Application of the Beneish Model on the Warsaw Stock Exchange

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ABSTRACT

This paper investigates irregularities in financial statements by applying the Beneish and Roxas models to Polish firms listed on the Warsaw Stock Exchange from 2015 to 2020. The total sample included 110 observations. The sample comprised companies that had received an adverse or disclaimer opinion by the auditors, but had not been fined by the Polish Financial Supervision Authority (KNF Board). The control firms were selected based on the industry as selected by the standard industrial classification code and on the financial year, with minimizing the difference in the size of total assets. The results indicate that the Roxas model revealed greater accuracy than the Beneish model on the tested sample. The use of logistic regression allowed a modification of the Beneish model to align it with the conditions of the Polish market. The modified Beneish model showed greater accuracy for the tested sample and companies fined by the KNF Board.

JEL Classification: C46, G00, G30, M40, M42

Keywords: Beneish model, Roxas model, Warsaw Stock Exchange, logistic regression.

1. INTRODUCTION

Based on research conducted by the Association of Certified Fraud Examiners (ACFE) in 2020, the majority of fraud schemes involved asset misappropriation (86%), corruption (43%) and the least common instance was financial statement fraud (10%), although the latter is the most harmful and costliest category of occupational fraud. Financial statement fraud is a serious threat to market participants' confidence in financial information; it is estimated to cost corporations substantial money and is viewed as unacceptable, illegitimate and illegal corporate conduct (Rezaee, 2005). Financial statement fraud is an intentional distortion of financial statements, which can include reporting sales that did not happen, reporting income in the current year that belongs in the next year, capitalizing expenses improperly or reporting an expense in the next year that should be reported in the current year (Ata & Seyrek, 2009). Overall, financial statement fraud techniques work by improper revenue recognition and overstatement of assets or understatement of expenses and liabilities (Beasley et al., 2010).

Advances in technology have significantly improved the detection process for frauds and embezzlements. Auditors have access to many tools used in the audit of financial statements,

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including Benford's Law, the financial statement ratio analysis or data mining techniques. These tools produce more relevant findings and identify the critical areas that should be further investigated by forensic accountants. Although it is a very new area, forensic accounting practices have played a prominent role in the detection and prevention of accounting frauds in recent years. The literature identifies various approaches to detecting fraud in corporate financial statements, and various techniques have been employed to analyze the likelihood of financial statement fraud, such as logistic regression or data mining techniques, which most often are decision trees, neural networks and Bayesian belief networks (Spathis et al., 2002; Gaganis, 2009; Gupta & Gill, 2012; Amara et al., 2013; Chen, 2016; Ozcan, 2016; Hajek & Henriques, 2017; Jan, 2019). Many researchers have used mathematical models to determine whether a company provides misleading information about assets, liabilities, revenues and costs with the help of probit and logistic regressions (Summers & Sweeney, 1998; Beneish, 1999; Spathis et al., 2002; Gaganis, 2009; Dechow et al., 2011; Amara et al., 2013; Kanapickiene & Grundiene, 2015; Sorkun & Toraman, 2017; Dong et al., 2018; Alfian & Triani, 2019; Yao et al., 2019). This study focuses on the Beneish model financial statement fraud detection tool as a cost-effective and efficient tool that should be utilized by auditors. The Beneish model is among the most used quantitative models in forensic accounting investigations, and it provides massive benefits to forensic accountants because it helps to fully examine financial statements disclosed by firms and analyze changes in the amounts of financial statement accounts from period to period.

This paper explores the potential of the Beneish model as an indicator of fraud in the Polish financial market. Therefore, two hypotheses were formulated: the 8-variable model will have greater accuracy than the 5-factor model on the sample of companies that have received an adverse or disclaimer opinion by the auditors (Hypothesis 1) and the modified M-Score model based on logistic regression results will be more accurate than the 8-variable (5-variable) M-Score model for companies fined by the KNF Board (Hypothesis 2). To test these hypotheses, the data were analyzed from the annual financial statements of companies listed on the main market of Warsaw Stock Exchange in the period 2015–2020 which have received an adverse or disclaimer opinion by the auditors but have not received a monetary fine from the Polish Financial Supervision Authority (KNF Board) for violation of IAS/IFRS principles related to the financial statements in the study period.

The rest of this paper is organized as follows. Section 2 contains a literature review. Section 3 describes the situation of the Polish financial market and research conducted using the Beneish model. Section 4 describes the data set and the hypotheses set in the analysis. Section 5 presents the results of the analysis, and Section 6 provides a summary and conclusion of the study.

