TEME, Vol. L, Nº 2, April – June 2026, pp. 437–460

Original research paper https://doi.org/10.22190/TEME260131028S
Received: January 31, 2026 UDC 343.983:343.53(497.11)
Revised: February 25, 2026 657.41/.45(497.11)
Accepted: March 3, 2026 347.736(497.11)

THE NEXUS BETWEEN FRAUDULENT FINANCIAL REPORTING AND COMPANY FAILURE – THE CASE OF BANKRUPT COMPANIES IN SERBIA

Dejan Spasić[1,2*], Jovana Stojanović[3]

[1]University of Belgrade, Faculty of Economics and Business, Belgrade, Serbia
[2]University of Niš, Faculty of Economics, Niš, Serbia
[3]University of Niš, Innovation Center, Niš, Serbia

ORCID iDs: Dejan Spasić https://orcid.org/0000-0002-8540-579X
Jovana Stojanović https://orcid.org/0000-0003-0190-3802

Abstract

Under conditions of financial crisis, companies may resort to manipulative practices in order to present their financial position and earning capacity more favourably than they actually are. Following the disclosure of financial statement manipulations, a significant number of companies enter bankruptcy, and even when they survive, recovery is often prolonged and challenging. A particular challenge in less developed economies is the limited transparency regarding the perpetrators of fraud, which hampers the development of reliable indicators that could serve as early warning signals (red flags). This paper examines the applicability of the Beneish M-score model with eight variables on a sample of 48 companies for which bankruptcy proceedings were initiated in the Republic of Serbia during the 2017–2024 period. The research objective is to identify potential red flags by isolating financial statement items that exhibited unusual movements in the years preceding the initiation of bankruptcy proceedings. The results indicate that 20.83% of the companies were classified as potential manipulators during the crisis period. The observed risk of fraudulent financial reporting is particularly associated with distortions in the relationship between receivables and sales, with an indicator pointing to problematic patterns related to intangible assets, as well as with faster growth of administrative expenses relative to the growth of sales revenue. The findings further confirm the need for enhanced analysis of accrual-based items that reflect mismatches in the recognition of revenues and expenses relative to the corresponding cash inflows and outflows. The results may be useful to investors, financial institutions, regulators and agencies involved in fraud prevention and bankruptcy proceedings, as well as to academic researchers in the further development of models tailored to the specific characteristics of national economies.

Key words: forensic accounting, financial statements, fraud indicators, M-score, bankruptcy.

* Corresponding author: Dejan Spasić, University of Belgrade, Faculty of Economics and Business, Kamenička 6, 11000 Belgrade, Serbia, dejan.spasic@ekof.bg.ac.rs

ВЕЗА ИЗМЕЂУ ПРЕВАРНОГ ФИНАНСИЈСКОГ ИЗВЕШТАВАЊА И ПОСЛОВНОГ НЕУСПЕХА – СЛУЧАЈ ПРЕДУЗЕЋА У СТЕЧАЈУ У СРБИЈИ

Апстракт

У условима финансијске кризе, компаније могу прибегавати манипулативним праксама како би финансијски положај и зарађивачку способност приказале повољнијим него што јесу. Након обелодањивања манипулација у финансијским извештајима, значајан број компанија одлази у стечај, а чак и када опстану, опоравак је често дуготрајан и отежан. Посебан изазов у недовољно развијеним економијама представља ограничена транспарентност у вези са починиоцима превара, што отежава развој поузданих индикатора који могу служити као рани сигнали упозорења. Овај рад испитује применљивост модела *Beneish M-score* са осам варијабли на узорку од 48 компанија над којима је у Републици Србији у периоду од 2017. до 2024. године покренут стечајни поступак. Циљ истраживања је идентификовање потенцијалних упозоравајућих сигнала кроз издвајање позиција финансијских извештаја које су испољавале неуобичајена кретања у годинама које су претходиле отварању стечајног поступка. Резултати указују да је 20,83% компанија класификовано као потенцијални манипулатори у периоду кризе. Уочени ризик преварног финансијског извештавања нарочито је повезан са нарушавањем односа између потраживања и прихода, са индикатором који указује на проблематичне обрасце у вези са нематеријалном имовином, као и са бржим растом административних трошкова у односу на раст прихода од продаје. Налази додатно потврђују потребу за појачаном анализом обрачунских позиција које одражавају неусаглашено признавање прихода и расхода у односу на одговарајуће новчане приливе и одливе. Резултати могу бити корисни инвеститорима, финансијским институцијама, регулаторима и агенцијама укљученим у спречавање превара и стечајне поступке, као и академским истраживачима у даљем развоју модела прилагођених специфичним карактеристикама националних економија.

Кључне речи: форензичко рачуноводство, финансијски извештаји, индикатори превара, М-скор, стечај.

INTRODUCTION

Although there are many ways to detect crisis in doing a business, accounting data and publicly available financial statements are the most important source to confirm a company distress. However, financial statements are occasionally misused to deceive stakeholders, thereby maintaining a company's legitimacy and concealing its true performance, rather than serving as a reliable indicator of impending insolvency or bankruptcy.

The widespread metaphor that financial reporting is the 'language of business' stems from its nature and importance to users who have a direct or indirect interest in the disclosed corporate reports. In fact, general purpose financial statements should provide stakeholders with useful and relevant information for assessing a company's financial position, profitability, cash flows and other performance. However, a fundamental prerequisite for the usefulness of reports and their faithful presentation is that they are free from subjectivity, errors, and fraudulent practices in their creation and disclosure. Under the influence of these anomalies, the monetary items in the financial reports obscure or conceal the company's true performance, which, among other things, can lead to bankruptcy (Rosner, 2003; Leach, 2007; Boateng, 2011; Campa & Camacho-Miñano, 2014). It is known that stakeholders have recently become increasingly interested in a wider range of non-financial (mostly sustainability-related) information, in addition to financial data. In other words, the "metaphor of the 'language of business' extends to corporate reporting as a whole" (Fülbier & Sellhorn, 2023, p. 1090). Consequently, intentional or accidental fraudulent reporting practices affect not only financial statements, but also other corporate reports, thereby expanding the scope of forensic and court bankruptcy investigations.

In court practice, however, investigations into fraud in the disclosure of non-financial (sustainability) information by companies are still not (sufficiently) applied. This can be explained by the fact that until recently, this information was mostly disclosed voluntarily, without any legal obligation. In addition, scientific models are still being created for academic studies of the crime nature of fraudulent non-financial reporting. On the other hand, various methods and models have already been developed to detect fraudulent financial reporting.

For the reasons mentioned above, the aim of this paper is to investigate whether the manipulation of financial statements and the monetary data they contain has an impact on a company's bankruptcy. Furthermore, the aim is to identify the red flags that could indicate possible fraudulent accounting practices that led to the company's failure. To achieve these objectives, two research questions were set:

Q1. How widespread was fraudulent financial reporting in the sampled companies before their bankruptcy filings?

Q2. Which key items of the financial statements were manipulated ('red flags') in the sampled companies with detected fraudulent reporting?

To answer these questions, we use a sample of 48 companies that filed for bankruptcy in the Republic of Serbia between 2017 and 2024. The extended Beneish model with eight variables ("Beneish M8-Score") is employed. In cases where this model indicates accounting fraud, we analyse individual indicators to identify specific areas of fraud as red flags in bankruptcy investigations.

