Selecting Indicators of Predicting Fraud Risk. Case Study for Romanian Business Environment

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Abstract: The act of fraud has been practiced since ancient times and manifests itself in different ways. The aim of the study is to apply the Beneish score on Romanian firms and to identify which indicators are sensitive to the state of fraud. The sample was selected from the Bucharest Stock Exchange and consists of 66 companies traded on the main market for the years 2016-2021. The collected data were analyzed year-by-year and cross-sectional methods (panel data) using manually collected information extracted from financial statements downloaded from the Bucharest Stock Exchange. Based on this data, the Beneish score was calculated and then statistical tests were performed. Using the results obtained from the Beneish Score calculation, we were able to divide the companies into two groups. The results clearly show that the group with no likelihood of fraud risk has lower scores for the eight indicators and the bankruptcy group has lower values. We identified sensitive items in both states such as DSRI (Days Sales Receivable Index), GMI (Gross Margin Index. In conclusion, several theories or hypotheses are offered to explain the underlying motivations for fraud. Romanian companies listed on regulated markets can be classified into risk groups in terms of fraudulent financial statements by applying the Beneish score. After statistical processing, it was concluded that not all models existing in the literature can be applied to any sample and cannot have the same purpose, because the type of companies differs, the financial data changes from one year to another, the object of activity changes from one year to another.

Key words: fraud, Beneish, fraud triangle theory, Romanian company

JEL classification: G17, G40

1. Introduction

The act of fraud has been practiced since ancient times, and manifests itself in various ways. The first definition of it was stated in the Code of Hammurabi, about 1800 years before the new era (Halilbegovic et al. 2020). According to the Oxford dictionary, the notion of fraud is defined as the act of deceiving parties' interests in order to obtain money or other property illegally. The notion of fraud, according to the explanatory dictionary of the Romanian language is defined as the act "of deceit, an act of bad faith committed by someone, usually to achieve a material profit by taking advantage of another person's rights, or theft." According to the International Standards on Auditing (ISA), financial fraud is defined as "an intentional act committed by one or more individuals at senior management level, persons charged with governance, employees or third parties, involving the use of deception to obtain an unfair or illegal advantage".

With the process of liberalization of developing economies, a number of manipulations of financial statements have emerged and have also occurred with some regularity. With digitization, fraud has become a global phenomenon. In developing economies, there has been a major increase in fraud within companies. According to Ibrahim et al. (2013) between corporate taxpayers and tax authorities there is an ongoing "war". Currently, actions taken by companies to manipulate financial statements continue and managers and accountants have become increasingly creative in resorting to different methods.

Fraudulent actions are either detected or undetected (Mohammad et al.2020). In regard of lack of the capabilities of not detecting the fraudulent actions, specialists have developed and are constantly improving models that can help identify the presence of financial fraud.

Several models exist in the literature to identify the presence of financial fraud: the Beneish model (Beneish 1999), the Dechow-Dichev model (Dechow and Dichev 2002), the Piotroski model (Piotroski 2002), the Lev-Thiagarajan model (Lev and Thiagarajan 1993), the Vladu model (Vladu et al. 2016), Robu and Robu (2013), the Hasan score (Hasan et al. 2017).

Through this study, we contribute to the literature by validating the existing model theory in the literature. It is important to note that the results may vary depending on the sample size, larger or smaller, the field of activity for which it is applied and, last but not least, the size of the company (small, medium or large).

The bibliometric analysis aims to provide an overview of existing publications on the topics of interest. For the purpose of our study, we have developed some research questions, which we aim to answer:

Research question 1: Can bibliometric analysis lay the foundation for qualitative research?

Research question 2: Can Romanian companies listed on regulated markets be classified into two groups: with probability of fraud risk, or without?

Research question 3: Which indicators have a significant impact on the Beneish score in the two groups (no likelihood of fraud risk - group 1 and likelihood of fraud risk - group 2)?

In order to answer the research questions, we first conduct a bibliometric analysis. Through bibliometric analysis, we can quantify the current state of knowledge. The main objective of this analysis is to study the trend of research in the field of interest. We calculate the Beneish score, which helps us to divide the societies into the two groups. For this purpose, we used a representative sample of 66 companies listed on the Bucharest Stock Exchange for the period 2016-2021. The results of our study show that a majority percentage of firms in Romania can be classified into two groups (with probability and without probability of fraud risk).

The main objective of our study is to validate the predictive accuracy of the Beneish model. In contrast to previous studies, which were based solely on the application of the model, we want in this study to consider the concomitant effects of both states on the indicators in the composition of the score.

The paper is structured as it follows: the Literature Review in the first section, where we have approached the existing researches, regarding of financial fraud and its evaluation models. In the second chapter, the Research Methodology was detailed. The section describes the techniques used, variables and data. Further, Results and Discussions, on the results of applying the M-Beneish fraud risk measurement model were issued. In the end, within the conclusions, we have outlined the main findings of the paper. The limitations of the research aimed to constitute future research directions on the researched topic.

