

INNOVATIVE APPROACH TO IDENTIFYING INCOME MANIPULATION FROM FRAUDULENT FINANCIAL SITUATIONS USING THE BENEISH M-SCORE MODEL

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Abstract

The use of statistical methods in the process of detecting financial fraud, specifically fraudulent financial reporting that includes creative accounting techniques, has occupied and continues to occupy an important place in scientific studies over the last few decades, but there is still plenty of room for empirical evidence in this area of research. The study's goal is to use the Beneish (1999) statistical model, both in its original formula (abbreviated MSCORE) and in a modified formula adapted by the author (abbreviated MSCOREM), to empirically validate the two models' ability to detect potential fraudulent financial reporting caused by the use of creative accounting techniques (undisclosed) at the level of a pilot sample of Romanian enterprises.

Keywords: BENEISH model, MSCORE, incomes, financial fraud, creative accounting.

JEL Classification: M41.

1. Introduction

Financial fraud has generated and continues to sustain interest in specialized studies concerning the definition and origins of the concept, the determining factors, the schemes under which it manifests itself, the implications it can determine, the measures of prevention, disclosure, combating, and investigation, as well as the legislative guidelines undertaken or that can be undertaken to diminish this phenomenon. This is because *financial fraud* is a problem that is constantly at the forefront of national and international affairs, with resonance in economic, political, social, religious, and other contexts. There has always been and undoubtedly will continue to be financial fraud, and it is impossible to predict its exact magnitude.

The concerns regarding the protection of the European Union's (EU) financial interests against fraud are currently reflected at the legislative level through the implementation of Directive (EU) 2017/137 on the fight against fraud affecting the Union's financial interests by means of criminal law (PIF Directive), which was adopted as part of the Commission's Anti-Fraud Strategy to strengthen the protection of the EU budget. The aim of the directive was to increase the level of protection of the EU budget by establishing common definitions for crimes against the EU's financial interests. EU law defines fraud as an intentional

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violation that harms or could harm the EU budget. All EU Member States have transposed the PIF Directive, although there are a number of differences in the extent to which it has been implemented and the types of measures adopted in practice.

The documentary research focused on verifying the existence of specific patterns of financial fraud involving European funds, using reports issued by control departments within the European Commission to extract relevant information on the extent of the problem affecting EU funds. An important source of information on fraud affecting EU funding programs, which also provides figures on the levels of fraud reported by Member States, are the Commission's annual reports on "the protection of the Union's financial interests" ("PIF Report"), which are submitted to the Council and the European Parliament. Based on an analysis of the PIF reports, cases of fraud related to EU expenditure accounted for an estimated 0.27% of total payments for the period 2013-2022. This figure, known as the "fraud detection rate" (FDR), measures the financial impact of detected fraud as a proportion of total revenue or expenditure and indicates differences in fraud across all areas of EU expenditure. However, we note that, in the opinion of the European Court of Auditors, "the Commission does not have comprehensive information on the extent, nature, and causes of fraud related to EU expenditure."

In January 2024, the European Commission's Centre for Strategy and Evaluation Services (CSES) published a report on identifying patterns of fraud involving EU funds under shared management – similarities and differences between Member States. The report was based on a study carried out in the second half of 2023 and involved desk research to examine existing material, a program of interviews with the European Commission, the European Court of Auditors, and other EU contacts, as well as national management authorities. In terms of the periods covered, the research focused on the 2014-2022 programming period. The value of fraud detected fluctuates, reaching a peak in 2017 (€527.4 million) and a low in 2020 (€293.4 million). From the integrated analysis of the studies and reports submitted to the Commission, the Council, and the European Parliament for the period 2014-2022, the following types and mechanisms of fraud in public procurement procedures related to EU funds were identified (Table 1.):

Table 1. Types and mechanisms of fraud in public procurement procedures related to EU funds

Types	Mechanisms of fraud
Amending documentation with the direct purpose of meeting eligibility criteria or	-falsification of documentation or implementation of collusive practices (single tenderer practice)

Types	Mechanisms of fraud
intentionally requesting reimbursement of ineligible expenses	-non-compliance with eligibility criteria through unlawful modification of documentation -violation of public procurement contract award rules
Failure to deliver goods or provide services	-European funds are collected by beneficiaries but the goods/services are not actually delivered/provided - falsification of documentation or implementation of collusive practices
Falsification of documentation during project implementation	- falsification of documentation (false or inaccurate invoices regarding financial values) - falsification of signatures or data in invoices (false accounts, missing or incorrect accounts)
Conflict of interest	Existing conflict of interest, but not declared or addressed appropriately
Illegal or false subcontracting	Implementation of collusive practices, through subcontracting to other beneficiaries (including those in conflict of interest), with the intentional violation of EU and national procedures
Tax overcharging	Overvalued invoices generating undue reimbursements from European funds for purchases with lower actual costs
Double financing	Receiving funds from multiple sponsors for the same project, a fraud that is carried out without the sponsors' knowledge.
Ethics and integrity (plagiarism)	Copying a project created by others and presenting it as one's own creation, on the basis of which European funds are collected.

