correlation between TATA and the other two control variables (RRE, REBI). There is a weak correlation between the Z score and TATA. For this reason, we will consider the RRE and REBI variables as instrumental variables and the TATA variable as endogenous variable. As a result, the indirect influence of the two independent variables, RRE and REBI, on the Z score variable through the endogenous variable TATA will be analyzed. The probit table includes these control variables as instrumental variables (iv). Applying a special probit model that takes endogeneity into account, we obtained the results from the last column of the Probit table (Table 5). The results are relevant. The negative sign and the statistical significance of the four variables in the model are preserved. The much more pronounced impact of the TATA variable as a result of the indirect impact of the two instrumental variables should be emphasized. We also note an increase in the correct percentage of selection to 93%.

**Table 6.** The correlation matrix (source: own processing)

| | Z score | TATA | RRE | REBI |
|---|---|---|---|---|
| Z score | 1.0000 | | | |
| TATA | –0.1149 | 1.0000 | | |
| RRE | –0.2601 | 0.8279 | 1.0000 | |
| REBI | –0.2979 | 0.8032 | 0.9728 | 1.00 |

## 5. Discussions

Our discussions are organized around explaining the way in which the results come to respond to the proposed hypothesis and research question and the way in which the results are aligned with the rest of the literature.

Regarding H1 we found evidence that manipulated data is correlated with failure risk only in a partial way. The Beneish score was not found to be a variable that discriminates the two groups of companies. A similar result was obtained by Abdul Aris et al. (2015), who suggest that companies engaging in earnings manipulation activities do not face the risk of insolvency. Our findings also support the theory that managers of firms that are a high risk of bankruptcy do not manipulate their financial statements and choose to reflect their real situation with various scopes, such as renegotiating debt covenants, obtaining government support, or because of pressure from various factors such as audit opinion and leaders (Agrawal & Chatterjee, 2015; Etemadi et al., 2013; Charitou et al., 2007b; Saleh & Ahmed, 2005; DeAngelo et al., 1994). However, analyzing the variables of the Beneish model, we found that three of them are significantly correlated with the failure risk (TATA was found to be the most significant variable, and then SGI and DSRI were found significant at 10%). Thus, our results partially support the problem of information asymmetry described in the agency theory and previous studies, such as Valaskova et al. (2021), who analyzed the relationship between failure risk measured with the Altman score and financial statement manipulation obtained using the Beneish M-score and modified Jones using a sample of 11,105 firms from the Visegrad countries and discovered a statistically significant relationship between financial distress and profit manipulation. Similarly, Thu (2023) found a statistically significant relationship between earnings manipulation and financial distress considering 601 firms listed on the Ho Chi Minh City Stock Exchange between 2010 and 2021. Our results are also aligned with the studies that found little evidence regarding this relationship. For instance, a weak relationship between risk failure and risk of data manipulation was also found by Agustia et al. (2020).

Concerning the research question (RQ), among all eight component variables from the Beneish model, we found that TATA (the level of accumulated accruals by the company) exerts the best impact on the level of bankruptcy risk. Our study provides clear evidence of the fact that the inclusion of some of the financial ratios which belong to the Beneish model can improve the accuracy of the prediction of failure risk. Our results are supported by other studies such as Grove et al. (2010), Lin et al. (2016), and Musanovic and Halilbegovic (2021). In this view, Grove et al. (2010) considered various models and ratios in order to develop a comprehensive method for evaluating and recognizing issues related to the process of reporting financial data. Similarly, Lin et al. (2016) discovered that incorporating the indicator variable for real earnings management significantly improves the explanatory power of Altman's Z-score components for business survival/default. Musanovic and Halilbegovic (2021) discovered a similar finding, suggesting a considerable difference between failing and non-failing small and medium-sized enterprises, particularly in accruals, asset quality, leverage, profitability, and liquidity.

Moreover, in addition to the main results, we obtained statistically significant results for the ratios of the Altman Z score, confirming the model's predictive power for company bankruptcy risk.

Another noteworthy outcome of our research is the corporate governance score (CG), which, even though it is negative (in line with our expectations), is not statistically significant. This can be explained by the relatively new code of corporate governance (2015), which needs time to be understood and applied by companies operating in Romania, an emerging country. The findings are consistent with earlier research for developing nations (Achim et al., 2016).