Due to the specific nature of our sample, we aim to fill a gap in this type of research, particularly in the Republic of Serbia. Namely, to the best of our knowledge, the Beneish M-Score model (both the initial version with five variables and the extended version with eight variables) has been widely employed in research in Serbia (Dimitrijević, Obradović & Milutinović, 2018; Knežević et al., 2021; Dimitrijević, Milutinović & Stanković, 2024; Dimitrijević, Stanković & Vržina, 2024; Malinić & Ribić, 2025) and worldwide (Chan & Landry, 2019; Repousis, 2016; Özari, Can & Demirkale, 2025; Svoboda et al., 2025). However, the aforementioned and other studies were conducted on samples that simultaneously include companies in crisis and/or exclusively companies with healthy performances, with the aim of predicting corporate failure due to manipulative financial reporting. On the other hand, as we already pointed out, our research contributes to the identification of possible frauds in the financial statements of bankrupt companies only, as a basis for crime investigation.

To achieve the research objective, this article is structured as follows. Following the Introduction, we provide a brief overview of the theoretical background of our research including legal treatment of accounting fraud in the Republic of Serbia. Subsequently, the research findings and their discussion, as well as a conclusion, are presented.

THEORETICAL BACKGROUND – A LITERATURE REVIEW

Accounting regulation (statutory and/or especially professional standards, such as IFRS or US-GAAP) provide options for recognising and measuring certain revenues, expenses, assets and liabilities, which ultimately affect reported profit and net assets. The different accounting options allow management to choose those that shape (non-)opportunistic reported earnings (a well-known term in the literature: 'earnings management'). Therefore, the question of accounting discretion becomes a central issue for standard setters and regulators – are these judgements being abused or not (Healy & Wahlen, 1999). Neither legislation nor literature provides unique criteria for answering this question.

Despite the negative connotation sometimes associated with the phrase 'earnings management,' not every instance of it is harmful to stakeholders (Christensen et al., 2022). This is the case when accrual-based accounting is applied ethically, without any intention of manipulating the reported earnings. Management's discretion to choice accounting policies and make accounting estimates falls within the scope of flexibility permitted by accounting standards, and it cannot be argued a priori that earnings management constitutes fraud.

Jackson (2018), for example, demonstrates "how discretionary accruals are inappropriate economic proxies for earnings management" (p. 137). Dichev et al. (2013) also provide evidence that fraud is less widespread than earnings management within GAAP, highlighting that "about 50% of earnings quality is driven by non-discretionary factors." Stolowy and Breton (2004), however, take a different view. They make a fundamental distinction between earnings management and fraud. In their view, earnings management is a form of manipulation using discretionary accounting in accordance with accounting standards, while fraud is an illegal act outside the scope of the GAAP. Nevertheless, there are numerous studies (Healy & Wahlen, 1999; Beneish, 2001; Perols & Lougee, 2010; Teixeira & Rodrigues, 2022; Bansal, 2024) that confirm the high probability of a correlation between profit manipulation and manipulative motives of managers, which is why it is treated as accounting fraud under certain circumstances.

The earnings management techniques used to deceive users of financial statements vary, as does the extend of earnings manipulation. Therefore, it can sometimes be difficult to determine when the manipulation of financial statements constitutes fraudulent activity and can be considered a criminal offense. Amiram et al. (2018) point out that "financial statement fraud, and financial reporting fraud *per se* is not a simple concept to define" ... and in this context "researchers use different terms – for example, fraud, misconduct, irregularities, misreporting, and misrepresentation – to describe similar events of financial reporting misconduct" (p. 732). Similar to the previous study, Stolowy and Breton (2004) find in a comprehensive literature review that various terms are used to describe accounting manipulation, which, while sharing common elements, nevertheless differ significantly.

Considering the goal of our research and the allowed length of the article, we will not discuss this topic in detail. In the context of our research, we consider the definition of Velte (2021) significant, according to which "firms' financial misconduct is violations of national and/or international accounting and related business law regulations and standards" (p. 354). For our further consideration, it is important to highlight the Association of Certified Fraud Examiners (ACFE) definition, according to which "financial statements fraud is the deliberate misrepresentation of an enterprise's financial condition, accomplished through the intentional misstatement or omission of amounts or disclosures in the financial statements to deceive statement users. It involves overstating assets, revenues and profits and understating liabilities, expenses and losses."

According to the ACFE, in 2024 "financial statement frauds, were the least common category (5% of the occupational fraud schemes) but also caused the greatest median loss (USD 766,000 per case)" (ACFE, 2024, p. 10).

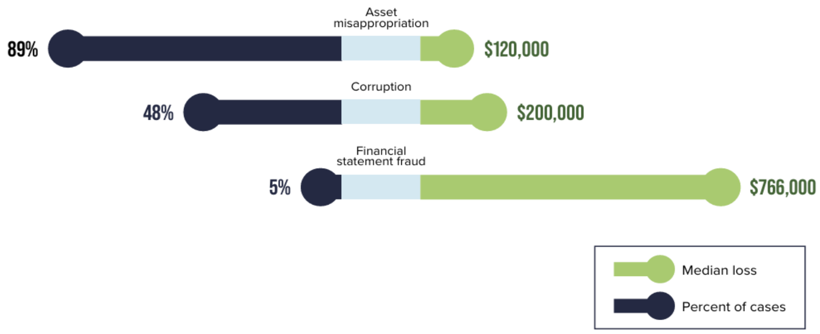


Fig. 1. Occupational fraud schemes worldwide in 2024
Source: ACFE (2024), p. 10

Fraudulent financial reporting not only harms investors, creditors and other stakeholders who make business decisions based on company's misleading financial reports, thereby jeopardising the functioning of the capital market and the economy in general, but also harms the company itself. The loss of legitimacy, the decline in company value, and financial distress in general can have fatal consequences for a company, i.e. bankruptcy. A corporate crisis and the resulting bankruptcy are not necessarily caused by objective factors. Bankruptcy can also result from deliberate actions by the owner and/or management of the company, actions that exclusively serve their own interests, to the detriment of creditors and other stakeholders. Financial statements can be one of the bankruptcy abuse tools they use.

Bankruptcy abuses can occur before or after bankruptcy proceeding is initiated (Škarić-Jovanović & Spasić, 2022, p. 319). Before bankruptcy proceedings are initiated, bankruptcy abuses are most often committed in the form of intentionally induced bankruptcy and false bankruptcy.

Namely, company owners and/or managers can use fraudulent transfers to intentionally cause bankruptcy and damage creditors. Their goal is to reduce the assets that could be used to cover the liabilities to creditors. Fraudulent transfers include "any transfer made with the intent to hinder, delay, or defraud creditors" (Janger, 2022, p. 379). The effects of such actions may affect the financial statements. Indications of intentionally caused bankruptcy that become apparent in company reports include: significant changes in profitability and cash flows that cannot be explained by the company's business activities, an extreme decline in the value of fixed assets and inventories, an extreme increase in receivables, excessive wage and bonus payments, and other indicators reflected in the financial statements. However, in order to conceal the mentioned activities, financial reports can also be forged.

A false bankruptcy, unlike an intentionally caused one, occurs due to actions by owners and management to create the impression that the conditions for bankruptcy are met by an apparent reduction, concealment, or actual reduction of assets under non-market conditions, while simultaneously maintaining the company's apparent debts. The aim is to avoid paying (part of) the liabilities to creditors through bankruptcy proceedings.

Fraudulent financial reporting and accounting manipulations of a company in general, carried out within the context of a false bankruptcy, are punishable as a criminal offense in the Republic of Serbia. Namely, in accordance with the Serbian Criminal Procedure Code (2011), "whoever conceals, destroys or alters statutory business records in such a way that the business results or the value of assets or liabilities cannot be discerned, or whoever produces false documents or otherwise presents a situation on the basis of which bankruptcy proceedings may be initiated, shall be punished by imprisonment for a term of six months to five years" (Article

232a). Therefore, the role of forensic accountants in detecting these crimes is becoming increasingly important.

In general, developing models for detecting fraudulent financial reporting is challenging, primarily due to the complexity of transactions, management discretion in recognising and measuring their effects in corporate reports, as well as other factors (for example corporate governance, effectiveness of internal control, external pressure, etc.).