Source: own processing

To discern the extent of fraud worldwide, we analyzed reports and studies published by the Association of Certified Fraud Examiners (ACFE) in the US, the world's largest anti-fraud organization and leading provider of anti-fraud training and education.

Since 1996, the Association of Certified Fraud Examiners (ACFE) in the United States has been conducting annual studies on financial fraud and professional misconduct. Since the launch of the first Report to the Nations in 1996, the ACFE has analyzed more than 20,000 cases of fraud in over 130

countries, with each study exploring the mechanisms used by perpetrators of financial fraud. The latest Report to the Nations on Financial Fraud (ACFE, 2023) shows that, following a study conducted in 133 countries, 2,110 cases of financial fraud were identified, causing losses of over USD 3.6 trillion at the organizational level.

According to ACFE, professional fraud¹ is probably the most expensive and common form of financial crime in the world. There are two key reasons why this type of crime is so widespread. The first is that any organization with employees must, to some extent, entrust them with access to or control over its assets, whether that means keeping accounting records, managing bank accounts, protecting inventory, etc. It is precisely this trust that makes organizations vulnerable to financial fraud, because all fraud is essentially based on breaches of trust. The second reason why financial fraud is so costly and common is simply that there are so many people in a position to commit these crimes.

According to the latest studies published by the World Bank, the global workforce consists of over 3.6 billion people, the vast majority of whom will never steal from or abuse the trust of their employers. But even if only a small percentage of these individuals do so, the result is millions of financial fraud schemes every year. The ACFE found that, from 1996 to 2023, on average, only 5% of people who commit fraud had been convicted of fraud-related crimes before. So, most people who commit fraud don't have a history of fraud convictions.

From analytical studies published by ACFE (1996, 2012, 2017, 2021, 2023), it appears that owners and managers are involved in about a quarter of all fraud cases, but when they do, they defraud significantly larger amounts than lower-level employees. Research suggests that although men are the most frequent perpetrators, women appear as perpetrators in approximately 30-35% of all cases. In most cases, a perpetrator does not act alone; however, when fraudsters work in collusion, the losses to the victim organization increase more than fourfold. The ACFE (2023) believes that the following profile summarizes the characteristics of the typical fraud perpetrator: male, middle-aged to retirement age, employed by the company for five years or more, with no criminal charges or convictions, highly educated, often with accounting training, in a senior management or executive position, and acting alone.

Furthermore, with the shift to digital payments, remote working environments, and technology-driven work arrangements, the schemes and methods that fraudsters use to commit financial fraud remain consistent over time. A taxonomy of these schemes is provided annually by the ACFE in its Financial Fraud and Professional Misconduct Classification System, also known

¹ Professional or occupational fraud is officially defined in the US as the use of one's occupation for personal gain through the misuse or deliberate misapplication of the resources or assets of the employing organization.

as the Fraud Tree. A model structure of the most well-known frauds in financial and accounting expertise case studies includes the following main categories of fraud: (a) fraudulent financial reporting; (b) misappropriation of assets; and (3) acts of corruption.

Asset misappropriation, which involves the stealing or misuse of employer resources by an employee, although the most common, with 86% of cases falling into this category, tends to cause the least loss, averaging \$100,000 per case (ACFE, 2022).

In contrast, financial reporting fraud schemes, in which the perpetrator intentionally causes a significant misstatement or omission in the organization's financial statements, are the least common category (9% of schemes) but the most expensive (\$593,000). The third category, corruption, falls in the middle in terms of both frequency and losses. These schemes occur in 50% of cases and cause an average loss of \$150,000. Analysis of the 2023 Report to Nations (ACFE, 2023) it appears that acts of corruption and fraudulent financial reporting are the most serious threats (50% and 86% of the total number of financial frauds, respectively), mainly because they are associated with other crimes such as embezzlement, asset stealing, or tax fraud.