## 6. Conclusions

In this paper, we investigated the existence and direction of a potential relationship between data manipulation and failure risk. For the purpose of our study, we used a sample of 63 non-financial Romanian firms listed on the Bucharest Stock Exchange over the period 2015–2020. Three types of statistical methods were employed to find and consolidate our results. Our study partially supports the strand in the literature, according to which there is a correlation between manipulated data and failure risk. Regarding the relationship between the Beneish Model and the Altman Z-score, the findings show no statistically significant relationship. However, if we consider the components of the Beneish Model, the results show that there is a strong correlation between the failure risk and three elements: days' sales in a receivable index, sales growth index, and total accruals to total assets.

The original value of this work consists of both theoretical and practical implications. The theoretical implications regard the fact that this study enhances the importance of data manipulation in providing real informational value on the risk of bankruptcy in companies. In addition to other studies on the link between the likelihood of bankruptcy and the manipulation of business data, this study explores the issue more deeply and examines the significance of each individual accounting indicator. More specifically, the discovery that three earnings management indicators were statistically significant for failure risk assessment implies that, when evaluating a company's performance, both financial performance ratios and indicators that reflect data manipulation should be considered. Only using financial accounting data without any evidence of the degree of data manipulation could be a high threat to the various users that have interests in a certain company. Practical implications regard the various users of financial data. Banks should be aware of the possible existence of data manipulation practices in the information provided by their clients and consider them in the process of assessing the creditworthiness of their clients. Moreover, while making decisions, policymakers should not neglect the possibility that financial data may have been altered. Investors should see behind the accounting data and take into consideration manipulation data ratios when they asses their investment decisions.

The paper also has several limitations due to the relatively brief period of data considered and the restricted area of Romania. Future research will overcome these limitations by utilizing a longer period of time and a larger sample of enterprises from the European Union or from around the world.

## Acknowledgements

This work is part of the project COST CA19130 FinAI – Fintech and Artificial Intelligence in Finance – Towards a Transparent Financial Industry and the Marie Skłodowska-Curie Actions under the European Union's Horizon Europe research and innovation program for the Industrial Doctoral Network on Digital Finance, acronym: DIGITAL, Project No. 101119635.

## Disclosure statement

The authors declare that they do not have any competing financial, professional, or personal interests from other parties.

## References

Abdul Aris, N., Mohd Arif, S. M., Othman, R., & Zain, M. M. (2015). Fraudulent financial statement detection using statistical techniques: the case of small medium automotive enterprise. *Journal of Applied Business Research*, *31*(4), 1469–1478. https://doi.org/10.19030/jabr.v31i4.9330

Achim, M. V., & Borlea, N. S. (2013). *Corporate governance and business performances*. *Modern approaches in the new economy*. Lap Lambert Academic Publishing.

Achim, M. V., Borlea, N. S., & Mare, C. (2016). Corporate governance and business performance: Evidence for the Romanian economy. *Journal of Business Economic and Management*, *17*(3), 458–474. https://doi.org/10.3846/16111699.2013.834841

Agrawal, K., & Chatterjee, C. (2015). Earnings management and financial distress: Evidence from India. *Global Business Review*, *16*, 140–154. https://doi.org/10.1177/0972150915601928

Agustia, D., Muhammad, N. P., & Permatasari, Y. (2020). Earnings management, business strategy, and bankruptcy risk: Evidence from Indonesia. *Heliyon*, *6*(2). https://doi.org/10.1016/j.heliyon.2020.e03317

Aldahray, A., & Alnori, F. (2021). Impact of regulatory environment on accruals manipulation of bankrupt firms. *Spanish Journal of Finance and Accounting*, *50*(1), 114–142. https://doi.org/10.1080/02102412.2020.1735209

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Arshad, R., Iqbal, S. M., & Omar, N. (2015). Prediction of business failure and fraudulent financial reporting: Evidence from Malaysia. *Indian Journal of Corporate Governance*, *8*(1), 34–53. https://doi.org/10.1177/0974686215574424

Bandyopadhyay, A. (2006), Predicting probability of default of Indian corporate bonds: Logistic and Z-score model approaches. *Journal of Risk Finance*, *7*(3), 255–272. https://doi.org/10.1108/15265940610664942

Beneish, M. D. (1999). The detection of earnings manipulation. *Financial Analysts Journal*, *55*(5), 24–36. https://doi.org/10.2469/faj.v55.n5.2296

Cameron, C., & Trivedi, P. K. (2022). *Microeconometrics using STATA* (2 ed.). STATA Press.