In the last few decades, a range of statistical models or data collection approaches have been developed in an effort to uncover hidden, uncommon, or contradictory patterns that might point to financial fraud. Forensic accountants and investigative authorities employ a wide range of analytical techniques, ranging from conventional to cutting-edge, supported by sophisticated software for detecting fraudulent accounting practices. It should be noted that the goal of this paper is not to offer a thorough review of all the techniques used to detect fraudulent financial reporting, but rather to highlight a few widely used methods.

Statistical and ratio analysis of monetary data in financial statements are conventional tools for detecting accounting manipulations. The Beneish M-score model (1999) is probably one of the most widely referenced and applied conventional models in the literature. Employing financial data from financial statements, five- and eight-variable M-Score models were developed by this author, which we will discuss in more detail in the next chapter and apply the second one in our empirical research. Although this model has limitations, it has proven sufficiently reliable in predicting fraudulent financial reporting (Dyck, Morse & Zingales, 2024) and identifying red flags (Sabău, Mare & Safta, 2021; Sylwestrzak, 2022), and could therefore be a useful tool for law enforcement agencies, auditors, and forensic accountants.

With the aim to detect critical areas of financial statements manipulation by managers, Dechow et al. (2011) developed the F-score model, which includes an analysis not only the financial statements' data, but also other risk factors for misleading reporting. Within the F-Score they examined five variables: "(i) accrual quality, (ii) financial performance, (iii) non-financial measures, (iv) off-balance sheet activities, and (v) market-based measures."

In addition to the M-score and F-score models, there are other models based on statistical and econometric methods with financial input variables that primarily serve insolvency prediction. In general, the findings indicate that an analysis of monetary data from financial statements provides a solid basis for detecting potential accounting fraud. However, it is also worthwhile to examine the narrative disclosures in the notes and the management report. For example, Craja, Kim, and Lessmann (2020) developed one of the models that employs the hierarchical attention network to extract management remarks at the word and sentence level. Their model is able to grasp not only the content but also the context of statements made by managers, which provide supplementary predictors to financial ratios. In addition to a high degree of reliability in identifying fraudulent corporate reporting, the model also provides insights into red flag, i.e. key areas of possible manipulative accounting practices.

Other conventional statistical methods, such as logistic regression analysis (Bell & Carcello, 2000; Yue et al., 2009; Kanapickienė & Grundienė, 2015; Yiannoulis, Vortelinos & Passas, 2025) are also widely employed in addition to the models mentioned. However, these and similar statistical methods often face the problem of collinearity of independent variables and data distribution, since financial variables often do not exhibit a normal distribution.

The limitations of conventional models should therefore be mitigated by methods based, for example, on machine learning, data mining, and the application of artificial intelligence (AI). Machine learning is designed to identify potential indicators of fraud by analysing financial ratios, accounting irregularities, textual information in notes and annual or ad-hoc management reports, and the consistency across different reporting periods.

Chen (2016) highlights, for example, the following models for detecting fraudulent financial reporting: "artificial neural network, decision tree, Bayesian belief network, and support vector machine methods" (p. 2). In a recent comprehensive literature review, Compagnino et al. (2025) identified Random Forest – a method that "combine multiple decision trees to improve classification accuracy while effectively reducing overfitting tendencies" (p. 5) – as the most widely used machine learning technique for detecting financial statements fraud.

However, the significant role of data mining as a tool for processing complex analyses and classifying data with modern fraud detection models is obvious. The latest advancement in detecting fraudulent financial reporting is certainly related to AI. Wang, Zhang, and Han (2025) point out that "by introducing intelligent automation, pattern recognition, and predictive analytics, AI technologies significantly enhance accounting accuracy, fraud detection, and financial transparency" (p. 404). The possibilities of detecting financial fraud on a daily basis with AI have already been confirmed (Bello et al., 2023).

METHODOLOGY

In our study, the Beneish model is applied as the methodological framework. The model generates a single composite score (M-score), and its comparison with a critical threshold is interpreted as a red flag indicating the likelihood that a company is engaged in fraudulent financial reporting. The Beneish model is based on financial indicators (variables) that quantify changes in financial statement items relative to the previous year

(Beneish, 1999). The model exists in two versions: one with five variables (M-score 5) and another with eight variables (M-score 8). This study employs the M-score 8, as the research conducted by Dimitrijević et al. (2018) in Serbia suggests that the extended version provides a more comprehensive insight into potentially risky areas of financial reporting compared to the M-score 5 model. Accordingly, the M-score 8 is calculated as follows:

$$M = -4.84 + 0.92 \times DSRI + 0.528 \times GMI + 0.404 \times AQI + 0.892 \times SGI + 0.115 \times DEPI - 0.172 \times SGAI - 0.327 \times LVGI + 4.697 \times TATA \quad (1)$$

The application of the model involves the calculation of eight variables, whose formulas and brief explanations are shown below.

1. Days' Sales in Receivables Index – DSRI

$$DSRI = \frac{\text{Receivables}_t/\text{Sales}_t}{\text{Receivables}_{t-1}/\text{Sales}_{t-1}} \quad (2)$$

The variable DSRI serves for "detecting variations in receivables relative to sales revenues over two consecutive years" (Malinić & Ribić, 2025, p. 12). A high DSRI value may represent a red flag that a company is 'inflating' revenues through premature revenue recognition, recognition of suspicious revenues or recognition of fictitious revenues, which may lead to an overstatement of reported financial performance.

2. Gross Margin Index – GMI

$$GMI = \frac{(\text{Sales}_{t-1} - \text{Cost of Goods Sold}_{t-1})/\text{Sales}_{t-1}}{(\text{Sales}_t - \text{Cost of Goods Sold}_t)/\text{Sales}_t} \quad (3)$$

High values of the GMI variable can be interpreted as a potential signal of an increased earnings manipulation risk. Such situations may arise as a result of a deterioration in the gross margin, i.e. a decline in the company's profitability, which intensifies pressure on management to resort to fraudulent financial reporting in order to preserve the appearance of financial stability.

3. Asset Quality Index – AQI

$$AQI = \frac{1 - (\text{Current Assets}_t + \text{Net PP\&E}_t)/\text{Total Assets}_t}{1 - (\text{Current Assets}_{t-1} + \text{Net PP\&E}_{t-1})/\text{Total Assets}_{t-1}} \quad (4)$$

The AQI variable indicates the share of intangible assets, whether internally generated or acquired, in total assets. This item is particularly susceptible to manipulation in financial reporting due to the high degree of managerial discretion, limited verifiability, the absence of active markets, the possibility of cost capitalisation, flexibility in amortisation policies and impairment testing. Accordingly, "an increase in this variable may signal manipulative practices involving intangible assets, aimed at artificially enhancing reported financial performance" (Malinić & Ribić, 2025, p. 12).

4. Sales Growth Index – SGI

$$SGI = \frac{\text{Sales}_t}{\text{Sales}_{t-1}} \quad (5)$$

The SGI variable is used to identify potential manipulations achieved through artificial inflation of sales revenue, aimed at creating the appearance of improved financial performance. However, Malinić and Ribić (2025) emphasise that caution is required when interpreting this indicator, as growth in sales revenue per se does not necessarily imply fraudulent reporting, just as a decline in sales does not preclude the presence of such practices.

5. Depreciation Index – DEPI

$$DEPI = \frac{\text{Depreciation}_{t-1}/(\text{Depreciation}_{t-1}+\text{Net PP\&E}_{t-1})}{\text{Depreciation}_t/(\text{Depreciation}_t+\text{Net PP\&E}_t)} \quad (6)$$

As noted by Beneish (1999), high values of DEPI may indicate depreciation-related manipulations: lower depreciation rates (resulting from longer estimated useful lives of fixed assets) reduce expenses and artificially increase reported earnings.