The main methods of concealing fraud in financial statements include:

- fraudulent physical documents created, altered, or destroyed (on average over 50%);
- fraudulent accounting records created, altered, or deleted (on average over 25%);
- deleted transactions in the accounting system, altered or deleted documents or electronic files (on average over 19%).

In the case of asset misappropriation, the most commonly used method is also the use of fraudulent physical documents created or altered (on average over 50%), transactions altered or deleted in the accounting system (on average over 25%), and electronic documents or files deleted (on average over 24%).

Sensing the existence of financial fraud on a permanent basis, the research seeks to investigate the possibilities of revealing it via the use of financial – accounting information. The scientific study is conceptually orientated towards this field of knowledge of financial fraud, and experimentally, it aims to apply the theoretical information gained in the building of statistical models that enable the discovery of fraud in financial-accounting synthesis reports. The statistical model developed by Beneish (1999) was chosen because it was recognized in the international specialized literature for its ability to detect the presence of creative accounting in fraudulent financial situations, with its findings later confirmed in the case of the Enron company bankruptcy.

Students at Cornell University (USA) employed this model in 1999 and accurately reported the existence of potential accounting manipulation techniques at Enron Corporation; however, these were only shown to be fraudulent in 2001 [Beneish M. D., Nichols C., (2005)].

The model's foundation is the examination of financial ratios that are computed using accounting data from business financial statements and their synthesis into a scoring function. The study by Shakouri [Shakouri et al., (2021)] is noteworthy in this respect, since it found that 73% of false financial statements were successfully detected.

Five or eight components (parameters or indicators) can be used to apply the Beneish model. After comparing them, Shakouri et al. (2021) concluded that the 5-parameter model outperforms the 8-parameter model. Inspired by Shakouri et al.'s qualitative investigation, this study used the five-element Beneish model.

The review of the specialized literature covers the research incentives dedicated to this topic; however, while the phenomenon of creative accounting in relation to financial fraud is studied globally, we believe that there is sufficient space for research focused on sectors of activity, regions, countries, and so on. Noting that most recent research has focused on the causes of creative accounting (on the link between manipulation and bankruptcy and the general selection of appropriate detection models), we consider that the research study conducted is timely because it seeks the link between creative accounting and fraud through the manipulation of income in financial statements and by creating a new statistical model, abbreviated MSCOREM, based on internationally recognized validity (MSCORE).

Three companies, two of which are listed on the Bucharest Stock Exchange (BvB), were selected as a pilot sample for the data topic of the applied research. Additionally, data about the presence of fraud activities (corruption and/or tax evasion) involving these companies was gathered from public sources (communications of the Prosecutor General's Office and the National Anticorruption Directorate).

In order to choose the best sample selection technique, we used data from the companies' financial statements. The data came from the Ministry of Public Finance's public database, which was taken over by lista.firme.ro, as well as financial reports released by companies listed on the stock exchange on the BvB's official website. We selected two BvB listed firms for research, and we found that one of them (abbreviated SX) had been cheated in 2021 based on public information as well. In order to compute the progression of the indicators in the subsequent fraud period, the years 2021 and 2022 were selected as the analysis period for this company.

The second pilot firm (abbreviated SY) was likewise selected from the group of companies registered on the BvB, but no information about the presence of a financial scam is known to the public. The third business (abbreviated SZ) was selected since it is not publicly known to be involved in financial fraud schemes and is not listed on the stock exchange. The years 2021 and 2022 were also selected as the analysis period for the last two companies.

2. Literature review

The intentional falsification of financial statements to deceive their users, frequently for individual or corporate benefit, is known as **financial fraud**. It can manifest itself in a number of ways, such as by inflating assets, understating liabilities or spending, or manipulating revenue [Singleton & Singleton, (2010)]. Organizations must establish strong internal control mechanisms, encourage an integrity-focused culture, and guarantee efficient board of director and independent auditor monitoring in order to prevent these types of financial fraud. According to recent research, using artificial intelligence and advanced data analytics technologies can greatly enhance the capacity to identify financial fraud [Brazel et al., (2023)].

One of the most prevalent types of financial fraud and financial statement deception is revenue manipulation. In order to give a more positive impression of the company's financial success, it entails the early or false recognition of revenue. A research by Dechow [Dechow et al. (2011)] found that about 60% of financial fraud instances that are discovered involve revenue manipulation. Creating fake transactions, recording sales before the transaction is actually completed, or recognizing revenue from long-term contracts before the recognition conditions are satisfied are just a few examples of this activity. This approach can have serious repercussions, including inflating profits and deceiving investors about the company's financial future.