2. Literature review

The literature states that fraud is perpetrated by applying various techniques to manipulate the results, depending on the expected outcome. Accounting manipulation is applied by those who draw up financial statements, who have different ways of thinking and perceiving things, and can give rise to different ways of applying accounting manipulation.

According to Wells (2011) and other scholars, "fraud" is defined in several ways, but the most suggestive definition is that fraud is committed to make a profit.

Financial fraud is committed as a result of a series of intentional acts in order to obtain an unfair, illegal gain or advantage. It is an act undertaken with the intent to deceive others, often ending in significant financial loss (Achim and Borlea 2020).

Financial fraud can occur in different business sectors. Thus, it can be seen that the responsibility to raise red flags is distributed to the company's management, the personnel in charge of corporate governance (Bilgin et al. 2017). Externally, auditors should also apply sufficient audit tests to be sure that financial statements are free from errors or financial manipulation. Therefore, the responsibility is not only assigned to management or the auditor, but is distributed fairly (Johnes 2010).

Thus, in order to present a positive image, pressure is put on managers to cosmeticize results in order to remain attractive to stakeholders (MacCarthy 2017)

The current economic and technological context is considered to be complex, uncertain due to the impossibility of identifying interdependencies between elements of financial statements (Alazard & Separ 2001). Studies by researchers Robu(2013), Beneish (1999), Dechow-Dichev (2001), Mantone (2013), Piotroski (2000),Lev-Thiagarajan(1993),Vladu(2017) are among the seminal works that have highlighted the importance of fraud detection using financial statements. By consulting the literature in the field, we were able to identify analytical models that allow us to catch financial fraud hidden in financial statements and define these models.

The authors Robu and Robu (2013) have made a classification of Romanian firms listed on the BSE into risk groups on fraudulent reporting based on indicators proposed by Beneish (1999). The sample that formed the basis of the study consisted of 64 companies; 27 companies with fraud risk and 37 without fraud risk were identified. In the article "Financial statement fraud detection model using financial ratios", an analysis of financial ratios was carried out, with which fraud can be identified. The sample that was used in the study consisted of 40 companies whose financial statements were classified as fraudulent and 125 companies with non-fraudulent financial statements. The conclusion of the research was that "red flags" signals can also be identified with the help of financial statements (Kanapickienė & Grundienė, 2015).

Hawariah Dalnial et al. (2014) identified in their article "Financial accountability: detecting fraudulent firms", conducted on a sample of 65 companies with fraudulent behaviors and 65 companies with honest behaviors, significant differences between the results of financial indicators of fraudulent and non-fraudulent companies.

Erdoğan and Erdoğan (2020) used the Beneish model to examine fraudulent companies at the Istanbul Stock Exchange. After identifying fraudulent companies, they obtain a positive relationship between fraudulent financial information and asset quality index and public, administrative and selling expenses.

Until recent studies, no researcher has applied the unmodified Beneish score on companies listed on the Bucharest Stock Exchange. There are studies in the literature approaching a similar idea, but they apply the Beneish adjusted score. We believe it is important to apply the original score in order to lay the groundwork for a thorough research decision. In future research we aim to develop a specific score which measures the presence of financial fraud appearance, in Romania.

To achieve the research objective, the following hypotheses are considered:

Hypothesis 1: The Beneish model can predict the manipulation of financial statements for BSE listed companies.

Hypothesis 2: The Beneish model has a predictive ability and divides companies into the two groups.

Following the review of the literature mentioned above, we will further present the research methodology for practical evidence of the application of the score.

3. Methods and data

Bibliometric methodology

In order to provide a comprehensive review of the knowledge on handling financial statements in correlation with developments in the bibliometric research field (Alshater et al., 2021; Anuar et al., 2022; Dabic et al., 2020), we conducted a database search following known review protocols. Using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, recently revised by Page et al. (2021), we followed the data extraction that we used in the bibliometric analysis. Data were extracted from the Web of Science and Scopus databases. The guide also provides a diagram that we use in this study. (Figure 1).

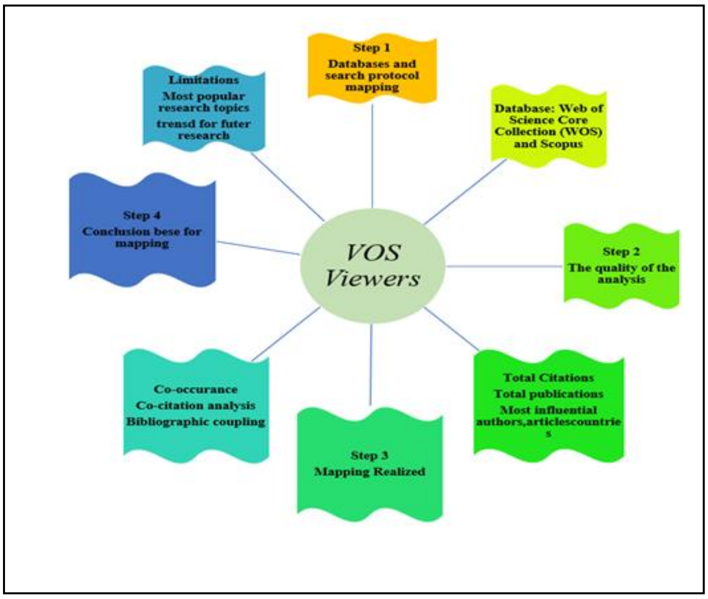

Fig. 1. Research methodology in bibliometric analysis
Source: created by the author