6. Sales, General, and Administrative Expenses Index (SGAI):

$$SGAI = \frac{\text{Sales,General,and Administrative Expense}_t/\text{Sales}_t}{\text{Sales,General,and Administrative Expense}_{t-1}/\text{Sales}_{t-1}} \quad (7)$$

The SGAI variable, in line with the suggestion of Lev and Thiagarajan (1993), is used to identify situations in which sales, general and administrative expenses grow faster than sales revenue, which analysts often interpret as an unfavourable signal regarding the company's future prospects. Accordingly, "it can be expected that companies would be more prone to manipulations as this index is higher than 1" (Dimitrijević et al., 2018, p. 1325).

7. Leverage Index – LVGI

$$LVGI = \frac{(\text{Long−term Debt}_t+\text{Current Liabilities}_t)/\text{Total Assets}_t}{(\text{Long−term Debts}_{t-1}+\text{Current Liabilities}_{t-1})/\text{Total Assets}_{t-1}} \quad (8)$$

The LVGI variable is included in the analysis to assess whether changes in leverage may be associated with stronger incentives for fraudulent financial reporting. Beneish (1999) relies on the findings of Beneish and Press (1993), according to which changes in capital structure are linked to default risk and potentially adverse market reactions.

8. Total Accruals to Total Assets – TATA

$$TATA = \frac{\Delta\text{Current Assets}_t - \Delta\text{Cash}_t - \Delta\text{Current Liabilities}_t - \Delta\text{Current Maturities of Long−term Debts}_t - \Delta\text{Income Tax Payable}_t - \text{Depreciation and Amortization}_t}{\text{Total Assets}_t} \quad (9)$$

The TATA variable represents the proportion of accruals in total assets. In the Beneish model, accruals are approximated through changes in net working capital, excluding cash, amortisation and depreciation. In this way, the effects of applying the accrual basis of accounting are captured, whereby revenues and expenses are recognised before or after the corresponding cash inflows and outflows. The underlying assumption is that a higher share of non-cash (accrual-based) components in earnings may indicate more intensive use of discretionary accounting estimates and, consequently, a higher risk of manipulation. In addition, the literature provides an alternative approach to calculating TATA (Mehta & Bhavani, 2017):

$$TATA = \frac{\text{Income from Continuing Operations}_t - \text{Cash Flow from Operating Activities}_t}{\text{Total Assets}_t} \quad (10)$$

The interpretation of the calculated M-score (Eq. (1)) is based on a comparison with a reference threshold: a score above -2.22 indicates an increased likelihood of fraudulent reporting, while a score below the threshold suggests a lower risk (Corsia et al., 2015). In this context, a higher M-score is interpreted as a stronger risk signal, as the model is constructed such that increases in individual variables are generally accompanied by an increase in the probability of manipulation. However, even when the model yields an elevated score, it should be interpreted solely as an indicator for deeper analysis rather than as confirmation of manipulation (Tarjo & Herawati, 2015; Ramírez-Orellana et al., 2017).

In addition to the primary decision criterion based on the M-score, further insights are provided by the analysis of individual model variables. Comparing these variables with the average values for manipulators and non-manipulators from Beneish's original sample (Table 2) allows for a more precise assessment of which financial statement items may generate red flags. More pronounced deviations in specific variables can direct the analysis toward particular areas and indicate where more detailed examinations are required to assess potential irregularities. Nevertheless, the results must be interpreted with caution, as elevated variable values do not necessarily indicate manipulation but may arise from normal business dynamics, industry-specific characteristics or stages of the business cycle (Malinić & Ribić, 2025).

The widespread use of the Beneish model largely stems from its relative simplicity of application: the required data is generally readily available from basic financial statements, and the model's output is interpreted by comparison with a clearly defined reference threshold. The Enron case is particularly illustrative, as the Beneish model indicated an elevated risk of fraudulent financial reporting one year before the first official warnings were issued (Beneish et al., 2013). In this regard, research findings suggest that red flags may be identified in a timely manner through the analysis of corporate financial statements in the years preceding bankruptcy (Mavengere, 2015).

DATA

The analysis in this study was conducted on companies for which bankruptcy proceedings were initiated in the Republic of Serbia during the period 2017–2024. This sample selection is justified by the fact that companies operating under conditions of financial distress often face impaired financial stability and profitability due to adverse economic, industry-specific or operational circumstances, such as intensified competition, declining demand, rapid technological progress, product obsolescence, operating losses and persistently negative cash flows from operating activities. In addition, the expectations of various stakeholders (analysts, owners and creditors) regarding profitability growth, additional financing and the implementation of planned activities may further intensify pressure on management, particularly when managers' personal financial interests are at risk. In such an environment, incentives increase to create, through fraudulent financial reporting, the appearance that earnings are higher, cash flows more stable and financial statement items more persistent than they actually are, thereby misleading investors and other stakeholders (Schilit et al., 2018). For these reasons, applying the Beneish M-score model to a sample of bankrupt companies enables the identification of potential red flags by isolating financial statement items that exhibited unusual movements in the years preceding the initiation of bankruptcy proceedings.

According to data from the Serbian governmental agency responsible for overseeing corporate bankruptcy proceedings (Bankruptcy Supervision Agency), a total of 3,319 companies entered bankruptcy proceedings during the period 2017–2024. In the next stage of selection, the sample was narrowed to medium-sized and large companies, of which there were 65 in the observed period. This focus on company size is based on the assumption that medium-sized and large companies are expected to devote greater attention to the quality of financial reporting and to the more effective functioning of internal control systems, which should reduce the risk of errors and managerial fraud. In addition, in Serbia, large companies apply IFRS, while medium-sized companies apply IFRS for SMEs (unless they are listed, in which case they also apply IFRS), ensuring comparability of results with many previous studies. Nevertheless, there is evidence that fraudulent financial reporting has characterised financial scandals and bankruptcies of large corporations (Beasley et al., 2010). The significance of this issue is further underscored by findings of prior research indicating that a substantial proportion of companies operating in Serbia, both large and medium-sized, have been identified as potential manipulators (Dimitijević et al., 2018; Malinić & Ribić, 2025).

Given the methodology underlying the Beneish model, the analysis was based on balance sheets and income statements obtained from the website of the Serbian Business Registers Agency for one or two years prior to the initiation of bankruptcy proceedings. Since financial statements for the observed period were unavailable for nine companies, the sample was subsequently reduced to 56 companies. Furthermore, for eight companies it was not possible to calculate the Beneish M-score indicators due to zero values in the denominators of certain ratios, and these companies were therefore excluded from further analysis. As a result, the final sample comprises 48 companies. The entire selection process is presented in Table 1.

Table 1. Sample formation process

Criterion	Number of companies
Total number of companies for which bankruptcy proceedings were initiated during the period 2017-2024	3,319
Medium-sized and large companies for which bankruptcy proceedings were initiated during the period 2017-2024	65
Companies for which basic financial statements were not available for one or two years preceding the initiation of bankruptcy proceedings	(9)
Companies for which it was not possible to calculate the Beneish M-score variables	(8)
Final sample size	48

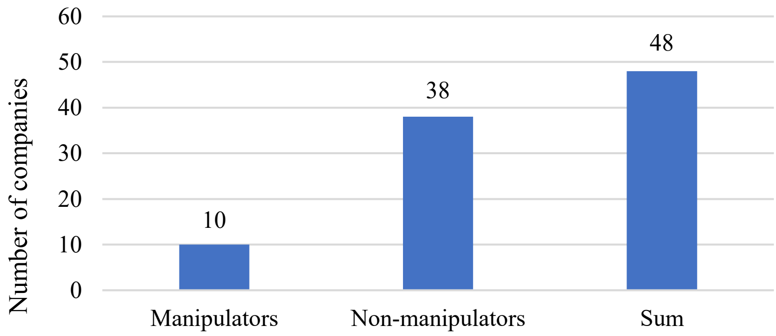
Source: Authors' calculations

It is important to note that the Beneish model (1999) was developed using data prepared under the cost of goods sold method, whereas the income statement format in Serbia is based on the total cost method. Accordingly, certain methodological adjustments were made to ensure the comparability of the calculated indicators.