Premature revenue recognition is a fraudulent accounting practice in which revenue is recorded before all of the conditions for recognition are met under applicable accounting standards, such as *IFRS 15 "Revenue from Contracts with Customers"* or *ASC 606 "Revenue Recognition from Contracts with Customers."* This financial manipulation approach can have a substantial impact on how investors and other stakeholders see a company's financial performance. According to research, one of the most common types of financial fraud is premature revenue recognition, which accounts for nearly 60% of reported occurrences of financial statement manipulation [Dechow et al., (2011)].

The principles of revenue recognition, as set out in international accounting standards, are based on three fundamental criteria:

- a. transfer of control over goods or services to the customer,
- b. probability of receiving the counter value,
- c. probability to really measure the income value.

These principles aim to promote fair and transparent financial reporting. However, many corporations modify these parameters in order to create a more favorable financial image [Penman & Zhang, (2002)].

Depending on the type of transactions and the nature of the firm, there are several ways that premature revenue recognition might occur. An electronics manufacturer, for instance, may record income for orders received in December even though the actual delivery is scheduled for January of the following year.

The transfer of control principle is broken by this approach, which also has the potential to significantly exaggerate revenue in the current period. Such tactics are especially prevalent during year-end reporting periods, when there is more pressure to reach financial targets, according to empirical investigations [Carslaw, (1988)].

Another area that is susceptible to manipulation is sales with a right of return. For instance, a book distributor may record all sales proceeds to bookshops while neglecting a substantial return history and any clauses pertaining to the right of return in the contract. This method can result in a large overstatement of income and is against the probability of collection principle. Research has indicated that companies with generous return policies are more likely to use this tactic to manipulate revenue [Altamuro et al., (2005)].

Premature revenue recognition in services can occur when all contract revenue is recorded at contract signing, even though the services will be rendered across a number of time periods. The transfer of control principle is broken by this technique, which also has the potential to seriously skew financial results. Service companies, particularly those with intricate or protracted contracts, have been found to be more vulnerable to this kind of manipulation [Schilit & Perler, (2010)]. Multi-component transactions are more susceptible to manipulation. For instance, a software maker may fail to appropriately allocate the revenue to each component when they recognise all revenue from the sale of a license that also includes implementation and maintenance services. This approach may cause long-term profitability to be distorted and revenue recognition to occur more quickly. According to studies, this kind of manipulation is more common in sectors with intricate goods and related services.

Premature revenue recognition might also happen in contingent sales. For instance, a pharmaceutical business may report revenue for medications that are sent to distributors even though they have not yet received final regulatory approval. This approach can put the business at serious danger and disregards the probability of collection concept. Studies have indicated that businesses with strict regulations, such as pharmaceuticals and medical equipment, are particularly vulnerable to this kind of manipulation [Healy & Wahlen, (1999)].

A number of strategies can be used to accomplish premature revenue recognition, such as early accounting period closure, partial deliveries, advance billing, document manipulation, and client pressure. These methods can be applied alone or in combination, to influence financial outcomes. According to studies, businesses that use these kinds of tactics typically have less effective corporate governance and poorer internal control mechanisms [Beasley et al., (2000)].

Premature revenue recognition can have a substantial influence on a company's reported financial situation, exposing it to a variety of serious hazards. This deceptive behavior not only distorts short-term financial success, but it can also have long-term effects on the company's legitimacy and stability.

The most evident result of premature revenue recognition is an overstatement of revenues and earnings in the current quarter. This can paint an inaccurate picture of a company's financial performance, deceiving investors, creditors, and other stakeholders. Empirical research have found that organizations who participate in such activities exaggerate their revenues by up to 20% during the impacted periods [Dechow et al., (2011)].

This overvaluation can lead to erroneous investment decisions and an inefficient allocation of resources within the economy.

One major effect of early revenue recognition is the *undermining of the expense recognition principle*. Regardless of when they are actually received or paid, this core idea of financial accounting makes sure that revenues and expenses are documented in the period in which they are earned or spent. In addition to jeopardizing the comparability of financial statements across periods and firms, breaking this rule may result in an erroneous depiction of the company's actual financial performance.

Another important effect of early revenue recognition is the distortion of financial performance metrics, such as *revenue growth rate*. Analysts and investors frequently use these metrics to evaluate a company's performance and prospects for expansion. Inappropriate investment choices and an overestimation of the company's worth might result from an artificially inflated revenue growth rate. According to research, businesses that recognize revenue too soon typically have higher stock price volatility and a higher long-term cost of capital.

