Application of Beneish M-score model on small and medium enterprises in Federation of Bosnia and Herzegovina

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Abstract

The last two decades have witnessed high-profile corporate accounting scandals and multi billion-dollar frauds. Since then, forensic accounting has been in focus and has played a prominent role in discovering financial statement frauds. This research aims to analyze the applicability of the Beneish M-Score model on small and medium enterprises (SMEs) in Federation of Bosnia and Herzegovina (FBiH). Based on a sample that includes 4,580 small and medium enterprises, data will be analyzed using audited financial statements in the period from 2008 to 2015. By using independent sample t-test, correlation, and regression, it has been concluded that Beneish model is indeed applicable on the market of FBiH and aids effectively in the detection of fraud in financial statements. The study describes the comparison of different industry sectors regarding the possible manipulators and serves as a solid foundation for further research in the area of forensic accounting.

Keywords: manipulative accounting, fraudulent activities, financial crime, forensic accounting, Beneish M-score

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Introduction

The role of forensic accounting and control carried out to prevent criminal activities is a topic that is currently insufficiently developed in the region of Central and South East Europe. The definition of criminal acts, frauds, delusions, and manipulations exists since Hammurabi's Code, about 1,800 years before the new era, thus, we may say that forensic accounting is very young as a science, but it has existed and at times, hibernated, for hundreds of years. The first significant crimes of this nature are recorded in the Middle Ages, and today there is a large number of frauds, manipulations, and criminal activities in the world, even on virtual networks. The development of IT was a contribution to the development of illegal activities, but also to the development of techniques and methods for detecting criminal activities. The most significant number of criminal acts occurs in the economy of post war – transitional economies such as the economy of Bosnia and Herzegovina (BiH). Therefore, in this study, it is important to mention the Criminal Code of BiH by which all criminal offenses can be seen and prescribed by specific regulations, but insufficiently so. Although Bosnia and Herzegovina has received and adopted the International Accounting and Auditing Standards, they are hardly sufficient to prevent criminal acts, manipulation, and fraud in BiH, where external and internal audits are not sufficiently developed.

There are scientific and social reasons for carrying out this study. The scientific purpose of the research is reflected in the connection of all elements contained in it, starting from the basics of defining criminal activities, criminal activity auditors, forensic accounting – more precisely the emergence, concept, development and importance of forensic accountants, and accounting as the first goal of the work. The social purpose represents the Beneish analysis used to find out if there were manipulations in the financial statements. The main research part of the paper aims to answer the question of whether these analyses are suitable instruments for detection of manipulations in financial reports in companies operating in the territory of BiH. Criminal acts, forensics, and scams are topics that have existed since ancient times and have been developing ever since. Forensic accounting is still undeveloped in our area, and as such, the problem of criminal activity and forensic accounting is a current topic in BiH.

The development of forensic accounting and auditing in BiH is not at a high level for several reasons, particularly because of the lack of specialized staff, knowledge, and experience of external and internal auditors, taxation auditors, inspectors and accountants in criminal investigations and other unauthorized acts. Internal audit and controls in BiH are definitely not sufficiently developed, which has been covered by other studies, and moreover, external auditing is not adequately applied, leading to fraud and fraudulent activities being carried out day after day (Vukoja, 2012).

The task of this research is to present the criminal acts and the forensic accounting – its significance and its application in general, as well as to illustrate how Beneish's analysis can discover manipulations or predict bankruptcy by analysing the financial statements of companies. In total, 4,580 small and medium enterprises were selected for this research, and their financial statements from the period between 2008 to 2015 were analyzed.

The primary objectives of the study are:

- to test the applicability of the Beneish M-Score model on the market of FBiH;
- to investigate the dominating ratios which indicate that a company is likely to be the manipulator and examine the frequency of types of financial scams commonly used;
- to compare results of the model and present the differences between industry sectors regarding the potential financial manipulators or bankrupt companies.