According to Caputo et al., (2021) and Raghuram et al., (2019), the WOS and Scopus databases present the highest quality publications being a trusted source of highly rated journals. The database selection started on September 1, 2022 and ended on October 30, 2022, it is very important the accuracy of the criteria in terms of bibliometric analysis (Alshater et al., 2021), which prompted us in our searches to lump all possible words associated with fraud, earning management, Beneish and creative accounting.

The key words according to which the selection was made, should be found in the abstract, title or in the content of the articles. The first search criterion returned for the 4 key words a total of 75,245 publications during the period 1996-2022, then the results were refined by applying the following filters, only articles, with open access, in English, in the field of finance, financial management and econometrics, excluding a part of the articles, resulting in a total of 43,548 articles, then in the second refinement according to Alshater et al. (2021) Caputo et al. (2021) and Khan et al. (2020), to confirm the accuracy of the research, the refinement was subjective, i.e. only papers strictly related to economics. The sample remained with a total of 35,578 articles. Moreover, in the term checking step, some of the common terms such as author, study, research, article, year, date, paper, etc. were deselected.

Data

In this study we selected 81 companies listed on the BSE. To construct the sample, we have set the base ground on two perspective. In the first perspective we have selected the type of company. The financial institutions and companies that had only a point of business in Romania, not headquarters, were eliminated. In the second perspective we selected only companies that had a constant listing, because the lack of data can lead to bias the research. With the application of the two perspectives the sample was filtered down to a total of 66 companies for the period 2016-2021.In the following, the Beneish score was calculated. The score for each company was calculated and then it was reported to the benchmark value of -2.22 so that the selected sample can be divided into the two categories: with probability of fraud risk and without probability of fraud risk. In the group with probability of fraud risk we have a number of 45 companies analyzed and for the group without probability of fraud risk we have a number of 21 companies. In both cases the data were in panel form over a period of 6 years (2016-2021). (Safta et al. 2020)

The steps that have been followed to carry out the study are the following:

*Centralization of data from financial statements downloaded from the Bucharest Stock Exchange (BSE);

*Calculation of the eight variables and finally the Beneish score;

* Segmentation of companies into two groups (the first group is the one that contains companies with no probability of fraud risk and the second group is the one that contains companies that are with probability of fraud risk. The groups were selected according to the result of the Beneish score;

*Application of the statistical model;

* The statistical testing is carried out in the identified states with the help of the Beneish score, in order to identify the indicators of sensitivity to the state without fraud risk and to the state with fraud risk.

Variables

Using the M-Beneish (1999) model it is possible to identify the presence or absence of fraud risk in the analyzed companies. The score was calculated using the information contained in the financial statements. The Beneish score is considered the dependent variable, the components of the Beneish score are the independent variables.

The M-Beneish equation is as follows:

M= -4.84 + 0.92* DSRI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI - 0.172*SGAI + 4.679* TATA - 0.327* LVGI (Beneish, 1999). (1)

The reference value is -2.22. Any score higher than this will indicate an increased likelihood of data manipulation.