One of the most severe types of financial fraud is ***fictitious income***, which is the willful fabrication of transactions or a major overstatement of already-existing transactions in order to artificially increase a company's sales. According to Zack [Zack (2013)], "Investors, regulators, and the general public continue to have serious concerns about financial statement fraud. Developing successful detection and prevention efforts requires an understanding of the techniques utilized to generate fake income".

The use of advanced analytical techniques to detect abnormalities in financial data is a contemporary method of detecting probable earnings manipulation. To uncover suspicious trends in financial data, tools such as large-scale data analysis, machine learning, and artificial intelligence may be used. Recent research has demonstrated that employing these advanced tools can considerably increase the detection rate of financial manipulation [Gepp et al., (2018)].

3. Research methodology

The Beneish MSCORE model, which is a methodical application of the investigational concepts in American forensic accounting, provides the study's foundation. Furthermore, a variety of research techniques were employed, including comparative analysis, inductive and deductive reasoning, a systematic

study of the specialized literature, and a quantitative and qualitative method of empirical verification of the Beneish model with five parameters.

Using innovative accounting approaches that are not revealed to consumers, this method especially uses a set of economic-financial indicators that can determine the extent to which fraud may damage a company's economic performance. The economic-financial indicators are derived from the financial-accounting data found in the pilot sample companies' financial statements. Following their analysis, an M score, or MSCORE, was established, indicating the degree to which profits and revenues have been manipulated through unreported creative accounting methods.

Each of the Beneish model's economic-financial indicators has its own set of guidelines for identifying potential fraud risk, or "fraud indicator."

According to Beneish's (1999) research, he established the elements of the model and the limits within which a number of five and eight economic-financial indicators fall, calculated at the level of two consecutive years (t – current year and $t-1$ the previous year), in order to reveal whether or not the financial statements of the companies studied are manipulated through creative accounting techniques, or if there are indications of the existence of fraud.

The elements of the Beneish model with five parameters, which are the subject of the research study, namely the economic and financial indicators taken into account and the value limits on the basis of which the existence of fraudulent financial situations (manipulation and non-manipulation) was analyzed, are presented in Table 2:

Indicator	Calculation formula:	Limited values:	
		manipulated value	unmanipulated value
Sales index relative to uncollected receivables / Days Sales in Receivables Index (DSRI)	$(\text{Customers balance } (t) / \text{Sales}(t)) (\text{Customers balance } (t-1) / \text{Sales } (t-1)) = \text{Uncollected receivables } (t) / \text{Turnover } (t) (\text{Uncollected receivables } (t-1) / \text{Turnover } (t-1))$	1.465	1.031
Gross margin index (GMI)	$(\text{Gross margin } (t-1) / \text{Sales } (t-1)) (\text{Gross margin } (t) / \text{Sales } (t))$	1.193	1.014
Assets quality index (AQI)	$\text{Current assets } (t) + \text{Net fixed assets } (t) / (\text{Total assets } (t)) (\text{Current assets } (t-1) + \text{Net fixed assets } (t-1) / (\text{Total assets } (t-1)))$	1.254	1.039

Indicator	Calculation formula:	Limited values:	
		manipulated value	unmanipulated value
	$(t-1) + \text{Net fixed assets } (t-1) / (\text{Total assets } (t-1))$		
Sales index (SGI)	$\text{Sales } (t) / \text{Sales } (t-1) \Rightarrow \text{Turnover } (t) / \text{Turnover } (t-1)$	1.607	1.134
Total assets index/ Depreciation index (DEPI)	$[\Delta (\text{Working capital} - \text{Cash} - \text{Taxes}) - \text{Depreciation} - \text{Provisions}] / \text{Total assets}$	0.031	0.018

Source: own processing after Beneish (1999) and Skousen and al. (2009)

The 5-parameter Beneish model, including the five economic-financial indicators, presented in table no. 1, is based on the following equation, called **MSCOR (M)**:

$$M = -6.065 + 0.823 \cdot \text{DSRI} + 0.906 \cdot \text{GMI} + 0.593 \cdot \text{AQI} + 0.717 \cdot \text{SGI} + 0.107 \cdot \text{IDEPI} \quad (1)$$

The Beneish model's basic working hypothesis is that there will be NO manipulative manipulations in the financial accounts being analyzed.

The validity of this statement depends on the value **MSCORE = M = (-2.21)**, which is the limit between financial statement manipulation and non-manipulation, which is determined by applying equation (1) and evaluating the outcome in accordance with the classification rule within the Beneish restriction.

✓ If the resulting MSCORE is below this value, it means that no manipulation of the financial statements is reported during the analyzed period.