1. Literature review

Consensus is that forensic accounting research stems from Spain where, in the 19th century, Pedro Antonio Alarcon first wrote about this topic and terminology (Crumbley *et al*., 2007). The beginnings of forensic accounting are related to the court proceedings – Meyer against Sefton in 1817 for causing bankruptcy. There is a belief that Maurice E. Peloubet first used the concept of "forensic accounting" in his article "Forensic Accounting: Its Place in Today's Economy" (Belak, 2011). Forensic accounting implies not only accounting and auditing but also different scientific disciplines such as statistics, economics, etc. (Budimir, 2013). In recent history, there has been a plethora of notorious accounting scandals, namely, Enron, Helmsley Enterprise, Parmalat S.P.A, Polly Peck, Tyco, WorldCom, Bernard L. Madoff Investment Securities LLC, Satyam Computer Services, etc. (Farrell, 2015). The audit is similar to forensic accounting if the fraud refers to the fraud investigation, because it is divided into internal and external auditing. Internal audit refers to the investigation of the business within a company, and most of the staff checks, thus in this context, internal auditors are associated with forensics. On the other hand, external forensics is based on auditors who are not employed by the company, but who are in work, who passed a state exam, or on an authorized accountant (Hopwood *et al*., 2012). What is common for both, forensic accounting and forensic audit, and the reason for studying these two concepts in the same work, is that forensic accounting and forensic audits deal with the detection of all criminal acts and scams, and both investigate all accounting records to prove or deny the criminal act in them (Spahic, 2014). There are three primary goals of analytical procedures. The first goal is to use preliminary analytical methods to detect the height of the risk of criminal activity; the second purpose of an independent analytical process is to gather evidence and establish the viability of information, documents, billing, and posting; the final goal refers to the last analytical procedure related to the conclusion on anomalies in the financial statements (Budimir, 2013). Beneish M-score model has been selected for this research because of its usage, applicability and popularity - it is a financial forensic tool often used to detect areas of possible manipulation on the company's financial statements by forensic accountants, auditors, and regulators. The score is determined from an intercept and eight independent variables to detect whether the management has manipulated the company's earnings. These variables are constructed from the data in the organization's financial statements and once computed, they create an M-Score to show the degree in which the gains or earnings have been manipulated (Brickell, 2011). This model assists the potential investors in examining the likelihood of the future collabourations and to improve the reliability of investments. In their articles, Beneish and Nichols (Beneish and Nichols, 2009) aim to determine the probability of financial statement fraud by using two alternative fraud detection models which involve five and eight variables of the model (Beneish, 1999). These eight variables are then calculated together using the following formula:

$$Beneish\ M\ score = -4.84 + 0.92*DSRI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI - 0.172*SGAI + 4.679*TATA - 0.327*LVGI \qquad (1)$$

Additionally, all eight computing variables of Beneish model can be divided into manipulation group and motivation group of signals:

- **Manipulation signals:** Day Sales in Receivables Index (DSRI) for revenue inflation; Asset Quality Index (AQI) for expenditure capitalization; Depreciation Index (DEPI) for declining rate; and Total Accruals to Total Assets (TATA) for accounting not supported by cash.
- **Motivation signals:** Gross Margin Index (GMI) for deteriorating margins; Sales Growth Index (SGI) for sustainability concerns; Selling, General, and Administrative Index (SGAI) for decreasing efficiency; and Leverage Index (LEVI) for tighter debt constraints.

DSRI ratio represents day sales in receivables in the first year in which earnings manipulation is uncovered (year *t*) to the corresponding measure in year *t- 1*. This variable gauges whether receivables and revenues are in or out-of-balance in two consecutive years. A large increase in DSRI could be the result of a change in credit policy to spur sales, but unusual increases in receivables relative to sales may also be suggestive of revenue inflation. GMI is the ratio of the gross margin in year *t-1* to the gross margin in year *t*. When the GMI is greater than 1, gross margins deteriorate. Certainly, the deterioration of gross margin is a negative signal about a company's prospects and can be a sign of poor management. This could drive managers (who are often under pressure to make budget) to manipulate earnings. AQI in a given year is the ratio of non-current assets other than property plant and equipment (PPE) to total assets. It measures the proportion of total assets for which future benefits are potentially less certain. It is the ratio of asset quality in year *t*, relative to asset quality in year *t-1*. It is an aggregate measure of the change in the asset realization risk analysis. When AQI is greater than 1, the company potentially increases its involvement in cost deferral. An increase in asset realization risk indicates an increased propensity to capitalize and defer costs which is a sign of earnings manipulation. SGI is the ratio of sales in year *t* to sales in year *t-1*. An SGI greater than 1 indicates the growth of sales over the previous year. If growth companies face substantial stock price losses at the first indication of a slowdown, they may have higher incentives than-growth companies to manipulate earnings. DEPI represents a rate of depreciation in year *t-1* vs. the certain rate in year *t*. The depreciation rate in a current year is equal to depreciation / (depreciation + net PPE). *"A DEPI higher than 1 indicates that the rate at which tangible assets are being depreciated has slowed-raising the possibility that the company has revised the estimates of assets' useful lives upward or adjusted a new method that is income increasing"* (Beneish,1999).