Table 1. The independent variables

Variables	Explanation	Calculation formula
Days' Sales in Receivables Index (DSRI)	This indicator should have a linear trajectory, if there are no major changes in terms of external lending. The value greater than 1 indicates that the number of receivables is higher in year t than in t-1. This could signal the presence of manipulated income (Mahama, 2015).	$\mathrm{DSRI} = \frac{\text{Net Receivables}_t}{\text{Sales}_t} / \frac{\text{Net Receival}}{\text{Sales}_{t}}$
Gross Margin Index – (GMI)	It was constructed by Beneish (1999) to detect irregularities in financial statements by measuring the ratio of a company's previous year's gross margin to the current year's gross margin (Beinesh 1999). Declining gross margin from one year to the next may indicate manipulation of the financial statements. A GMI score greater than 1 is an important red flag for any auditor and accountant (Robu&Robu, 2013).	$\mathrm{GMI} = \frac{\text{Gross margin}_{t-1}}{\text{Sales}_{t-1}} / \frac{\text{Gross margin}_t}{Sales_t}$
Asset quality index (AQI)	A value greater than 1 of the AQI variable can signal the presence of financial fraud. The cases where AQI has a higher value is when the accounting professional uses asset/asset revaluation techniques, research and development costs, advertising are capitalized as intangible assets (Ibadin and Ehigie, 2019). A high value of the variable indicates the presence of creative accounting/fraud through the use of excessive capitalization of expenses (Ibadin and Ehigie, 2019).	$\mathrm{AQI} = \frac{\text{Fixed assets}_t - \text{Net tangible fixed}}{\text{Total assets}_t}$
Sales Growth Index - SGI	In the situation where the index has a high value, then it may be about the manipulation of financial statements (Mahama, 2015).	$\mathrm{SGI} = \frac{\text{Sales}_t}{\text{Sales}_{t-1}}$
Depreciation Index (DEPI)	Depreciation index is the ratio of depreciation expenses to gross value (Mahama, 2015). A value greater than 1 of this index indicates that the rate of asset depreciation has slowed (Beneish, 1999). Thus, "red flags" could be raised when revenues are increasing and depreciation expenses are decreasing (Ibadin and Ehigie, 2019).	$\mathrm{DEPI} = \frac{\text{Value adjustments expense}}{\text{Value adjustments expenses}_{t-1} + \text{Tangil}}$
Sales, General, and Administrative Expenses Index (SGAI)	The index could include a number of incentives or bonuses for managers.	$\mathrm{SGAI} = \frac{\frac{\text{General management expenses}}{\text{Sales}_t}}{\frac{\text{General management expenses}_{t}}{\text{Sales}_{t-1}}}$
Leverage Index (LVGI)	A value greater than 1 may suggest the possibility that the enterprise is involved in financial fraud (Ibadin and Ehigie, 2019).	$\mathrm{LVGI} = \frac{\text{Total debts}_t}{\text{Total liabilities}_t} / \frac{\text{Total debts}_{t-}}{\text{Total liabilities}}$
Total Accruals to Total Assets Index (TATA)	The alarm signal in the case of this index can be raised if the degree of commitments increases as a share of total assets. Also, an increase in income or a decrease in expenses, in accrual accounting, indicates the presence of a manipulation of financial information (Aghghaleh, 2016).	$\mathrm{TATA} = \frac{\text{Net outcome of exercis} \quad \mathit{Cash\ flows\ from\ exploitatior}}{\text{Total assets}_t}$

Source: own processing

4. Results and discussions

4.1 Bibliometric analysis

The analysis we have carried out is the one concerning the identification of research topics, selected according to keywords. Our study is based on 35578 articles, published in journals on economics, business and finance. The maps are mainly aimed at mapping the links between the research area and its links with other research areas (Donthu et al., 2021).

In terms of co-occurring keyword analysis, this allows us to identify connections between keywords in a selected sample of publications. Fakhar Manesh et al. (2021), explain in their paper, that this type of analysis gives us the opportunity to identify as many thematic areas related to the research topic as possible, grouped into clusters.
For the analysis we considered the minimum threshold of 158 repeated words out of a total of 15886 words. Therefore, the most frequently occurring words were fraud, earning management, Beneish model, financial statements,companies. In figure 2, it can be seen the links between the keywords within the clusters. The colors of the keywords is shown distinctly for each cluster. In figure 3 we have captured the links between our keywords, which confirms that Beneish model helps us to detect manipulation or fraud in financial statements. Keywords are colored according to a score that is calculated by the Vosviewer program.(Safta and Achim,2021)

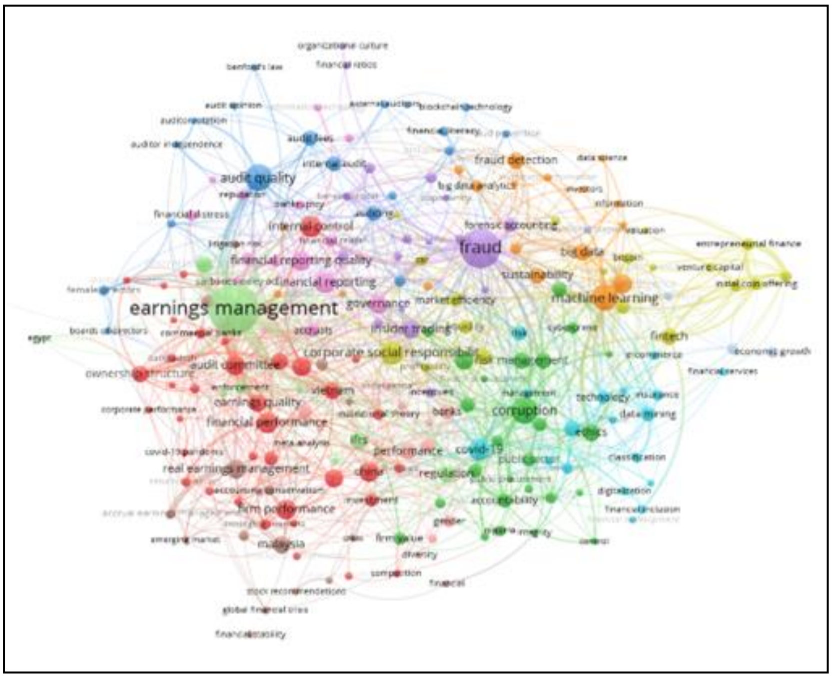

Fig. 2. The co-occurrence of keywords
Source: created by the author based on the VOSviewer analysis