✓ If MSCORE is greater than (-2.21), probable manipulations in the financial statements are indicated.

4. The working methodology applied to capitalize on the analysis performed

The author suggested a different method for Beneish's research, which would involve changing equation (1) with the five parameters of the Beneish model by substituting the leverage index LVGI for the total asset index DEPI from the MSCORE model.

We emphasize that the leverage index, also known as the asset debt ratio, was validated in the statistical study as the most valued by accounting

professionals for its capacity to reflect probable fraud in financial statements through income manipulation.

The LVGI is a company's ratio of total liabilities to total assets, with the following limit values proposed by Beneish in the 8-parameter model: The altered value equals 1.111, and the unmanipulated value = 0.014.

The LVGI index, proposed by the author to modify equation (1) of the 5-parameter Beneish model, known as the leverage effect or asset debt ratio, was also empirically studied by Skousen et al. (2009) to analyze the efficiency of the fraud theory initiated by Cressey (1953), corroborated with the adoption of SAS No. 99² for detecting fraud in financial statements. We determined that leverage is also relevant for this research because the findings of the previously mentioned study demonstrated that it is an indicator that makes it easier to spot financial statement fraud.

Under these conditions, the second **equation** modified according to the Beneish model, as **suggested by the authors**, has the following score formula represented by MSCOREM.

(MM):

$$MM = -6.065 + 0.823 \cdot DSRI + 0.906 \cdot GMI + 0.593 \cdot AQI + 0.717 \cdot SGI - 0.327 \cdot LVGI \quad (2)$$

The economic-financial indicators (abbreviated form) and the fraudulent and non-fraudulent value limitations, as determined by Beneish in the 8-parameter model, are shown synthetically in table no. 3 along with the individual values of the elements of equation (2).

Table nr. 3. Limited values for fraud MSCORE index

		DSRI	GMI	AQI	SGI	DEPI	LVGI	MSCORE
1	Fraud	≥ 1.465	≥ 1.193	≥ 1.254	≥ 1.601	≥ 1.077	≥ 1.111	> -2.21
2	NON-fraud	< 1.031	< 1.014	< 1.039	< 1.134	< 0.018	< 0.014	< -2.21

Source: own processing after Beneish (1999) and Skousen and al. (2009)

In table no. 2, exceeding the limit values on line 1 indicates a signal (red flags) about the presence of fraud. Depending on the situation, each indication can provide a different signal.

As can be seen, reporting fraud and non-fraud at the level of one or more individual indicators of the 5-parameter Beneish model provides a better localization of the problem of financial – accounting data manipulation. Each of these indicators is characterized by a calculation formula, previously specified,

² The Auditor's Responsibilities Concerning Fraud in an Audit of Financial Statements (ISA 240) outlines this particular element. The SAS 99 auditing standard defines external pressure as when the management of the organization is under pressure from outside sources to achieve its goals.

which suggests which elements of the financial statements could be manipulated, respectively:

- an extraordinary increase in DSRI shows a reasonable chance of income overstatement as shown by an increase in net receivables (changes in commercial lending policy);
- a significant decrease in GMI denotes a concern regarding compliance with the principle of continuity of operating activity, in which case the financial statements may be manipulated in order to hide the situation from investors, creditors or employees;
- an asset impairment reflected by the evolution of AQI may signal the application of accounting policies based on professional judgment, although some assets do not meet the depreciation conditions;
- an increase in SGI does not usually constitute a signal of account manipulation, but monitoring the sudden evolution of this indicator should not be ruled out;
- significant fluctuations in DEPI may signal the introduction of a revenue growth policy;
- a large variation in SGA disproportionately correlated with a decrease in sales is a signal of possible distortion of financial and accounting information;
- a negative shift in LVGI is an indication of concern regarding the company's ability to pay its debts, even though the value of trade receivables is on an upward trend (without the same trend in collections).

In order to achieve the purpose proposed in the study, the following **calculation steps** were implemented:

- i. collecting data from the financial statements of the enterprises included in the sample regarding each element included in the calculation formula of the 6 economic-financial indicators (five established by Beneish and one introduced by the author by replacement);
- ii. systematizing the data in Excel format and the actual calculation of the economic-financial indicators, according to the formulas previously presented;
- iii. integrating the numerical values of the economic-financial indicators in equation (1) to obtain the Beneish score (MSCORE);
- iv. integrating the numerical values of the economic-financial indicators in equation (2) to obtain the modified Beneish score (MSCOREM);
- v. comparing the results of the two scores MSCORE and MSCOREM;
- vi. Analysis and conclusions.