Beneish (1999) hypothesized a positive correlation between DEPI and the likelihood of earnings management. SGAI is calculated as the ratio of SGA to sales in year *t* relative to the certain measure in year *t-1*. A GAI greater than 1 means that the cost of selling, general, and administrative expenses increased proportionally more than sales. According to some research, analysts interpret a non-proportionate increase in sales as a negative signal of a company´s prospects. LVGI is the ratio of total debt to total assets in year *t* relative to the corresponding ratio in year *t-1*. An LVGI greater than 1 is equivalent to an increase in the financial leverage (leverage). This index is used to capture the incentives in debt covenants that can lead to manipulating earnings. The situation when the debt is at risk of violation is easier than when managers artificially increase profits to avoid the effects of a breach – an increase in the portion of the debt. Total Accruals were used by prior researchers to assess the extent to which managers make discretionary accounting choices to alter earnings (Healy, 1985). The value of the TATA is used to proxy for the extent to which cash underlay reported earnings might be contrary, when the operating cash flow greatly exceeds net profits. Therefore, there are negative accruals, or reach unity, which means that all assets are made up of accruals. Beneish expected a strong positive association between accruals (less cash) and a higher likelihood of earnings manipulation.

According to the formula (1), the eight variables should be applied to compute the calculation. The variables are not measured contemporaneously with manipulation discovery since manipulation becomes public on the average of 19 months after the end of the budgetary year of the first reporting violation.

The Earnings Management literature provides two alternatives to the Beneish model to identify the propensity of a company to manipulate earnings. The first one (the full model – the 8M Score) involves all eight variables. On the other hand, the second alternative (the simple model – the 5M score) selects only five variables, omitting those less relevant and meaningful. An M-Score less than -1.78 suggests the company will not be a manipulator. An M-Score greater than -1.78 signals that the company is likely to be a manipulator. It is interesting to note that, in testing out his model, Beneish used all the companies in the Compustat database between the years 1982-1992 (Beneish *et al*., 2011). He also developed a profit model that can be used to provide study of a structured relationship between the financial statement data and likelihood of manipulation. This model is a cost-effective tool.

The result showed that Beneish's weighted and unweighted probabilities of earning manipulation are significantly associated with the existence of fraud. It is important to mention that the M-score model is a probability model, and therefore cannot detect 100% manipulation. Beneish found that he could accurately identify 76% manipulators, while only 17.5% non-manipulators could be incorrectly identified (Brickell, 2011). The analysis of the financial statement required at least two periods of financial reporting to detect the unusual event. However, to identify the trend of the company's financial statement reporting, it is suggested to analyse the data for five reporting periods. Moreover, it will show the details by doing the vertical and horizontal analysis. Aside from this, in their study, Beneish, Lee, and Nichols (2011) used the Beneish model (Beneish, 1999), which was estimated using data from the period 1982-1988 and its holdout sample performance assessed in the period 1989-1992 to show forensic accounting has significant out-of-sample ability to detect fraud and predict stock returns. Moreover, they provided evidence that the efficacy of the model derives substantially from its ability to predict in advance the likely persistence (or reversal) of the accrual component of the current year earnings.

Franceschetti and Koschtail study used Beneish's approach to detect earnings manipulations between bankrupt and non-bankrupt small and medium-sized enterprises. Based on a sample of thirty bankrupt and thirty non-bankrupt companies, they found that sales growth index, gross margin index, asset quality index, days' sales in the receivable index, and total accruals to total assets contribute to the detection of financial statement fraud committed by bankrupt companies. The bankrupt sample reported 1.6 times more red flags than the nonbankrupt one (Franceschetti and Koschtial, 2013). Curtis and Thalassinos' study utilized Beneish Model to examine the financial statements of companies listed on Athens Stock Exchange. It was posited that Beneish Model yielded more accurate results when the return on equity and Altman's Z score accompanied Beneish Model (Curtis and Thalassinos, 2005)**.** Grove and Cook tested the usefulness of Beneish Model in detecting financial statement frauds. In their study, Beneish Model was used in the highly-profitable fraud cases such as Qwest, Enron, Global Crossing, and WorldCom. They found that the ratios of Beneish Model worked well in the detection of financial statement frauds that occurred in Qwest, Enron, Global Crossing, and WorldCom. Additionally, they state that forensic accountants should use Beneish Model together with traditional vertical, horizontal, and ratio analysis to efficiently detect financial statement frauds. (Grove and Cook, 2004). Ramirez-Orellana *et al*. (2017) applied Beneish Model to a Spanish food company, Pescanova, which went bankrupt in 2013. The period analyzed in the study was of four years. Authors concluded that Pescanova manipulated the days' sales in the receivable index (DSRI), and total accruals to total assets (TATA) before its bankruptcy. They claimed that the empirical results strongly demonstrated the validity of Beneish Model for the Pescanova case (Orellana *et al*., 2017). In 2016, Aghghaleh *et al.* investigated whether Beneish Model had any relations with the detection of financial statements frauds committed by companies operating in Malaysia. They found that Beneish Model was effective in detecting fraud companies with an accuracy rate of 73% (Aghghaleh *et al*., 2016). Paolone and Magazzino conducted a study in Italy and examined the risk of earnings manipulation amongst some leading industrial sectors. The analyzed companies had a low probability of manipulating income. (Paolone and Magazzino, 2014). In a 2015 study of Enron (US), Altman's Z-score and Beneish M-score were used to determine how early investors, regulators, and other stakeholders could have detected the financial distress of the company. Both models indicated that Enron was in economic turmoil as early as 1997, and for that matter was engaged in earnings manipulation (Mahama, 2015). This study aims to contribute to the existing literature in the field of forensic accounting through the investigation of financial statement manipulation practices in the transition economies such as Bosnia and Herzegovina, the society characterized by a lack of transparency when it comes to financial statement data presentation and collection, and prosecution of fraudsters. Through the analysis of the significant sample size of 4 580 small and medium companies, this study takes the first steps in fraud investigation in FBIH, and aims to provide a basis and motivation for further researches that will develop the model for timely fraud detection, which should bring significant benefits to the society as a whole.