The following section presents a descriptive analysis of large and medium-sized companies for which bankruptcy proceedings were initiated in Serbia during the period 2017–2024, with the aim of assessing: (1) the extent of the risk of fraudulent financial reporting under conditions of financial distress, and (2) the most frequently observed red flags within the analysed sample. Taking into account the above considerations, as well as additional limitations that will be discussed in more detail later, the findings should primarily be interpreted as indicative of potential signs of fraudulent financial reporting.

RESULTS AND DISCUSSION

After defining the sample, the Beneish M-score was applied to the collected data. The results are shown below.



Graph 1. Structure of the final sample
Source: Authors' illustration

Graph 1 illustrates the sample structure according to the Beneish M-score classification: 10 companies are classified as manipulators (20.83%), while 38 companies belong to the non-manipulator group (79.17%). Following this group-wise distribution, Table 2 provides a more detailed overview of the average values of the Beneish M-score indicators and M-score results for manipulators and non-manipulators, along with a comparison to the average values reported in Beneish's original study. The results show that the average M-score for the manipulator group is well above the threshold (8.15), whereas for non-manipulators it is clearly below the threshold (-4.89). Individual variables in both groups exhibit mixed patterns.

Table 2. Average values of variables and M-score for manipulators and non-manipulators

	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA	M-score
Non-Manipulators									
Values for sampled companies	1.40	-1.74	1.12	0.68	1.55	1.97	2.02	-0.97	-4.89
Beneish benchmark	1.031	1.014	1.039	1.134	1.001	1.054	1.037	0.018	< -2.22
Manipulators									
Values for sampled companies	14.31	0.07	1.90	0.49	1.00	6.93	1.20	0.09	8.15
Beneish benchmark	1.465	1.193	1.254	1.607	1.077	1.041	1.111	0.031	> -2.22

Source: Authors' calculation

The average DSRI value for non-manipulators slightly exceeds the reference threshold, indicating revenue recognition that is not accompanied by adequate collection of receivables, i.e. corresponding cash inflows. Given that these companies were experiencing severe financial difficulties, faster growth in receivables relative to sales growth may be interpreted as a reflection of a genuine deterioration in collection capacity. In contrast, the extremely high average DSRI value observed for manipulators points to a serious distortion in the relationship between receivables and sales; however, the nature of this phenomenon appears to differ from that observed among non-manipulators. In this case, DSRI may reflect not only the effects of the crisis and weak collection performance, but also the use of receivables as a mechanism of fraud, primarily through the extension of customer credit periods (Frank et al., 2011). A particular concern is that changes in customer credit policies are not always accompanied by adequate disclosure, further reducing the transparency of financial statements and enabling the accumulation of receivables from prior periods.

Moreover, an examination of the balance sheets of the sampled companies reveals that one-third of the manipulators report significant amounts of receivables from parent companies, subsidiaries and other related parties, both domestically and abroad. Such a receivables structure is questionable, as transactions with related parties are often not conducted under market conditions and may serve as a channel for manipulative financial reporting (Lo et al., 2010; Marchini et al., 2018). The situation is further aggravated when companies avoid writing off doubtful receivables, thereby creating the appearance that their financial position and profitability are stronger than they actually are. In light of these findings, DSRI can be viewed as a red flag that warrants more detailed examination of revenue recognition, the structure of receivables and customer credit policies. Furthermore, our findings should also be interpreted in the context of the conclusions of Henry et al. (2012), who in their empirical research emphasised the need to consider related-party transactions within a broader corporate context, as top management is most involved in potential manipulation in this regard.

With regard to the GMI variable, the results show that average values of this indicator are relatively low for both non-manipulators and manipulators, pointing to very low gross margins across the sample. Although this finding primarily reflects weak financial performance, given that the companies are operating under conditions of financial distress, the observed GMI values suggest that these companies did not resort to fraudulent financial reporting. However, companies tend to manipulate profits to avoid reporting losses (Burgstahler & Dichev, 1997). This becomes particularly evident during times of crisis, which can lead to bankruptcy and necessitate additional forensic investigations.

The average AQI value for non-manipulators slightly exceeds the reference threshold, which in itself does not indicate systematic attempts at fraudulent financial reporting. In contrast, the significantly higher average AQI value observed for manipulators points to a stronger reliance on valuation-sensitive items, such as acquired internally generated intangible assets. When considered in conjunction with other Beneish M-score variables, this result takes on the characteristics of aggressive accounting treatment, for example through postponing impairment expense recognition, thereby artificially improving reported financial performance. Accordingly, the findings highlight the need for additional analysis of policies related to the recognition and measurement of intangible assets, as well as the implementation of impairment testing procedure.

Empirical studies generally provide evidence that companies that manipulate earnings primarily artificially inflate revenues (Stubben, 2010; Perols & Lougee, 2010). Within the analysed sample, low SGI values in both observed groups indicate that companies were operating under conditions of financial distress, resulting in sales that did not vary significantly between two consecutive periods. Consequently, SGI cannot be regarded as an indicator of manipulation for the sampled companies. Our results are consistent with the findings of an earlier study by Dimitrijević et al. (2018) in the Republic of Serbia, conducted before the COVID-19 crisis.

Although DEPI is not elevated among companies identified as manipulators, higher values of this indicator are observed among non-manipulators. This suggests that a reduction in amortisation rates should not be automatically interpreted as a signal of manipulation, but may also reflect legitimate business circumstances or asset structure characteristics. Nevertheless, bearing in mind the scope for the application of "aggressive accounting practices" as a tool used by "typical earnings manipulator" (Steingen & Löw, 2025, p. 10), an additional examination of the accounting policy of subsequent measurement of fixed assets is necessary, particularly due to possible manipulations of depreciable assets.

The average SGAI value for non-manipulators is significantly above the reference level and indicates faster growth in administrative expenses relative to sales growth. However, given that these companies were in a pre-bankruptcy state, this finding is more likely attributable to declining sales combined with relatively rigid or even increasing administrative costs (e.g. legal and consulting services, restructuring costs etc.) rather than to attempts at manipulative reporting. In contrast, the extremely high SGAI value observed for manipulators points to a dramatically faster growth of administrative expenses relative to sales growth, which, when combined with other Beneish M-score variables, may indicate fraudulent behaviour. In such cases, administrative expenses may function as a discretionary category used to shift expenses across accounting periods and to mitigate the negative effects of poor performance (Arman & Sharmin, 2019). Therefore, within the subsample classified as manipulators, SGAI can be viewed as a red flag that justifies a more detailed examination of the structure of administrative expenses and their recognition practices.

In the observed sample, LVGI is elevated for both manipulators and non-manipulators, which is expected given that the companies are experiencing financial distress and are in the period immediately preceding bankruptcy, when increasing leverage often reflects a genuine deterioration in financial structure (Repousis, 2016). Among manipulators, LVGI slightly exceeds the reference value, indicating the presence of financial pressure, although the magnitude of the deviation is not pronounced. Similarly, the elevated LVGI observed among non-manipulators can primarily be interpreted as a consequence of economic deterioration rather than necessarily as a signal of fraudulent reporting. Accordingly, in this study LVGI should be regarded as an auxiliary pressure indicator whose interpretive value is confirmed only when considered in combination with other Beneish M-score variables.

Negative TATA values among non-manipulators may be interpreted as reflecting more conservative recognition of losses and write-offs, resulting in reported performance that is more closely aligned with realised cash flows. In contrast, the positive TATA value observed for manipulators, which also exceeds the threshold value, suggests that reported earnings are more heavily shaped by accrual-based items and are not adequately supported by cash inflows. Consequently, TATA can be viewed as an important red flag that justifies a more detailed examination of the structure of accruals, expense recognition policies and potential accounting estimates affecting reported performance (Sylwestrzak, 2022).