Campa, D., & Camacho-Minano, M.-d.-M. (2015). The impact of SME's pre-bankruptcy financial distress on earnings management tools. *International Review of Financial Analysis*, *42*, 222–234. https://doi.org/10.1016/j.irfa.2015.07.004

Charitou, A., Lambertides, N., & Trigeorgis, L. (2007a). Earnings behaviour of financially distressed firms: The role of institutional ownership. *Abacus-A Journal of Accounting Finance and Business Studies*, *43*(3), 271–296. https://doi.org/10.1111/j.1467-6281.2007.00230.x

Charitou, A., Lambertides, N., & Trigeorgis, L. (2007b). Managerial discretion in distressed firms. *The British Accounting Review*, *39*(4), 323–346. https://doi.org/10.1016/j.bar.2007.08.003

Cho, S., Fu, L., & Yu, Y. (2012). New risk analysis tools with accounting changes: Adjusted Z-score. *Journal of Credit Risk*, *8*(1), 89–108. https://doi.org/10.21314/JCR.2012.137

Costa, M., Lisboa, I., & Gameiro, A. (2022). Is the financial report quality important in the default prediction? SME Portuguese construction sector evidence. *Risks*, *10*(5), Article 98. https://doi.org/10.3390/risks10050098

DeAngelo, H., DeAngelo, L., & Skinner, D. (1994). Accounting choice in troubled companies. *Journal of Accounting and Economics*, *17*(1–2), 113–143. https://doi.org/10.1016/0165-4101(94)90007-8

Du Jardin, P., Veganzones, D., & Severin, E. (2019). Forecasting corporate bankruptcy using accrual-based models. *Computational Economics*, *54*, 7–43.

Etemadi, H., Dehkordi, H. F., & Amirkhani, K. (2013). Effect of auditor opinion on discretionary accruals behavior of distressed firms: Empirical evidences from Iran. *African Journal of Business Management*, *7*(20), 1956–1965.

Fang Li, S. (2010), Determinants of management's preferences for an earnings threshold, *Review of Accounting and Finance*, *9*(1), 33–49. https://doi.org/10.1108/14757701011019808

Goh, E., Mat Roni, S., & Bannigidadmath, D. (2022). Thomas Cook(ed): Using Altman's z-score analysis to examine predictors of financial bankruptcy in tourism and hospitality businesses. *Asia Pacific Journal of Marketing and Logistics*, *34*(3), 475–487. https://doi.org/10.1108/APJML-02-2021-0126

Greene, W. G. (2008). *Econometric analysis* (6 ed.). Pearson International edition.

Grove, H., Cook, T., Streeper, E., & Throckmorton, G. (2010). Bankruptcy and Fraud Analysis: Shorting and selling stocks. *Journal of Forensic and Investigative Accounting*, *2*(2), 276–293.

Jaggi, B., & Lee, P. (2002). Earnings management response to debt covenant violations and debt restructuring. *Journal of Accounting, Auditing & Finance*, *17*(4), 295–324. https://doi.org/10.1177/0148558X0201700402

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Johnson, R., & Wichmen, D. (2020). *Applied multivariate statistical analysis* (6 ed.). Pearson Education.

Kassem, R., & Higson, A. (2012). Financial reporting fraud: are standards' setters and external auditors doing enough? *International Journal of Business and Social Science*, *3*(19), 283–290.

Koerniadi, H. (2023). Do firms manage earnings after a downgrade in their credit rating? *Review of Accounting and Finance*, *22*(5), 602–619. https://doi.org/10.1108/RAF-10-2022-0299

Li, C., Lou, C., Luo, D., & Xing, K. (2021). Chinese corporate distress prediction using LASSO: The role of earnings management. *International Review of Financial Analysis*, *76*, Article 101776. https://doi.org/10.1016/j.irfa.2021.101776

Lin, H.-W., Lo, H.-C., & Wu, R.-S. (2016). Modeling default prediction with earnings management. *Pacific Basin Finance Journal*, *40*, 306–322. https://doi.org/10.1016/j.pacfin.2016.01.005

Mahama, M. (2015). Detecting corporate fraud and financial distress using the Altman and Beneish models. *International Journal of Economics, Commerce and Management*, *3*(1), 1–18.

Musanovic, E. B., & Halilbegovic, S. (2021). Financial statement manipulation in failing small and medium-sized enterprises in Bosnia and Herzegovina. *Journal of Eastern European and Central Asian Research*, *8*(4), 556–569. https://doi.org/10.15549/jeecar.v8i4.692

Nyakarimi, S. (2022) Probable earning manipulation and fraud in banking sector. Empirical study from East Africa. *Cogent Economics & Finance*, *10*(1), Article 2083477. https://doi.org/10.1080/23322039.2022.2083477

Saji, T. G. (2018). Financial distress and stock market failures: Lessons from Indian realty sector. *Vision*, *22*(1), 50–60. https://doi.org/10.1177/0972262917750244

Saleh, N., & Ahmed, K. (2005). Earnings management of distressed firms during debt renegotiation. *Accounting and Business Research*, *35*(1), 69–86. https://doi.org/10.1080/00014788.2005.9729663