Beneish M-Score model will be employed to empirically demonstrate its validity in the context of FBIH business environment.

2. Research methodology

Secondary data was collected and later analyzed in order to answer the research questions. Secondary data sources were used in the theoretical part of the research to expose the research problems and to receive more information about the research purposes. Since Beneish M-score model is not extensively covered in the academic literature, the theory was analyzed from different perspectives by relying on the vast set of different scientific and mathematical research and publications. The subsequent outcome was the opportunity to gain precise, relevant, and contemporary data. The next step of the research – empirical studies allowed to analyze and to bolster recent researches in this field. Financial statement data is obtained from secondary sources – private data collection companies for the period 2008-2015. The subsequent financial data as reliable and precise because the financial statement is the official form of representing the corporate numeric data. A transparent and sound financial reporting is based on the International Financial Reporting Standards (IFRS).

For the purpose of this Law, legal entities shall be classified as small, medium, and large legal entities depending on the indicators determined on the day of creation of financial reports in a fiscal year according to the following criteria:

- income,
- value of business assets,
- average number of employees for the year of the financial report.

Small enterprises are legal entities that meet at least two of the criteria presented in Table 1 (Official Gazette of the FBiH No 83/09).

Table 1. Classification of SMEs in Bosnia and Herzegovina

Category of Enterprise	Number of employees	Annual Turnover (BAM)	Annual Balance Sheet (BAM)
Small	<50	≤ 1,000,000	≤ 2,000,000
Medium	50<X<250	1,000,000<X<4,000,000	1,000,000<X<4,000,000

Source: Official Gazette of FBiH No 83/09.

In total, 4,580 small and medium enterprises were selected for research, and financial statements were analyzed from the period from 2008 to 2015. Bosnia and Herzegovina has experienced a huge expansion in SMEs in the post-war era. More visible investment opportunities in local markets are related to the privatization of government's entities and development of competitive markets where SMEs led the way (Halilbegovic *et al*., 2018). With the violent shove from socialistic to capitalistic economy, SMEs are faced with the temptations to manipulate financial statements, both intentionally and unintentionally. In this manuscript, compiled data represents information extracted from companies' financial statements, namely income statement and balance sheet. By using these two statements, the researcher calculated the cash flow from the operating activities. The data withdrawn from the financial statements of Beneish models includes the following variables: Net Sales, Cost of Goods Sold (COGS), Net Receivables, Current Assets, Property, Plant and Equipment (PPE), Depreciation, Total Assets, SGA Expenses, Net Income, Cash Flow from Operating Activities, Current Liabilities, Long-term debt, Total Liabilities, Operating Income, Retained Earnings, and Book Value of Equity. The sampling frame of this study included private companies operating in the area of the FBiH. For the purpose of the analysis, two samples were used:

Sample 1 consists of 68 companies that have been accused of tax evasion, money laundering and financial statement manipulation in 2017. Information related to the 68 fraud committed cases was based on media reports and court proceedings. Beneish M-Score model has been applied to this sample in order to evaluate the strength of the model in predicting the financial statement manipulation prior to fraud discovery. The sample 1 data was collected for the period of eight consecutive years. This data consists of financial statements, balance sheet and income statement and represents an official financial statement data that companies submit to the FBIH Financial Intelligence Agency.

Sample 2 consists of 4,580 companies that have submitted their financial statement reports to the FBiH Financial Intelligence Agency. After testing the applicability of M-score model to the BH market, and making an inference about its use in FBIH market, the Sample 2 data has been used to answer the remaining research questions related to the extent to which companies are prone to manipulate statements, fraud schemes used and to draw a comparison of industry sectors based on the extent of potential financial statement manipulation.

Table 2 represents the sector classification of Sample 2 companies. Therefore, there are 2,264 medium companies and 2,316 small companies, which is in total 4,580 companies.