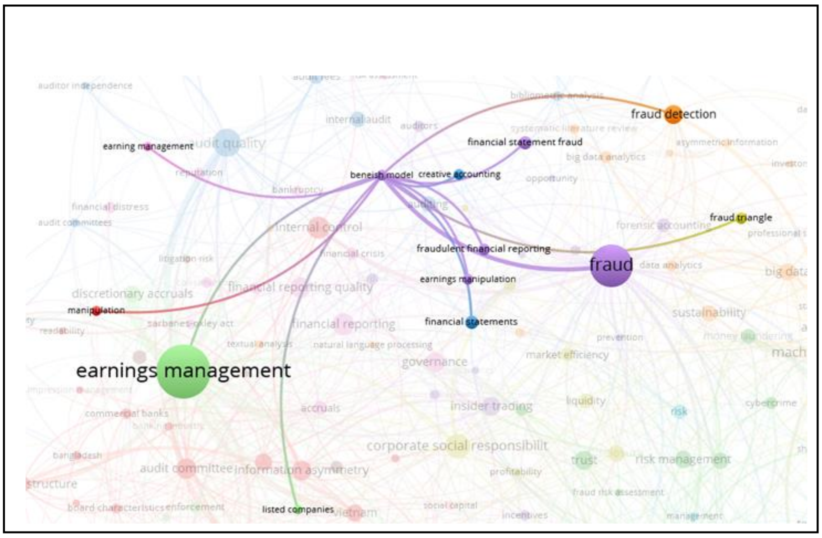

Fig. 3. The co-occurrence of keywords
Source: created by the author based on the VOSviewer analysis

4.2 Statistical analysis

The descriptive statistics part is shown in Table 2. In table 2, the main variables can be seen, both the dependent variable and the independent variables, divided into two groups (with probability and without probability of fraud risk). We can see that the scores are lower for the group of the companies which do not find themselves in the fraud risk area. This aspect can be seen at the average, minimum and maximum levels.

According to the statistical results, in the situation of companies without probability of fraud risk, the maximum value of the Beneish score is -2.221, the minimum value is -58.971, and the standard deviation is 4.7234. This indicates the amount by which the Beneish score varies approximately from one company to another. At the same time, in the state of fraud risk probability, the maximum value of Beneish score is 132.06 and the minimum value is -2.199 and the standard deviation is 16.504 compared to that of companies without fraud risk probability. The results highlight the differences between companies with fraud risk probability, and those without risk of financial fraud appearance.

Table 2. Descriptive statistics of the main variables

Variables	Fraud	Average	Std.Dev.	Min	Max	Observations
BENEISH	No risk	-4.068	4.7234	-58.971	-2.221	232
	With risk	3.0489	16.5048	-2.199	123.206	146
DSRI	No risk	1.1623	1.3467	0.23	17.84	232
	With risk	2.8177	10.6713	0.06	103.6	146
GMI	No risk	-0.7715	8.6009	-105.08	17.4	232
	With risk	4.9322	22.8148	-8.46	235.61	146
AQI	No risk	1.0057	1.0281	-4.39	9.69	232
	With risk	3.8066	17.9901	0	206.82	146
SGI	No risk	1.0019	0.3396	-0.73	2.11	232
	With risk	1.0693	0.35838	0.08	2.17	146
DEPI	No risk	1.0822	0.6395	0.01	7.72	232
	With risk	2.4780	12.2186	0.01	144.01	146
SGAI	No risk	1.2799	2.3054	0.36	33.95	232
	With risk	1.1814	1.0973	0.15	12.31	146
LVGI	No risk	0.9456	0.4118	0	3.05	232
	With risk	0.9393	0.6672	0	5.25	146
TATA	No risk	-0.0888	0.1491	-1.2	0.44	232
	With risk	-0.01226	0.1927	-1.2	1.2	146

Source:own processing

The GMI index signals irregularities in financial statements by measuring the ratio of a company's gross margin in the previous year to its gross margin in the current year (Beneish 1999). A decrease in the gross margin index in the current year compared to the previous year's index is a signal for the presence of earnings manipulation. With the AQI, it is possible to identify whether the company falls into the group with a high likelihood of fraud or the group with no likelihood of fraud. If significant year-on-year variations can be observed for this index. This aspect should be a warning signal for those checking financial statements. (Sabău et al. 2021)

Table 3. Descriptive statistics of the main variables

	Beneish	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA
Beneish	1								
DSRI	-0.2703***	1							

GMI	0.9189***	0.0273	1						
AQI	0.0957	-0.1319***	0.0523	1					
SGI	-0.0378	-0.5130***	-0.2227***	0.0180	1				
DEPI	0.0421	-0.1431**	-0.0095	-0.0318	0.0993	1			
SGAI	-0.0125**	0.2898***	0.0148	0.0099	-0.2677***	-0.0394	1		
LVGI	-0.0381**	0.0911	0.0543	0.0118	-0.1179	-0.0457	-0.1094	1	
TATA	0.1536**	-0.3689***	-0.0269	0.0032	0.2078***	0.0305	0.0166	-0.1595***	1

Source: Source: own processing
Note: * p < 0,1, ** p < 0,05 and *** p < 0,01.