The original Beneish model with five parameters was computed first, followed by the modified Beneish model with five parameters that was suggested in the study. This was based on the first two phases of gathering and processing data from the financial statements of the businesses in the pilot sample. A comparative analysis was then developed using the previously indicated

calculation algorithm to demonstrate whether of the five-parameter MSCORE or MSOREM models is superior, more accurate, and yields more trustworthy data.

5. Blockchain technology integration model in the financial-accounting information flow

5.1. Assessment of each indicator's specific limit values

The six economic and financial indicators listed in equations (1) and (2) were computed using the accounting and financial data from the financial statements of the businesses that were part of the pilot sample (SX, SY, and SZ for the years 2021 and 2022). Table No. 4 displays the outcomes of figuring out the limit values for the financial and economic variables that comprise equations (1) and (2).

Table 4. Result regarding the limit values of the elements of the equations (1) and (2)

	DSRI	GMI	AQI	SGI	DEPI	LVGI
Fraud³	≥ 1.46	≥ 1.19	≥ 1.25	≥ 1.61	≥ 1.08	≥ 1.11
SX (2022/2021)	1.16	1.02	0.99	1.03	0.01	1.29
SY (2022/2021)	1.21	1.15	1.01	1.68	0.10	1.79
SZ (2022/2021)	3.26	0.52	1.00	0.98	0.20	1.20

Source: result of own research based on analyzed financial statements (2023)

According to the results, the debt-to-asset ratio (LVGI) indicator values for the three businesses (SX, SY, and SZ) are marginally higher than the 1.11 threshold, indicating the possibility of accounting account manipulation with respect to the calculation elements (e.g., an undervaluation of payables accounts, an overvaluation of receivables accounts, or a weak ability of the business to pay its future debts).

For the first company (SX), no other possible manipulation is reported based on the other indicators.

The figures recorded by the SGI indicator, the gross margin index, and the second company (SY) both give indications of potential accounting account manipulation.

The idea that any potential accounting account manipulation could be documented at the level of receivables accounts linked to revenue accounts is made clearer by correlatively analyzing the values of the two indicators, LVGI and SGI.

The figures reported by the DSRI indicator, the Sales Index pertaining to uncollected receivables, provide indications of potential manipulations for the

³ Limits according to the model established by Beneish in 2009

third business (SZ). It becomes clearer that a potential manipulation of the accounting accounts could be documented at the level of the income accounts by correlatively analyzing the values of the two indicators, LVGI and DSRI.

5.2. Comparative analysis, MSCORE calculation for equation (1), and MSCOREM calculation for equation (2)

They computed MSCORE and MSCOREM. The outcomes of the two equations (1) and (2), MSCORE and MSCOREM, respectively, were then compared. Table No. 5 displays the overall findings of the comparative study at the level of the two scores, MSCORE and MSCOREM, as well as at the level of each economic-financial indicator.

Table 5. Comparative results of equation calculations (1) si (2)

	Ecuations	DSRI	GMI	AQI	SGI	DEPI	LVGI	M/MM
SX	MSCOREM	0.953706	0.920090	0.589816	0.741364		(0.420296)	(3.280320)
SX	MSCORE	0.953706	0.920090	0.589816	0.741364	0.001070		(2.858954)
SY	MSCOREM	0.994219	1.038056	0.597504	1.202454		(0.585330)	(2.818096)
SY	MSCORE	0.994219	1.038056	0.597504	1.202454	0.010700		(2.222066)
SZ	MSCOREM	2.683584	0.474594	0.593000	0.702074		(0.392400)	(2.004148)
SZ	MSCORE	2.683584	0.474594	0.593000	0.702074	0.021400		(1.590348)

Source: result of own research based on analyzed financial statements (2023)

The results presented show that:

(a) There may have been accounting account manipulations in the first business (SX) based on the MSCORE calculation, but no manipulations were found in the third firm (SZ) using the identical calculation formula.

(b) Using the MSCOREM calculation, there may have been accounting account manipulations in the first company (SX) and the second business (SY); nevertheless, using the same calculation formula, no manipulations were found in the third company (SZ);

(c) We observe that the results of both MSCORE and MSCOREM scores for the second company (SY) point to potential financial statement manipulation; this has not yet been verified by state investigations that have been made public up until March 2025 (though we do not rule out the possibility that, given how recent the period 2021–2022, it has not yet been the focus of such checks, including by the competent bodies).