Table 2. Sector Classification of Sample Companies

Row Labels	medium	small	grand total
Administrative and support services	188	432	620
Health care and social work	43	41	84
Finance and insurance (excluding banks)	11	9	20
Construction	225	176	401
Hotel management and hospitality	41	54	95
Information and communication	10	10	20
Education	11	23	34
Water supply; sewerage, waste management	26	12	38
Real estate	36	34	70
Manufacturing	496	463	959
Transportation and storage	205	237	442
Professional, scientific, and technical services	51	73	124
Wholesale and retail trade	858	651	1,509
Arts, entertainment, and recreation	48	85	133
Geological industry; mining and quarrying	14	15	29
Electricity	1	1	2
Grand Total	**2,264**	**2,316**	**4,580**

Source: Authors' calculations.

Table 2 indicates that companies operating in wholesale and retail trade industry have the highest percentage share in the sample, followed by manufacturing, administrative and support services, transportation and storage, and construction industry.

2.1. Hypothesis and research questions

Since Beneish M-Score model is developed in the United States, in a kind of a different business environment, its applicability to the FBIH market had to be tested. Therefore, the study hypothesis is:

The Beneish M-score model can efficiently detect the fraud in financial statements of SMEs in the market of the FBiH.

The following research questions are tested:

- At what level are SMEs prone to engage in the financial statement fraud?
- What are the dominating ratios that indicate whether a company is likely to be the manipulator?
- Which kind of financial scams are generally used to manipulate the financial statements of SMEs?
- Which industry sectors are in the highest probability of potential manipulation practice considering SMEs?

In order to analyze these questions, the SPSS software was used to assist the analysis of the study. In addition to the basic methods (method of analysis, deduction/induction and concretization), other statistical methods were used, such as an independent sample t-test, correlation, and regression.

2.2. Data analysis

The data was collected and systematized in the Microsoft Office Excel, where Beneish model was calculated and all variables compared. Computed variables were transmitted into SPSS where independent sample t test and correlation analysis have been performed. The analysis was done on 4,580 SMEs that were operating in the market in the FBiH, from 2008 to 2015. The main point of this research revolves around the applicability of the Beneish M-Score in the market of FBiH. For testing the applicability of the Beneish M-score model, the Sample 1 data has been used. The results are presented in Table 3.

By examining the Beneish model, the authors found that it can detect the manipulations in financial statements for the majority of companies classified as manipulators. Out of 68 companies that were manipulating the financial statements, the Beneish model correctly identified 54 of them, which represents 79.41% in total. On the other hand, 14 companies in total were incorrectly identified (20.59%). It is important to mention that the M-score model is a probability model and as such cannot detect 100% manipulation. However, the results above are a decent indicator that the Beneish model can be applied to the SMEs in FBiH. Therefore, the first hypothesis is accepted, and it can be concluded that the Beneish M-score model can efficiently detect the fraud in the financial statements of SMEs in FBiH.

Table 3. Probability of Classification Error

Number Correct	Number Incorrect	TOTAL	Percent Correct	Percent Error
54	14	68	79.41%	20.59%

Source: Authors' calculations.

The next section identifies the level at which SMEs are prone to engage in the financial statement fraud. Data were tested by using the eight-variable in the Beneish model. Table 4 also shows the number of companies that belong to the group of likely manipulator companies and non-likely manipulator companies. To classify the companies into two groups, this study employs the broadly used benchmark of -1.78 score.

Table 4. Proportion of Likely Manipulator to Non-Likely Manipulator Companies

	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15
Likely manipulators	38%	42%	47%	30%	32%	31%	33%
Non-likely manipulators	62%	58%	53%	70%	68%	69%	67%

Source: Authors' calculations.

The results suggest that the proportion of likely manipulator companies showed an increasing trend over the first three years and after that, the percentages have sharply decreased. For the last three years, percentages varied year by year. In 2008/09 – the first period of the study, 38% of the tested companies appear to be likely manipulators and 62% non-likely manipulators. The percentage of likely manipulators increased in 2009/10 to 42%, and in 2010/11 to 47%. The reason for an increasing trend of likely manipulators during the first three years of the study could be the financial crisis which happened in that period, more specifically from 2007-2009. The companies were more prone to engage in financial statement fraud during the crisis period. Also, it is important to note that, in 2010, the new Rulebook on the form and content of financial statements were adopted. These reforms might have been the reasons why company manipulation sharply decreased during that time.

The next phase of this study was to identify the dominating ratios that would indicate whether a company is a likely manipulator or not. Based on the M-Scores, the companies were divided into two groups: group 1 – likely manipulator companies) and group 2 – non-likely manipulator companies. To answer the second research question, this study used Beneish benchmarks for identifying in which of the eight ratios manipulation was made. And for this purpose, only group 1 – likely manipulators was used. Beneish benchmarks are outlined in Table 5.