Table 4. Fraud risk probability state variable correlation matrix

	Beneish	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA
Beneish	1								
DSRI	0.5521***	1							
GMI	0.6927***	-0.0237	1						
AQI	0.3698***	-0.0294	-0.0438	1					
SGI	0.0586	-0.3070***	0.2376***	0.1627***	1				
DEPI	0.0356	-0.0248	-0.0253	-0.0237	-0.1594	1			
SGAI	0.1763**	0.4387***	-0.0719	-0.0276	-0.4249***	0.0191	1		
LVGI	0.0262	0.2697***	-0.0876	-0.1067	-0.0281	-0.1282	-0.0061	1	
TATA	-0.0740	0.1644***	-0.0165	-0.3495***	-0.0846	-0.0262	0.0195	-0.1698***	1

Source: Source: own processing
Note: * p < 0,1, ** p < 0,05 and *** p < 0,01.01

We can see that in both groups there are Beneish score items that are statistically significant at a 1% significance level, such as DSRI, GMI, SGAI, but we can also identify Beneish score items that are not significant in both groups.

In Table 5 we find the regressions for the group with no likelihood of fraud risk. For these regressions the tests were performed using the random effect test because the significance coefficient of the model is less than 0.05. For each individual model the random effect was applied, in each test which we have performed. The models presented in Table 5, have Beneish score as dependent variable. Model 1 has Beneish score as dependent variable and DSRI as independent variable. For this model, it can be seen that the independent variable is statistically significant but negative. Model 2 has GMI as the independent variable, after testing it can be seen that this variable is also statistically significant. For model 3 we have AQI as independent variable. After testing its relationship with the dependent variable, we have seen that it is the case of an insignificant relationship. In case of model 4, we have SGI as independent variable and for model 5 we have DEPI as independent variable. Model 6 uses SGAI as the independent variable and model 7 has LVGI as the independent variable, as for the independent variables forming model 4,5,6,7, none of the variables is statistically significant. It can be seen that model 8, has statistically significant independent variable. In terms of testing all independent variables with the dependent variable, it can be seen in model 9, that statistically significant and positive are the indicators GMI, SGAI and TATA, and statistically significant and negative are DSRI and LVGI.

Regarding the probability of fraud risk, the test was also performed with random effect, which can be seen in Table 6. We test each model individually. Model 1 has Beneish score as dependent variable and DSRI as independent variable, for this model it can be seen that the independent variable is statistically significant. Model 2 has GMI as the independent variable, after testing it can be seen that this variable is also statistically significant. For model 3 we have as independent variable AQI, following the test of its relationship with the dependent variable it is significant. For model 4 we have SGI as independent variable, for model 5 we have DEPI as independent variable. Model 6 uses SGAI as the independent variable and model 7 has LVGI as the independent variable. As for the independent variables forming model 4,5,6,7,8 none of the variables is statistically significant. In terms of testing all the independent variables with the dependent variable, it can be seen in model 9, that statistically significant and positive are the indicators DSRI, GMI,AQI,DEPI and statistically significant and negative are SGAI,TATA and LVGI.

We can see that in both states the DSRI, GMI indicators are statistically significant when we test the indicators in turn, this suggests that we have a share of sensitive indicators in both groups.

The DSRI and GMI indicators, can be associated with bifurcated accounts in the accounts, as they indicate both the occurrence of fraud and the absence of fraud. An increase in DSRI is the result of a change in lending policy, which leads to a boost in sales, but unusual increases in receivables relative to sales also suggest a fluctuation in revenue. GMI is the ratio of gross margin in year t-1 to gross margin in year t. When GMI is greater than 1, gross margins deteriorate. Clearly, deteriorating gross margin is a negative signal about a company's prospects and may be a sign of poor management. this could cause managers (who are often under pressure to budget) to manipulate profits.

Our results are similar with those of Li and Zaitas (2018) who focus in their study on identifying information contained in financial statements that indicate profit manipulation. They indicated that companies with high Asset quality index have a good platform for profit manipulation and managers of these companies are more motivated to manage profits. On the same note, Rahimian and Heidari (2019), conducting their research, find that the ratio of sales to total assets and equity to total assets are two fraud sensitive financial indices. Similarly, Shirazi and Mehrdad (2018) in their study focused on the topic of "Investigating the relationship between business strategy and fraudulent financial reporting", revealed through their results that management strategy influences fraud in financial statements

This section provides an overview of the results on the applicability of the Beneish M-Score model to the regulated market. In this regard, the research had two research hypotheses "The Beneish model can predict the manipulation of financial statements for BSE listed companies. And The Beneish model has a predictive ability and divides companies into the two groups. Based on the results, it was concluded that the Beneish model can indeed be applied to BSE listed companies that are part of the regulated market and with the help of the score can be divided into two groups and the research hypotheses are validated.