LIMITATIONS OF EMPIRICAL RESEARCH

The most significant limitation of the study relates to the fact that the Beneish M-score does not allow for a reliable and precise classification of companies, but merely indicates an increased likelihood of fraudulent financial reporting. In addition, certain variables may exhibit high values even in the absence of manipulation, reflecting normal business conditions or, in the context examined, the specific characteristics of operating under crisis conditions. This effect is particularly evident for the DSRI, DEPI, SGAI and LVGI variables, whose values may be driven by economic deterioration and weakened performance rather than by manipulative behavior. Accordingly, any conclusions drawn from the model should be preceded by a thorough qualitative analysis. Our study is also subject to limitations arising from differences between the institutional and structural framework of the Serbian economy and the environment in which the model was developed (the United States). On the one hand, the model was constructed using data from publicly listed companies, whereas the Serbian economy is characterised by a relatively small and illiquid capital market. Finally, the calculation of the M-score 8 requires certain adjustments to input data for domestic companies due to differences in accounting practices, which may further affect the comparability and interpretation of the obtained results.

CONCLUSION

The conducted research, based on the Beneish M-score (M8) model, indicates that potential signals of manipulation in financial statements can be identified among Serbian companies for which bankruptcy proceedings were initiated during the period 2017–2024. Within the sample of 48 large and medium-sized companies, 20.83% were classified as potential manipulators under conditions of financial distress. The observed risk of fraudulent financial reporting is particularly associated with distortions in the relationship between receivables and sales, with indicators pointing to problematic patterns related to intangible assets, as well as with faster growth of administrative expenses relative to sales growth. The findings further confirm the need for enhanced analysis of accrual-based items that reflect mismatches in the recognition of revenues and expenses relative to the corresponding cash inflows and outflows. Nevertheless, reliable determination of whether and to what extent companies actually prepare manipulative financial statements is possible only after detailed examinations of their operations, which go beyond the scope of this study.

Our finding that one-fifth of the sampled companies were very likely to have (un)intentionally published false financial statements highlights the importance of permanent monitoring of the financial reporting process and early detection of possible fraudulent accounting practices. Namely, if these mechanisms had already been in place, the bankruptcy of some companies could likely have been avoidable. This would allow the owners to retain control over their company and potentially provide creditors with a better position through an out-of-court financial restructuring. Furthermore, avoiding formal insolvency proceedings helps preserve employees' jobs, thereby ensuring the socio-economic stability of the industry and the national economy as a whole. On the other hand, the subsequent detection of fraudulent financial reporting helps bankruptcy investigators identify and prosecute those responsible.

Given that fraudulent practices are becoming increasingly complex and sophisticated, and that they can generate severe economic consequences affecting the welfare of a large number of individuals, it is evident that combating fraud requires strong infrastructural foundations. A key role in this process is played by independent institutions which, through cooperation, should build an effective and sustainable system resilient to criminal activities. One of the pillars of such a system is the education of forensic accountants, aimed at developing highly competent professionals with unquestionable integrity and a strong commitment to protecting the public interest. Drawing on experiences from major corporate scandals worldwide, substantial potential for early fraud detection also exists within auditing, either through the application of forensic procedures that require specialised forensic accounting expertise or through the involvement of forensic accountants as specialists in audit engagements. The expertise of forensic accountants is of particular importance in judicial investigations of potential fraudulent financial reporting by bankrupt companies, treated as criminal offenses.

Effective prevention of manipulation can be further strengthened through the application of complementary approaches that enable earlier and more reliable detection of irregularities in financial reporting. Of particular importance is the development of analytical models tailored to domestic conditions, especially for application to financially distressed companies, where incentives to distort representations of earning capacity and financial position are more pronounced. Future research should therefore focus on the development and testing of such models, the application of which could contribute to more effective case processing and to the restoration of trust in the quality of the accounting, auditing and judicial professions.

ACKNOWLEDGEMENTS:
For the first author (Dejan Spasić): The paper is the result of research based on the commitments made under the Funds Transfer Agreement for the financing of NIR in 2026 (registration number 451-03-34/2026-03), concluded between the Ministry of Science, Technological Development and Innovation of the Republic of Serbia and the Faculty of Economics of the University of Niš.
For the second author (Jovana Stojanović): This research was financially supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia (Contract No. 451-03-33/2026-03/200371).

REFERENCES

ACFE (2024). *Occupational Fraud 2024: A Report to the Nations*. Available at: https://legacy.acfe.com/report-to-the-nations/2024/

Amiram, D., Bozanic, Z., Cox, J. D., Dupont, Q., Karpoff, J. M., & Sloan, R. (2018). Financial reporting fraud and other forms of misconduct: a multidisciplinary review of the literature. *Review of Accounting Studies, 23*(2), 732-783. https://doi.org/10.1007/s11142-017-9435-x

Arman, M., & Sharmin, S. (2019). Likelihood of a company's manipulation of its financial statement: An empirical analysis using Beneish M-score model. In *International Conference on Management and Information Systems* September 2019 (pp. 117-125).

Bansal, M. (2024). Earnings management: a three-decade analysis and future prospects. *Journal of Accounting Literature, 46*(4), 630-670. https://doi.org/10.1108/JAL-10-2022-0107

Beasley, M. S., Hermanson, D. R., Carcello, J. V., & Neal, T. L. (2010). Fraudulent financial reporting: 1998-2007: an analysis of U.S. public companies. *Association Sections, Divisions, Boards, Teams*. 453. https://egrove.olemiss.edu/aicpa_assoc/453

Bell, T. B., & Carcello, J. V. (2000). A decision aid for assessing the likelihood of fraudulent financial reporting. *Auditing: A Journal of Practice & Theory, 19*(1), 169-184. https://doi.org/10.2308/aud.2000.19.1.169

Bello, O. A., Ogundipe, A., Mohammed, D., Adebola, F., & Alonge, O. A. (2023). AI-driven approaches for real-time fraud detection in US financial transactions: Challenges and opportunities. *European Journal of Computer Science and Information Technology, 11*(6), 84-102. Available at: https://eajournals.org/ejcsit/wp-content/uploads/sites/21/2024/06/AI-Driven-Approaches.pdf

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

Beneish, M. D. (2001). Earnings management: A perspective. *Managerial Finance, 27*(12), 3-17. https://doi.org/10.1108/03074350110767411

Beneish, M. D., Lee, C. M., & Nichols, D. C. (2013). Earnings manipulation and expected returns. *Financial Analysts Journal, 69*(2), 57-82. https://doi.org/10.2469/faj.v69.n2.1

Beneish, M. D., & Press, E. (1993). Costs of technical violation of accounting-based debt covenants. *Accounting Review, 68*(2), 233-257.