Table 5. Beneish Benchmarks for Manipulators – Breakdown by Variable

Variable	Lower limit	Upper limit	Manipulators
DSRI	0.2700	3.1200	>=1.055
GMI	1.1050	2.9900	>1.0305
AQI	0.1000	4.0120	>1.0505
SGI	0.4900	4.8800	>1.1705
DEPI	0.3600	2.6500	>=1.0291
SGAI	0.3700	2.1900	>=1.1261
TATA	-0.0010	0.2500	>0
LVGI	0.1700	3.1300	>1.04605

Source: Beneish Calculator / Authors' calculations.

The Beneish benchmarks in Table 5 are applied to the sample of likely manipulator companies, and the results are shown in Table 6.

Table 6. Comparison of the Dominating Ratios

Variable	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15
DSRI	2.700	2.412	2.422	2.423	2.303	2.132	2.141
GMI	1.350	1.465	.675	.923	.915	.918	.953
AQI	.620	.608	.578	.666	.673	.673	.730
SGI	1.070	1.532	1.498	1.123	1.195	1.351	1.183
DEPI	953	1.184	1.521	1.488	1.598	1.670	1.535
SGAI	1.322	1.146	1.320	1.387	1.317	1.429	1.343
TATA	2.372	2.270	2.413	2.216	2.183	2.205	2.310
LVGI	1.259	1.674	1.214	1.397	1.343	1.377	1.470

Source: Authors' calculations.

Table 6 shows that the financial fraud was done in all of the eight variables among the selected sample and across the selected period. The most dominating ratios are DSRI, TATA, SGAI, LVGI, & SGI, which means that the companies were prone to engage in the financial statement fraud mostly within these variables. However, the highest number of companies practised fraud in DSRI.

The third research question describes the kind of financial scams that are generally used to manipulate financial statements. Thus, by using the manipulator's decision indicators from Table 5, this study portrays the highlights of the following implications of the Beneish Model's outcome:

- DSRI >=1.055: Possible revenue inflation – assess revenue recognition.
- GMI >1.0305: Gross margin is deteriorating and the company is more likely to manipulate earnings.
- AQI >1.0505: Tendencies of capitalising and deferring costs that should have been expensed.
- SGI >1.1705: High sales growth – companies under possible pressure manipulate earnings to keep up appearances.
- DEPI >=1.0291: Declining depreciation rate – tendencies of assets being depreciated at a slower rate to boost earnings.
- SGAI >=1.1261: Increasing expenses – possible company manipulation of earnings to defer costs, especially when the coefficient is negative.
- TATA >0: Asset changes in working capital – accruals possibly used to manipulate earnings.
- LVGI >1.04605: Increased borrowings – reflecting pictures of increase in leverage.

According to the previous analysis, all kinds of financial scams are used to manipulate the financial statements. However, the following manipulations were most frequently used:

- Possible revenue inflation (assess revenue recognition) – A large abnormal increase in a day's sales in receivables can be the result of revenue inflation. A large increase in the DSRI would be associated with a higher likelihood that revenues/profits are overstated.
- Asset changes in working capital (accruals possibly used to manipulate earnings) – It describes the extent to which managers alter earnings by making discretionary accounting choices. Thus, the higher positive accruals are positively associated with the likelihood of earnings management.
- Increasing expenses (company's possible manipulation of earnings to defer costs, especially when the coefficient is negative). Therefore, there is a positive relationship between the SGAI and earnings management.
- Increased borrowings – It represents an increase in leverage, and it shows the incentives in debt covenants which lead to the manipulation of earnings. Therefore, there is a positive relationship between the LVGI and earnings management.
- High sales growth – companies under possible pressure manipulate earnings to keep up appearances. Growth can put a pressure on managers in

maintaining a company's position and achieving earnings targets, so that they may have greater incentives to manipulate earnings.

The next section is used to answer research question number 4 and is related to the industry sectors that are in the highest probability of potential manipulation practice. Findings show that, after using the benchmark of -1.78, there are five sectors among all SMEs with a high probability of earnings manipulation, while the rest of the sectors do not show any sign of manipulation.

Five industry sectors with highest probability of earnings manipulation are wholesale and retail trade industry, manufacturing industry, administrative and support services industry, transportation and storage industry, and construction industry. Those are also the industries with the highest percentage share in the sample. The results are shown in Table 7.