As shown in table no. 4's informative content, somewhat different values were obtained for the author's modified M Beneish score (MSCOREM) and the

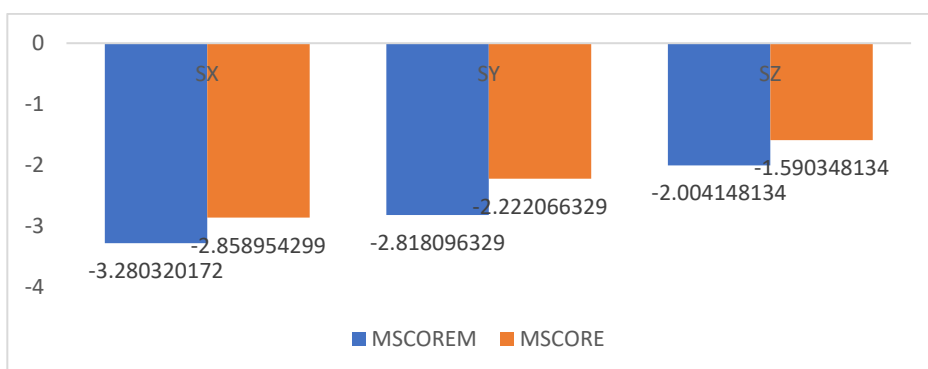
original M Beneish score (MSCORE), **but both show whether or not manipulation occurred in the same way.**

MSCOREM displays a value further away from the fraud threshold: (-3.28) and (-2.81), respectively, compared to (-2.85) and (-2.22) as displayed by MSCORE. This indicates a higher degree of fidelity regarding the potential fraudulent action. Both scores for the first company (SX) and the second company (SY) have values higher than the fraud threshold (> -2.21).

For the third enterprise (SZ), both MSCORE and MSCOREM score values are below the manipulation threshold (< -2.21), but the modified MSCOREM model shows a value closer to this threshold (-2.004) compared to (-1.59) as shown by MSCORE, indicating an insignificant probability of future manipulation detection at this enterprise level. This assertion is based on the DSRI index, which has a value greater than the fraud threshold (3.26).

Figure 1 shows a comparison of the two models for the three companies, set in the period 2021-2022.

Figure 1. Comparative results of MSCORE and MSCOREM



Source: result of own research based on analyzed financial statements (2023)

Using this graphical representation, the two forms of the Beneish model were compared, and the modified 5-parameter model, MSCOREM, was found to be more accurate.

6. Conclusions

From the specialized literature analyzed in the research study, we have deduced the existence of a phenomenology of financial fraud. According to the structured and systematized analysis of the last five decades and beyond, it has been concluded that studies focused on the phenomenon of financial fraud reflect the concerns of the accounting profession regarding the detection and combating of financial fraud. Therefore, liberal accounting professions must develop new

skills that enable them to uncover and investigate fraud, but also to offer appropriate prevention solutions.

We conclude that, globally, financial fraud is a phenomenon that causes significant losses to organizations, and the schemes and methods that fraudsters use to commit financial fraud remain consistent over time, even in the context of the current expansion of the digitization of economies.

We also note that, although it accounts for a relatively small proportion of all forms of financial fraud, fraudulent financial statements cause the greatest loss in terms of value, a reality that provides sufficient motivation for further scientific study of this taxonomy.

The empirical study demonstrates a clear connection between a company's deceptive financial reporting as identified by the MSCORE and MSCOREM statistical models, inventiveness, and the quality of financial-accounting information. Because these statistical models have been empirically proven by many writers in the specialized literature as well as through the research conducted, they are appropriate for predictively assessing the existence of fraud in financial statements.

Without the need of complex financial-accounting information processing software, the two models can detect the potential presence of fraud in financial statements. We think that the MSCOREM model can be utilized alone or in conjunction with MSCORE, specifically to increase the validity of empirical research, even if only MSCORE is globally acknowledged as a scientific approach.

Both the MSCORE and MSCOREM models can be used successfully to predict financial fraud at the enterprise level as well as when comparing firms in the same area. An immediate use can also be found in the field of tax risk management, where it is important to validate tax inspection choices by identifying tax fraud signals that are associated at the level of both scores.

Last but not least, we emphasized in the study that applying the MSCOREM model adds value to the empirical analysis of the qualitative characteristics of the financial – accounting information contained in the financial statements, demonstrating its usefulness to any user interested in identifying the risk of using creative accounting techniques for fraudulent purposes. We stress, however, that if the creative accounting techniques for income recognition are declared and described in an understandable manner in the annexes to the financial reports, we can conclude that we are not in the process of financial fraud.

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