Serrano-Cinca, C., Gutiérrez-Nieto, B., & Bernate-Valbuena, M. (2019). The use of accounting anomalies indicators to predict business failure. *European Management Journal*, *37*(3), 353–375. https://doi.org/10.1016/j.emj.2018.10.006

Séverin, E., & Veganzones, D. (2021). Can earnings management information improve bankruptcy prediction models? *Annals of Operations Research*, *306*(1–2), 247–272. https://doi.org/10.1007/s10479-021-04183-0

Shakouri, M. M., Taherabadi, A., Ghanbari, M., & Jamshidinavid, B. (2021). Explaining the Beneish model and providing a comprehensive model of fraudulent financial reporting (FFR). *International Journal of Nonlinear Analysis and Applications*, *12*, 39–48.

Sincerre, B. P., Sampaio, J. O., Famá, R., & Santos, J. O. (2016). Debt issues and earnings management. *Revista Contabilidade & Finanças*, *27*(72), 291–305. https://doi.org/10.1590/1808-057x201601660

Singh, S., Raghuvanshi, A., & Anant, S. (2023). Evaluating financial distress: With special reference to the Navratna companies of India. *Journal of Statistics and Management Systems*, *26*, 771–786. https://doi.org/10.47974/JSMS-1067

Srivastava, A., Assaf, R., Pandey, D. K., & Kumar, R. (2024). Stock price crash risk research: Current trends and future directions. *Journal of Risk Finance*. https://doi.org/10.1108/JRF-12-2023-0331

Sujeewa, G. M. M., & Kawshalya, M. D. P. (2020). Detecting red flags of corporate financial statement frauds using Beneish M score model in Sri Lanka. *International Journal of Accounting & Business Finance*, *6*(2), 71–81. https://doi.org/10.4038/ijabf.v6i2.72

Süsi, V., & Lukason, O. (2019). Corporate governance and failure risk: Evidence from Estonian SME population. *Management Research Review*, *42*(6), 703–720. https://doi.org/10.1108/MRR-03-2018-0105

Tarighi, H., Hosseiny, Z. N., Abbaszadeh, M. R., Zimon, G., & Haghighat, D. (2022). How do financial distress risk and related party transactions affect financial reporting quality? Empirical evidence from Iran. *Risks*, *10*(3). https://doi.org/10.3390/risks10030046

Thu, Q. L. (2023). Impact of earning management and business strategy on financial distress risk of Vietnamese companies. *Cogent Economics & Finance*, *11*(1). https://doi.org/10.1080/23322039.2023.2183657

Valaskova, K., Androniceanu, A.-M., Zvarikova, K., & Olah, J. (2021). Bonds between earnings management and corporate financial stability in the context of the competitive ability of enterprises. *Journal of Competitiveness*, *13*(4), 167–184. https://doi.org/10.7441/joc.2021.04.10

Xu, C., Zhang, H., Hao, J., & Guo, L. (2021). Real earnings management in bankrupt firms. *Journal of Corporate Accounting & Finance*, *32*(2), 22–38. https://doi.org/10.1002/jcaf.22483

Zagers-Mamedova, I. (2009). *The effect of leverage increases on real earnings management*. http://hdl.handle.net/1765/15572

# APPENDIX

## 1. Description of Z Altman score

Ratio of working capital to total assets (*RWC*)

$$RWC = \frac{\text{Working Capital}}{\text{Total Assets}}.$$

This ratio is a trustworthy marker of business difficulties. Given that there aren't enough current assets to pay short-term obligations, a company with negative working capital is likely to have issues meeting its obligations in the short term.

Ratio of retained earnings to total assets (*RRE*)

$$RRE = \frac{\text{Retained Earnings}}{\text{Total Assets}}.$$

This ratio quantifies how much profit or loss is reinvested. Companies with low values for ratio of retained earnings to total assets are using borrowings rather than retained earnings to finance capital expenditures. Companies with high values for ratio of retained earnings to total assets have a history of profitability and the ability to overcome a bad year of losses.

Ratio of earnings before interest and taxes to total assets (*REBI*)

$$REBI = \frac{\text{Earnings Before Interest \& Tax}}{\text{Total Assets}}.$$

This ratio is a variation of return on assets (ROA), a useful metric for determining whether a company can make a profit from its assets before deducting expenses like interest and taxes.

Ratio of market value of equity to book value of total liabilities (*RMVE*)

$$RMVE = \frac{\text{Market Value of Equity}}{\text{Total Liabilities}}.$$

This ratio indicates how much a company's market value would drop in the event of insolvency before liabilities exceed assets on the financial statements. A stable market capitalization indicates that the market has trust in the company's strong financial position.