Table 7. Comparison of the Industry Sectors in Terms of the Probability of Potential Manipulation Practice

Industry	**2008 / 09**	**2009 / 10**	**2010 / 11**	**2011 / 12**	**2012 / 13**	**2013 / 14**	**2014 / 15**
Administrative and support services	15%	15%	14%	15%	14%	15%	12%
Health care and social work	2%	2%	2%	2%	1%	2%	2%
Finance and insurance (excluding banks)	1%	0%	1%	1%	0%	1%	1%
Construction	10%	8%	10%	11%	10%	11%	10%
Hotel management and hospitality	2%	2%	2%	1%	2%	2%	2%
Information and communication	1%	0%	1%	1%	0%	0%	1%
Education	1%	1%	1%	1%	1%	1%	0%
Water supply; sewerage, waste management and remediation	1%	1%	1%	1%	0%	1%	0%
Real estate	2%	1%	2%	1%	2%	2%	1%
Manufacturing	20%	22%	18%	19%	21%	19%	20%
Transportation and storage	10%	9%	10%	8%	9%	9%	9%
Professional, scientific, and technical services	2%	3%	3%	4%	2%	3%	2%
Wholesale and retail trade	31%	33%	32%	34%	33%	32%	36%
Arts, entertainment, and recreation	3%	3%	4%	2%	3%	3%	2%
Geological industry; mining and quarrying	1%	1%	1%	1%	1%	1%	1%
Electricity	0%	0%	0%	0%	0%	0%	0%

Source: Authors' calculations.

In this section, the ratios used in the Beneish (M-score) model were tested in order to analyze its efficiency in the detection of fraud. For this purpose, the independent sample t-test is used.

Based on the M-Scores, the companies were divided into two groups: Group 1 – likely manipulator companies and Group 2 – non-likely manipulator companies.

Results are shown in Table 8. Data is tested through the "p-value" at 5% level of significance with the help of the SPSS. When the significance column of the result of independent t-test shows a value greater than .05, it means that the variability in the variable is about the same and that the difference between one group and the second group is not significant. However, if the value is less than .05, it means that the variability of the variable in question is significantly different.

Table 8. Statistical Properties of Beneish Analysis

BENEISH MODEL (M-SCORE)				
	mean difference	std. error difference	t-test	p-value
DSRI	.77544984	.01010337	76.752	.000
GMI	.14689635	.00477455	30.767	.000
AQI	.19252401	.00830576	23.180	.000
SGI	.27678252	.01022626	27.066	.000
DEPI	.06007055	.00733961	8.184	.000
SGAI	-.03832214	.00512611	-7.476	.000
TATA	.09344119	.00100023	93.420	.000
LVGI	-.15574045	.00562993	-27.663	.000

Source: Authors' calculations.

This analysis provides an understanding of the statistical characteristics of ratios in Beneish model. The t-test results of this study suggest that Beneish model ratios have a strong variation between the groups, and there are significant differences with regard to these ratios. The p-values at 5% level of significance are less or equal to (0.05). Hence, it can be concluded that these variables differ significantly between the two tested groups. Thus, the ratios were related and efficient in detecting the fraudulent financial statements of SMEs. It means that the ratios may be helpful in predicting fraudulent financial statements.

Discussions and conclusions

This section provides the insights into the results regarding the applicability of the Beneish M-Score model on the market of FBiH. In this regard, the research study has the following hypothesis: the Beneish M-score model can efficiently detect the fraud in financial statements of SMEs in the market of FBiH.

Based on the results, it was concluded that Beneish model can be indeed applied to the SMEs of FBiH, and research hypothesis stands.

As far as the first research question goes, from the study, it is noted that the proportion of likely manipulator companies showed an increasing trend over the first three years and after that, the percentages have sharply decreased. It was concluded that the reason for a rising trend could be the financial crisis which happened in that period, and the companies were more prone to engage in financial statement fraud during the crisis period. On the other hand, the declining pattern in 2011 was the indication of improvement in reporting practices, possibly due to the implementation of the new accounting rules which brought several changes in the disclosure requirement.

The second question aimed to look for the significant ratios responsible for the classification of companies into the two groups – likely manipulator companies and non-likely manipulator companies. It was concluded that the most dominating ratios were DSRI, TATA, SGAI, LVGI & SGI, which means that the companies were prone to engage in financial statement fraud mostly within these variables. Also, the highest number of companies practiced fraud in DSRI. Thus, the forensic accountants and auditors should pay particular attention to those accounts.

The third question aims to describe the kind of financial scams that are generally used to manipulate financial statements. It was found that the following financial scams are predominantly used: possible revenue inflation (assess revenue recognition), asset changes in working capital (accruals possibly used to manipulate earnings), increasing expenses (possible company manipulation of earnings to defer costs, especially when the coefficient is negative), increased borrowings, and high sales growth.

Finally, the fourth research question relates to the industry sectors that were in the highest probability of potential manipulation practice. It was concluded that there are five sectors with the highest likelihood of earnings manipulation. Those are wholesale and retail trade sectors, manufacturing, administrative and support services, transportation and storage, and construction sectors.