Boateng, D. A. (2011). A theoretical construct for explaining the impact of financial distress on unethical earnings management decisions. *The Journal of American Academy of Business, 16*(2), 89-95. Avalilable at: http://www.jaabc.com/Jaabc16-2March2011Boateng2.html

Burgstahler, D., & Dichev, I. (1997). Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics, 24*(1), 99-126. https://doi.org/10.1016/S0165-4101(97)00017-7

Campa, D., & Camacho-Miñano, M. del M. (2014). Earnings management among bankrupt non-listed firms: evidence from Spain. *Spanish Journal of Finance and Accounting / Revista Española de Financiación y Contabilidad, 43*(1), 3-20. https://doi.org/10.1080/02102412.2014.890820

Chan, C., & Landry, S. P. (2019). Financial Statements Too Good to be True? An Instructional Case Assessing that Question Using Analytical Procedures and Beneish's M-Score. *Journal of Forensic and Investigative Accounting, 11*(2), 380-394. Available at: https://www.nacva.com/content.asp?contentid=711#10

Chen, S. (2016). Detection of fraudulent financial statements using the hybrid data mining approach. *SpringerPlus, 5*, 89. https://doi.org/10.1186/s40064-016-1707-6

Christensen, T. E., Huffman, A., Lewis-Western, M. F., & Scott, R. (2022). Accruals earnings management proxies: Prudent business decisions or earnings manipulation?. *Journal of Business Finance & Accounting, 49*(3-4), 536-587. https://doi.org/10.1111/jbfa.12585

Compagnino, A. A., Maruccia, Y., Cavuoti, S., Riccio, G., Tutone, A., Crupi, R., & Pagliaro, A. (2025). An Introduction to Machine Learning Methods for Fraud Detection. *Applied Sciences, 15*(21), 11787. https://doi.org/10.3390/app152111787

Corsi, C., Di Berardino, D., & Di Cimbrini, T. (2015). Beneish M-score and detection of earnings managements in Italian SMEs. *Ratio Mathematica, 28*, 65-83. https://doi.org/10.23755/rm.v28i1.28

Craja, P., Kim, A., & Lessmann, S. (2020). Deep learning for detecting financial statement fraud. *Decision Support Systems, 139*, 113421. https://doi.org/10.1016/j.dss.2020.113421

Criminal Procedure Code (2011). Official Gazette of the Republic of Serbia, Nos. 72/11 of 28 September 2011, 101/11 of 30 December 2011, 121/12 of 24 December 2012, 32/13 of 8 April 2013, 45/13 of 22 May 2013, 55/14 of 23 May 2014, 35/19 of 21 May 2019 and 27/21 of 24 March 2021 (CC). Available at: https://propisi.pravno-informacioni-sistem.rs/article?productId=1657&articleId=54814

Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (2011). Predicting material accounting misstatements. *Contemporary accounting research, 28*(1), 17-82. https://doi.org/10.1111/j.1911-3846.2010.01041.x

Dichev, I., Graham, J., Harvey, C., & Rajgopal, S. (2013). Earnings quality: Evidence from the field. *Journal of Accounting and Economics, 56*(2-3), Supplement 1, 1–33. https://doi.org/10.1016/j.jacceco.2013.05.004

Dimitrijević, D. S., Obradović, V. M., & Milutinović, S. (2018). Indicators of fraud in financial reporting in the Republic of Serbia. *Teme, 42*(4), 1319-1338. https://doi.org/10.22190/TEME1804319D

Dimitrijević, D., Milutinović, S., & Stanković, P. (2024). Determinants of the occurrence of financial distress in medium-sized and big public jointstock companies. *Economic Horizons/Ekonomski Horizonti, 26*(3), 301-319. https://doi.org/10.5937/ekonhor2403301D

Dimitrijević, D., Stanković, P., & Vržina, S. (2024). Warnings of financial fraud in travel agencies in the Republic of Serbia during the COVID-19 pandemic. *Menadžment u hotelijerstvu i turizmu, 12*(2), 75-88. https://doi.org/10.5937/menhottur2400003D

Dyck, A., Morse, A., & Zingales, L. (2024). How pervasive is corporate fraud?. *Review of Accounting Studies, 29*(1), 736-769. https://doi.org/10.1007/s11142-022-09738-5

Frank, J. J., Jansen, D., & Carey, M. (2011). Financial Statement Fraud: Revenue and Receivables. Chapter 22, In: Golden, T. W., Skalak, S. L., Clayton, M. M., & Pill, J. S. (Eds). *A Guide to Forensic Accounting Investigation*, 2nd Edition (pp. 433-466). John Wiley & Sons, Inc., Hoboken, New Jersey.

Fülbier, R. U., & Sellhorn, T. (2023). Understanding and improving the language of business: how accounting and corporate reporting research can better serve business and society. *Journal of Business Economics, 93*, 1089-1124. https://doi.org/10.1007/s11573-023-01158-4

Healy, P. M., & Wahlen, J. M. (1999). A review of the earnings management literature and its implications for standard setting. *Accounting Horizons, 13*(4), 365-383. https://doi.org/10.2308/acch.1999.13.4.365

Henry, E., Elizabeth, A. G., Brad, R., & Timothy, L. (2012). The Role of Related Party Transactions in Fraudulent Financial Reporting. *Journal of Forensic & Investigative Accounting, 4*(1), 186-213. Available at: https://www.nacva.com/content.asp?admin=Y&contentid=469#7

Jackson, A. B. (2018). Discretionary accruals: earnings management. or not?. *Abacus, 54*(2), 136-153. https://doi.org/10.1111/abac.12117

Janger, E. J. (2022). Aggregation and Abuse: Mass Torts in Bankruptcy. *Fordham Law Review, 91*(2), 361-383. Available at: https://ir.lawnet.fordham.edu/flr/vol91/iss2/3

Kanapickienė, R., & Grundienė, Ž. (2015). The model of fraud detection in financial statements by means of financial ratios. *Procedia-Social and Behavioral Sciences, 213*, 321-327. https://doi.org/10.1016/j.sbspro.2015.11.545

Knežević, S., Špiler, M., Milašinović, M., Mitrović, A., Milojević, S., & Travica, J. (2021). Using Beneish M-Score and Altman Z-Score models to detect financial fraud and company failure. *Tekstilna industrija, 69*(4), 20-29. https://doi.org/10.5937/tekstind2104020K

Leach, R. (2007). Do firms manage their earnings prior to filing for bankruptcy?. *Academy of Accounting and Financial Studies Journal, 11*(3), 125-137. Available at: https://www.abacademies.org/articles/aafsjvol1132007.pdf

Lev, B., & Thiagarajan, S. R. (1993). Fundamental information analysis. *Journal of Accounting Research, 31*(2), 190-215. https://doi.org/10.2307/2491270

Lo, A. W., Wong, R. M., & Firth, M. (2010). Can corporate governance deter management from manipulating earnings? Evidence from related-party sales transactions in China. *Journal of Corporate Finance, 16*(2), 225-235. https://doi.org/10.1016/j.jcorpfin.2009.11.002

Malinić, D., & Ribić, M. (2025). Identifying indicators of fraudulent financial reporting under conditions of institutional opacity: the relevance of the Beneish model. In Malinić, D., & Vučković Milutinović, S. (Eds.), *Conference Proceedings of the Second Conference on Forensic Accounting "Contemporary Forensic Accounting Trends in Combating Financial Fraud: Global and National Perspectives",* Belgrade, 3-4 October (pp. 1-22). Belgrade: Faculty of Economics and Business & Centre for Forensic Accounting.

Marchini, P. L., Mazza, T., & Medioli, A. (2018). The impact of related party transactions on earnings management: Some insights from the Italian context. *Journal of Management and Governance, 22*(4), 981-1014. https://doi.org/10.1007/s10997-018-9415-y

Mavengere, K. (2015). Predicting Corporate Bankruptcy and Earnings Manipulation Using the Altman Z-Score and Beneish M Score. The Case of Z Manufacturing Firm in Zimbabwe. *International Journal of Management Sciences and Business Research, 4*(10), 8-14. https://ssrn.com/abstract=2739676

Mehta, A., & Bhavani, G. (2017). Application of forensic tools to detect fraud: The case of Toshiba. *Journal of Forensic and Investigative Accounting, 9*(1), 692-710.