Ratio of sales to total assets (*RSTA*)

$$RSTA = \frac{\text{Sales}}{\text{Total Assets}}.$$

This ratio reflects how effectively management handles competition and how effectively the business utilizes assets to generate sales.

The *Z*-score is then calculated using the following equation:

$$Z = 1.2 \times RWC + 1.4 \times RRE + 3.3 \times REBI + 0.6 \times RMVE + 1.0 \times RSTA.$$

The companies are ranked by the *Z*-score as follows:

- $z > 3$: the company is solvent;
- $z$ € [1.8,3): the company is in financial difficulty but can recover activity if a corresponding strategy is implemented;
- $z < 1.8$: the company is about to go bankrupt.

## 2. Description of M Beneish score

The description of the variables which compose the Beneish model is presented below (Beneish, 1999).

Days' sales in a receivable index (*DSRI*)

$$DSRI = \frac{\text{Net Receivables}_t}{\text{Sales}_t} \Big/ \frac{\text{Net Receivables}_{t-1}}{\text{Sales}_{t-1}}.$$

A significant increase in the number of days for receivable accounts could indicate accelerated revenue recognition in order to increase profitability.

Gross margin index (*GMI*)

$$GMI = \frac{\text{Gross margint}_{t-1}}{\text{Sales}_{t-1}} \Big/ \frac{\text{Gross margint}_{t}}{\text{Sales}_{t}}.$$

A deteriorating gross margin gives an unfavorable view of a company's prospects and encourages earnings manipulation.

Asset quality index (*AQI*)

$$AQI = \left[1 - \frac{\text{Current Assets}_t + \text{Tangible fixed assets}_t}{\text{Total Assets}_t}\right] \Big/ \left[1 - \frac{\text{Current Assets}_{t-1} + \text{Tangible fixed assets}_{t-1}}{\text{Total Assets}_{t-1}}\right].$$

An increase in long-term assets as a percentage of total assets suggests that a company may have raised its use of cost deferral to inflate profits.

Sales growth index (*SGI*)

$$SGI = \frac{\text{Sales}_t}{\text{Sales}_{t-1}}.$$

High sales growth is not an indication of manipulation, but businesses with rapid growth are more prone to commit financial fraud since managers are under pressure to meet profitability goals due to their precarious financial situations and capital requirement.

Depreciation index (*DEPI*)

$$DEPI = \frac{\text{Depreciation}_{t-1}}{\text{Depreciation}_{t-1} + \text{Tangible fixed assets}_{t-1}} \Big/ \frac{\text{Depreciation}_t}{\text{Depreciation}_t + \text{Tangible fixed assets}_t}.$$

A company may have extended the anticipated useful life of assets or implemented a new, income-increasing approach if its rate of depreciation related to net fixed assets is declining.

Sales and general and administrative expenses index (*SGAI*)

$$SGAI = \frac{\text{SG\&A Expense}_t}{\text{Sales}_t} \Big/ \frac{\text{SG\&A Expense}_{t-1}}{\text{Sales}_{t-1}}.$$

A firm's future prospects may be influenced negatively by a growth in SG&A that is out of proportion to sales, which could be used as an incentive to inflate earnings.

Leverage index (*LVGI*)

$$LVGI = \frac{\text{Current Liabilities}_t + \text{Total Long Term Debt}_t}{\text{Total Assetst}_t} \Big/ \frac{\text{Current Liabilities}_{t-1} + \text{Total Long Term Debt}_{t-1}}{\text{Total Assetst}_{t-1}}.$$

An incentive to manipulate profits in order to meet debt covenants can be represented by an increase in leverage.

Total accruals to total assets (*TATA*)

$$TATA = \frac{\text{Income from Continuing Operations}_t - \text{Cash Flows from Operations}_t}{\text{Total Assets}_t}.$$

Accruals at least partially represent the extent to which managers use discretionary accounting decisions to change earnings. As a result, there is a direct correlation between accruals levels and the likelihood of earnings manipulation.

The Beneish *M*-Score is then derived using the formula below:

$$M = -4.84 + 0.92 \times DSRI + 0.528 \times GMI + 0.404 \times AQI + 0.892 \times SGI + 0.115 \times DEPI - 0.172 \times SGAI + 4.679 \times TATA - 0.327 \times LVGI.$$

The M-score has a threshold value of –2.22. More specifically, a business is unlikely to be a manipulator if the estimated score is lower than the threshold value. In contrast, a business is likely to manage profits if the computed manipulation score is higher than the limit value.