Based on the above-mentioned results, it was concluded that these models are applicable to the market of FBiH. Apart from the main objective of the study, there were three additional objectives which were fulfilled by answering the respective research questions. Based on that, this research concluded that there was a significant number of both manipulators operating on the market of FBiH from 2008 to 2015. Additionally, the study described the comparison of different industry sectors regarding possible manipulators. Based on the analyses conducted for the period from 2008 to 2015, it can be concluded that there are areas that need further research. The outcomes of these analyses are helpful in identifying the manipulators and areas of manipulation based on the variables included in the model.

As mentioned above, Beneish M-Score model is the probabilistic method and as such, its results are not 100% accurate, which represents one of the main limitations of the study. Also, the sample 1 size of the 68 companies that committed fraud is rather small for testing the applicability of M-score model. However, when it comes to the FBIH market, this is amongst pioneer research studies in the area of forensic accounting and fraud investigation and, bearing that in mind, the results of the research serve as a solid ground and motivation for further investigation in this field. One of the greatest challenges of the FBIH society is the lack of transparency when it comes to presentation and collection of financial statement data, so the size of the sample 2 – 4580 companies financial statement data being investigated is the notable advantage of the presented study. The forthcoming research studies should focus more on the audit reports of the companies and, in combination with ratio analysis of financial statement data, they should come up with the model that suits the FBIH market.

References

Aghghaleh, S.F., Mohamed, Z.M. and Rahmat, M.M. (2016), Detecting financial statement frauds in Malaysia: Comparing the abilities of Beneish and Dechow models, *Asian Journal of Accounting and Governance,* 7(1), pp. 57-65.

Belak, V. (2011), Business Forensics and Forensic Accounting - The Fight Against Corruption, *Belak Excellens doo, Zagreb*.

Beneish, M. (1999), The Detection of Earnings Manipulation, *Financial Analysts' Journal*, 55(5), pp. 24-36.

Beneish, M.D., Nichols, C. and Lee, C. (2011), To Catch a Thief: Can Forensic Accounting Help Predict Stock Returns?, *SSRN*, 36.

Beneish, M. and Nichols, D. (2009), *Identifying Overvalued Equity*, Johnson School, Research Paper Series, 09-09.

Brickell, D. (2011), The Beneish M-Score: Identifying Earnings Manipulations and Short Candidates, *iStockAnalyst*.

Budimir, N. (2013), Forensic Accounting, *Business economists,* 8(13), pp. 1-16.

Crumbley, L.D., Heitger, L.E., and Smith, S.G. (2007), Forensic and Investigative Accounting, *CCH a Wolters Kluwer Business*.

Curtis, P. and Thalassinos, J. (2005), Equity fund raising and creative accounting practices: Indications from the Athens Stock Exchange for the 1999-2000 period, *European Research Studies Journal*, 8(1-2), pp. 127-135.

Farrell, S. (2015), *The world's biggest accounting scandals*, Preuzeto od The Guardian (retrieved from https://www.theguardian.com/business/2015/jul/21/the-worlds-biggest-accounting-scandals-toshiba-enron-olympus).

Franceschetti, B.M., and Koschtial, C. (2013), Do bankrupt companies manipulate earnings more than the non-bankrupt ones?, *Journal of Finance and Accountancy,* 12(1), pp. 4-24.

Grove, H. and Cook, T. (2004), Lessons for auditors: Quantitative and qualitative red flags, *Journal of Forensic Accounting,* 5(1), pp. 131-146.

Halilbegovic, S., Celebic N. and Idrizovic A. (2018), Reward System Effects on Employees in Small and Medium Enterprises-Case of Federation Bosnia and Herzegovina, *European Journal of Economic Studies*, 7(2), p. 69.

Healy, P.M. (1985), The Effect of Bonus Schemes on Accounting Decisions, *Journal of Accounting & Economics*, 7(1-3), pp. 85-107.

Hopwood, W., Leiner, J. and Young, G. (2012), Forensic Accounting and Fraud Examination, *New York: McGraw-Hill Higher Education*, 656.

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

Paolone, F. and Magazzino, C. (2014), Earnings manipulation among the main industrial sectors: Evidence form Italy, *Economia Aziendale*, 5, pp. 253-261.

Ramírez-Orellana, A., Martínez-Romero, M.J. and 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), pp. 41-53

Spahic, N. (2014), Detecting fraud and embezzlement in financial reports, *International Scientific Conference of IT and Business-Related Research*, p. 579.

Vukoja, B. (2012), The importance of forensic accounting and auditing for reliability of fiancial statements in B&H, *Financing - Journal of Economics*, 02(12), pp. 38-44.