Table 5. Beneish Regression Result and Components (no probability of fraud risk)

BENEISH	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
DSRI	-0.9261***								-0.9293***
GMI		0.5004***							0.5136***
AQI			0.42180						0.0522
SGI				-0.8024					0.3947
DEPI					-0.52298				0.0633
SGAI						-0.02975			0.1072***
LVGI							0.1064		-0.5128***
TATA								4.7594**	2.1161***
NR OBS	232	232	232	232	232	232	232	232	232
R^2 WITHIN	0.0563	0.8522	0.0073	0.0322	0.0048	0.0006	0.0001	0.0155	0.9364
R^2 BETWEEN	0.0962	0.8648	0.0082	0.0779	0.0033	0.0000	0.0203	0.0563	0.9602
R^2 OVERALL	0.0731	0.8443	0.0092	0.0014	0.0018	0.0002	0.0014	0.0236	0.9428
WALD CHI2(1)	17.10	1293.36	1.98	0.78	0.50	0.05	0.02	5.23	3673.02
PROB > CHI2	0.000	0.000	0.1597	0.3773	0.4778	0.8241	0.8969	0.022	0.000

Source: own processing

Note: * p < 0,1, ** p < 0,05 and *** p < 0,01.

Table 6. Beneish Regression Result and Components (probability of fraud risk)

BENEISH	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL8	MODEL 9
DSRI	0.85704***								0.9364***
GMI		0.5002***							0.5218***
AQI			0.3351***						0.3762***
SGI				4.26059					0.2575
DEPI					0.0451				0.1032***
SGAI						1.8793			-0.3759**
LVGI							1.1923		-0.5831**
TATA								-4.3202	-1.6594***
NR OBS	146	146	146	146	146	146	146	146	146
R^2 WITHIN	0.3701	0.5732	0.0022	0.0144	0.0022	0.0001	0.0218	0.0045	0.9797
R^2	0.1590	0.2843	0.4422	0.0156	0.0002	0.0427	0.0488	0.1113	0.9926

BETWEEN									
R^2 OVERALL	0.3048	0.4798	0.1367	0.0034	0.0013	0.0311	0.0007	0.0055	0.9851
WALD CHI2(1)	64.80	142.93	21.95	1.2	0.17	2.15	0.37	0.37	9049.96
PROB > CHI2	0.000	0.000	0.000	0.2739	0.6813	0.0.1423	0.5443	0.5439	0.000

Source: own processing
Note: * p < 0,1, ** p < 0,05 and *** p < 0,01

5. Conclusions

In conclusion, several theories or hypotheses are offered to explain the motivations behind co-professional fraud. However, it is fair to say that no hypothesis has received overwhelming empirical support that refutes reasonable alternative explanations. Some of the simplistic explanations end up raising more questions than providing convincing answers.

Through the bibliometric study, we have answered research question 1, as it presents us with a holistic picture of the structure of the research on the link between for security and the Beneish model, providing a comprehensive assessment of the literature on this topic over the past quarter century.

By applying the Beneish score, we succeed in answering research question two, by affirming the fact that Romanian companies listed on regulated markets can be classified into risk groups, in terms of fraudulent financial statements. After statistical processing, we concluded that not all models existing in the literature can be applied to every sample and cannot have the same purpose, because the type of companies differs, the financial data changes from one year to another, the object of activity changes from one year to another. With the help of the statistical tests, we were able to identify the indicators that have the highest significance on the Beneish score.

A first, limitation of this study is the size of the sample, but we would like to extend the sample to all companies listed on the Bucharest Stock Exchange in order to analyze all companies listed on the Bucharest Stock Exchange. Even the object of activity of the analyzed companies can be considered as another limitation. The companies analyzed belong to various sectors, and this could be the second improvement that could be added to the thesis: the selection of all listed companies and the calculation of indices for each sector of activity.

The second limitation of the study may be the limitation of searches from only two sources (Web of Science and Scopus) and the use of only one bibliometric analysis software

Improvement is a constant, and for each study carried out, another research opportunity may arise. The more we research, the more we realize we know less. We aim to remove these limitations by expanding the database, both in forming a larger sample and downloading data from both the BSE and the Thomson Reuters Eikon platform and selecting articles for bibliometric analysis from several international databases.