Özari, Ç., Can, E. N., & Demirkale, Ö. (2025). Financial Fraud Detection with Altman Z-Score and Beneish M-Score via Random Forest: Verified by Borsa Istanbul Fines (2018–2022). *Sage Open, 15*(4). https://doi.org/10.1177/21582440251386174

Perols, J. L., & Lougee, B. A. (2010). The relation between earnings management and financial statement fraud. *Advances in Accounting, 27*(1), 39-53. https://doi.org/10.1016/j.adiac.2010.10.004

Ramírez-Orrelliana, A., Martínez-Romero, M. J., & Marino-Garrido, T. (2017). Measuring fraud and earnings management by a case of study: Evidence from an international family business. *European Journal of Family Business, 7*(1-2), 41-53. https://doi.org/10.1016/j.ejfb.2017.10.001

Repousis, S. (2016). Using Beneish model to detect corporate financial statement fraud in Greece. *Journal of Financial Crime, 23*(4), 1063–1073. https://doi.org/10.1108/JFC-11-2014-0055

Rosner, R. L. (2003). Earnings Manipulation in Failing Firms. *Contemporary Accounting Research, 20*(2), 361–408. https://doi.org/10.1506/8EVN-9KRB-3AE4-EE81

Sabău, A.-I., Mare, C., & Safta, I. L. (2021). A Statistical Model of Fraud Risk in Financial Statements. Case for Romania Companies. *Risks, 9*(6), 116. https://doi.org/10.3390/risks9060116

Schilit, H. M., Perler, J., & Engelhart, Y. (2018). *Financial Shenanigans. How to Detect Accounting Gimmicks and Fraud in Financial Reports*. New York: McGraw-Hill.

Škarić-Jovanović, K., & Spasić, D. (2022). *Specijalni bilansi [Special Purpose Financial Statements]*. Beograd: CID Ekonomskog fakulteta Beograd.

Steingen, L., & Löw, E. (2025). Using Machine Learning to Detect Financial Statement Fraud: A Cross-Country Analysis Applied to Wirecard AG. *Journal of Risk and Financial Management, 18*(11), 605. https://doi.org/10.3390/jrfm18110605

Stolowy, H., & Breton, G. (2004). Accounts Manipulation: A Literature Review and Proposed Conceptual Framework. *Review of Accounting and Finance, 3*(1), 5-92. https://doi.org/10.1108/eb043395

Stubben, S. (2010). Discretionary revenues as a measure of earnings management. *The Accounting Review, 85*(2), 695-717. https://doi.org/10.2308/accr.2010.85.2.695

Svoboda, J., Berková, I., Pražáková, J., & Vejsadová Dryjová, M. (2025). Relationships Between the Beneish M-Score and Bankruptcy Models: Insights from Financial Models in Czech Manufacturing Firms. *Zbornik radova Ekonomskog fakulteta u Rijeci: časopis za ekonomsku teoriju i praksu/ Proceedings of Rijeka Faculty of Economics: Journal of Economics and Business, 43*(2), 465-484. https://doi.org/10.18045/zbefri.2025.2.7

Sylwestrzak, M. (2022). Application of the Beneish Model on the Warsaw Stock Exchange. *Journal of Banking and Financial Economics, 18*(2), 5-16. https://doi.org/10.7172/2353-6845.jbfe.2022.2.1

Tarjo, & Herawati, N. (2015). Application of Beneish M-score models and data mining to detect financial fraud. *Procedia-Social and Behavioral Sciences, 211*, 924-930. https://doi.org/10.1016/j.sbspro.2015.11.122

Teixeira, J. F., & Rodrigues, L. L. (2022). Earnings management: a bibliometric analysis. International *Journal of Accounting & Information Management, 30*(5), 664-683. https://doi.org/10.1108/IJAIM-12-2021-0259

Velte, P. (2023). The link between corporate governance and corporate financial misconduct. A review of archival studies and implications for future research. *Management Review Quarterly, 73*(1), 353-411. https://doi.org/10.1007/s11301-021-00244-7

Wang, M., Zhang, X., & Han, X. (2025). AI Driven Systems for Improving Accounting Accuracy Fraud Detection and Financial Transparency. *Frontiers in Artificial Intelligence Research, 2*(3), 403-421. https://doi.org/10.71465/fair398

Yiannoulis, Y., Vortelinos, D., & Passas, I. (2025). Exploring Audit Opinions: A Deep Dive into Ratios and Fraud Variables in the Athens Exchange. *Accounting and Auditing, 1*(1), 3. https://doi.org/10.3390/accountaudit1010003

Yue, D., Wu, X., Shen, N., & Chu, C. H. (2009). Logistic regression for detecting fraudulent financial statement of listed companies in China. In *2009 International Conference on Artificial Intelligence and Computational Intelligence* (Vol. 2, pp. 104-108). IEEE. https://doi.org/10.1109/AICI.2009.421

ВЕЗА ИЗМЕЂУ ПРЕВАРНОГ ФИНАНСИЈСКОГ ИЗВЕШТАВАЊА И ПОСЛОВНОГ НЕУСПЕХА – СЛУЧАЈ ПРЕДУЗЕЋА У СТЕЧАЈУ У СРБИЈИ

Дејан Спасић[1,2], Јована Стојановић[3]

[1]Универзитет у Београду, Економски факултет, Београд, Србија
[2]Универзитет у Нишу, Економски факултет, Ниш, Србија
[3]Универзитет у Нишу, Иновациони центар, Ниш, Србија

Резиме

Компаније које послују у условима кризе често се суочавају са нарушеном финансијском стабилношћу услед пада реализације, флуктуације менаџерских и извршних структура запослених, као и погоршања кључних рачуноводствених индикатора. У таквом окружењу расте подстицај да се преварним финансијским извештавањем створи привид већих добитака, компактнијих новчаних токова и пер-

зистентнијих вредности позиција финансијских извештаја него што то економска реалност оправдава. Након обелодањивања манипулација у финансијским извештајима, значајан број компанија одлази у стечај. Последице се тада огледају у губитку уложеног капитала: власници су први на удару, а финансијски терет преноси се и на кредиторе, запослене и државу. Чак и када опстану, опоравак таквих компанија је често дуготрајан и отежан, будући да финансијске преваре не доносе само високе санкције, већ и нарушавају репутацију, подривају поверење инвеститора, повећавају трошкове капитала и доводе до пооштравања критеријума профитабилности.

Ефикасно спречавање манипулација може бити оснажено применом савремених аналитичких алата, од појединачних и композитних модела до решења заснованих на вештачкој интелигенцији. У том контексту, овај рад истражује применљивост модела Beneish M-Score са осам варијабли на узорку 48 великих и средњих компанија над којима је у Републици Србији у периоду од 2017. до 2024. године покренут стечајни поступак. Циљ истраживања је идентификовање потенцијалних упозоравајућих сигнала кроз издвајање позиција финансијских извештаја које су испољавале неуобичајена кретања у годинама које су претходиле отварању стечајног поступка. Резултати указују да је 20,83% узрокованих компанија класификовано као потенцијални манипулатор у периоду финансијске кризе. Уочени ризик преварног финансијског извештавања нарочито је повезан са нарушавањем односа између потраживања и прихода, са индикатором који указује на проблематичне обрасце у вези са нематеријалном имовином, као и са бржим растом административних трошкова у односу на раст прихода од продаје. Налази додатно потврђују потребу за појачаном анализом обрачунских позиција које одражавају неусаглашено признавање прихода и расхода у односу на одговарајуће новчане приливе и одливе.

Уважавајући раније истакнута ограничења модела Beneish M-Score, евидентна је потреба за развојем приступа који ће поузданије одражавати специфичности српске економије. Стога би будућа истраживања требало усмерити ка развоју и емпиријском тестирању модела прилагођених домаћим условима, са посебним фокусом на компаније у финансијским неприликама, када су подстицаји за изобличавање приказа о зарађивачкој способности и финансијском положају израженији. Примена таквих модела могла би унапредити капацитете стручњака рачуноводственог, ревизијског и истражног профила за идентификовање ризичних образаца, чиме би се макар ублажиле негативне последице све сложенијих и софистициранијих превара по благостање великог броја корисника финансијских извештаја.