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6. References

- Achim, M. V., & Borlea, S. N.Ghid penru analiza-diagnostic a stării financiare. Editura Risoprint, Cluj-Napoca (2020).
- Achim, M.V., Borlea, N.S. Economic and financial crime. Corruption, shadow economy and money laundering. *Springer Publishing House Switzerland* (2020).
- Mantone, P. S. Using analytics to detect possible fraud: tools and techniques. Editura John Wiley and Sons, Inc. New Jersey, USA (2013).
- Alazard, C., & Separi, S., Contrôle de gestion, Paris, Dunod (2001).
- Abdullahi, R., and N. Mansor.. Concomitant Debacle of Fraud Incidences in the Nigeria Public Sector: Understanding the Power of Fraud Triangle Theory. International Journal of Academic Research in Business and Social Sciences 5 (9): 241–255.(2015)
- Alshater, M. M., Atayah, F. O., & Khan, A. What do we know about business and economics research during COVID-19: A bibliometric review. Economic Research-Ekonomska(2021).
- Anuar, A., Marwan, N. F., Smith, J., Siriyanun, S., & Sharif, A. Bibliometric analysis of immigration and environmental degradation: Evidence from past decades. Environmental Science and Pollution Research International. (2022).
- Beneish, Messod D. The Detection of Earnings Manipulation. Financial Analysts Journal 55: 24–36. (1999)
- Bilgin, Mehmet Huseyin, Giray Gozgor, and Chi Keung Marco Lau.. Institutions and gravity model: The role of and corporate governance. Eurasian Business Review 421–36.(2017)
- Caputo, A., Pizzi, S., Pellegrini, M., & Dabic, M. Digitalization and business models: Where are we going? A science map of the field. Journal of Business Research, 123, 489–501. (2021).
- Dabic, M., Maley, J., Dana, L.-P., Novak, I., Pellegrini, M. M., & Caputo, A. Pathways of SME internationalization: A bibliometric and systematic review. Small Businessn Economics, 55, 705–725 (2020).
- Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research, 133,285–296(2021).
- Erdoğan, M. and Erdoğan, E. O. Financial Statement Manipulation: A Beneish Model Application, Contemporary Issues in Audit Management and Forensic Accounting Contemporary Studies in Economic and Financial Analysis,o102, pp. 173-188. (2020).
- Fakhar Manesh, M., Pellegrini, M. M., Marzi, G., & Dabıc, M. Knowledge management in the fourth industrial revolution: Mapping the literature and scoping future avenues. IEEE Transactions on Engineering Management, 68(1), 289–300. (2021).

- Halilbegovic, Sanel, Celebic Nedim, Cero Ermin, Buljubasic Elvisa, and Mekic Anida.. Application of Beneish M-score model on small and medium enterprises in Federation of Bosnia and Herzegovina. Eastern Journal of European Studies 11: 146–63.(2020)
- Ibrahim, Aramide Salihu, Siti Normala Sheikh Obid, and Hairul Azlan Annuar. Measures of Corporate Tax Avoidance: Empirical evidence from an emerging economy. International Journal of Business and Society 14: 412–27.(2013.)
- Johnes, Martyn. Auditors and Fraud—And the end of Watchdogs and Bloodhounds, The Magazine Financial Auditor. Bucharest: CAFR, vol. 8, pp. 46–49.(2010.)
- MacCarthy, John. Using Altman Z-score and Beneish M-score Models to Detect Financial Fraud and Corporate Failure: A Case Study of Enron Corporation. International Journal of Finance and Accounting 6: 159–66. (2017.)
- Mahama, Muntari. Detecting Corporate Fraud and Financial Distress Using the Altman and Beneish Models. International Journal of Economics, Commerce and Management (2015.)
- Mohammad, Mahdi Shakouria, AliAsghar Taherabadib, Mehrdad Ghanbaric, and Babak Jamshidinavidd. Explaining the Beneish model and providing a comprehensive model of fraudulent financial reporting (FFR). International Journal of Nonlinear Analysis and Applications 12: 39–48. (2020.)
- Khan, A., Hassan, M. K., Paltrinieri, A., Dreassi, A., & Bahoo, S. A bibliometric review of takaful literature. International Review of Economics & Finance, 69, 389–405. (2020).
- Li, T. and Zaiats, N. Corporate governance and firm value at dual class firms. Review of Financial Economics. Review of Financial Economics, Vol. 36(1), pp. 47-71. (2018).
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D.,Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hrobjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S.,… Moher, D. PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ (Clinical Research Ed.), (2021).
- Piotroski, Joseph D. Value Investing: The Use of Historical Financial Statement Information to manipulations in financial statements of listed companies. Journal of Financial Crime 24: 656–77.(2002.)
- Robu, Ioan Bogdan, and Mihaela Alina Robu. Proceduri de Audit Pentru Estimarea Riscului de Frauda Bazate pe Indici de Detectare a Manipularilor Contabile. Audit Financiar 106: 4–16. (2013.)
- Rahimian, N. and Haji Heydari, R. Detection of fraud using the modified model and financial ratios, Empirical Accounting Research, 8(3), pp. 47-69. (2019).
- Raghuram, S., Hill, N. S., Gibbs, J. L., & Maruping, L. MVirtual work: Bridging research clusters. Academy of Management Annals, 13(1), 308–341. . (2019).
- Safta, I. L., Achim, M. V., & Borlea, S. N. Manipulation of financial statements through the use of creative accounting. Case of Romanian companies. Studia Universitatis Vasile Goldiș Arad, Seria Științe Economice, 30(3), 90-107. (2020).
- Safta, I. L., Sabău, A. I., & Muntean, S. N. Bibliometric analysis of the literature on measuring techniques for manipulating financial statements. Risks, 9(7), 1-16. (2021).
- Sabău, A. I., Mare, C., & Safta, I. L. A statistical model of fraud risk in financial statements. Case for Romania companies. Risks, 9(6), 116. (2021).
- Shirazi Dehkharghani, M. and Haghgoo Mehrdad, N. Investigating the Relationship between Business Strategy and Fraudulent Financial Reporting with Emphasis on the Role of Disclosure Quality, Accounting Perspective and Management, 1(1), pp. 60-76. (2018).