2. LITERATURE REVIEW

The Beneish model (M-Score model) is one of the best-known methods for detecting accounting manipulations in the world. It is a mathematical model based on a probit regression method and indicates the perspectives concerning the tendency of companies to engage in fraudulent accounting processes. The M-Score model measures the level of earning management in various financial situations. The 8-variable M-Score model was conceived based on a sample of 74 U.S. manipulator companies that committed financial fraud according to the U.S. Securities and Exchange Commission (SEC) in the years 1982–1992 and 2,332 public non-manipulators. The Beneish model has a high accuracy rate (76%) in detecting potential financial statement fraud in the U.S. sample. The marginal value of M-Score is (−2.22), where a higher value indicates a probability that the company applied financial statement fraud techniques (Beneish, 1999); however, the relative cost function of Type I and Type II classification errors indicates that the marginal value of the Beneish model should equal (−1.78) (Beneish et al., 2013).

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Several researchers prefer an alternative 5-variable M-Score model created by Roxas (2011) rather than the 8-variable Beneish model. The Roxas model omits the Sales, General, and Administrative Expenses Index (SGAI), Leverage Index (LEVI) and Total Accruals to Total Assets (TATA) indicators and changes the marginal value of M-Score to (−2.76). The research by Roxas showed that the 5-variable model correctly identified more companies than the 8-variable on a sample of U.S. companies, 62% versus 46% observations. Numerous studies have found the Roxas model more accurate than the Beneish model (Anning & Adusei, 2020; Lehenchuk et al., 2021), but some authors did not confirm these results (Buljubasic & Halilbegovic, 2017). Paolone and Magazzino (2014) have also drawn attention to the existence of many differences between U.S. and European accounting principles, so they reclassified the model with SGAI equal to one. Equation 1 and Equation 2 present the calculation of M-score models:

$$\begin{aligned}\text{M-Score (Beneish)} = &-4.84 + 0.920{*}\text{DSRI} + 0.528{*}\text{GMI} + 0.404{*}\text{AQI} + 0.892{*}\text{SGI} + \\ &+ 0.115{*}\text{DEPI} - 0.172{*}\text{SGAI} + 4.679{*}\text{TATA} - 0.327{*}\text{LEVI}\end{aligned} \tag{1}$$

$$\begin{aligned}\text{M-Score (Roxas)} = &-6.065 + 0.823{*}\text{DSRI} + 0.906{*}\text{GMI} + 0.593{*}\text{AQI} + \\ &+ 0.717{*}\text{SGI} + 0.107{*}\text{DEPI}\end{aligned} \tag{2}$$

where:
DSRI – Days Sales in Receivables Index
GMI – Gross Margin Index
AQI – Asset Quality Index
SGI – Sales Growth Index
DEPI – Depreciation Index
SGAI – Sales, General, and Administrative Expenses Index
LEVI – Leverage Index
TATA – Total Accruals to Total Assets

Table 1 reports the method of calculating the individual ratios of the Beneish model.

Table 1
The M-Score model indicators

Ratio	Formula
DSRI	(Net receivables$_t$ / Sales$_t$) / (Net receivables$_{t-1}$ / Sales$_{t-1}$)
GMI	[(Sales$_{t-1}$ – Cost of goods sold$_{t-1}$) / Sales$_{t-1}$] / [(Sales$_t$ – Cost of goods sold$_t$) / Sales$_t$]
AQI	[1 – (Current Assets$_t$ + PPE$_t$)/Total Assets$_t$] / [1 – (Current Assets$_{t-1}$ + PPE$_{t-1}$) / Total Assets$_{t-1}$]
SGI	Sales$_t$ / Sales$_{t-1}$
DEPI	[Depreciation$_{t-1}$ / (Depreciation$_{t-1}$ + PPE$_{t-1}$)] / [Depreciation$_t$ / (Depreciation$_t$ + PPE$_t$)]
SGAI	(SGA Cost$_t$ / Sales$_t$) / (SGA Cost$_{t-1}$ / Sales$_{t-1}$)
LEVI	[(Current Liabilities$_t$ + Total Long Term Debt$_t$) / Total Assets$_t$] / [(Current Liabilities$_{t-1}$ + Total Long Term Debt$_{t-1}$) / Total Assets$_{t-1}$]
TATA	[(Change in Current Assets – Change in Cash) – (Change in Current Liabilities – Change in Current maturities of Long Term Debt – Change in Income Tax payable) – Depreciation and Amortization$_t$] / Total Assets$_t$]

Source: Beneish (1999).

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M-Score calculations and the calculations of the component indices provide a general benchmark that can be used to predict variance in financial statements. The TATA index is one of the elements of the Beneish M-Score model, which measures the ratio of total accruals to total assets for each period. Accruals provide information linking business activities unrelated to cash transactions or future costs incurred by the company. This is why accruals provide a playing field for potential financial manipulation and earnings management. TATA is not the only way to measure accruals; in the literature, are several models that analyze the relationship between firms' accruals and their net income or cash flows, e.g. Jones model, modified Jones model, Sloan model, Dechow-Dichev model, Dechow model (Mantone, 2013). These models are designed to detect the total value of discretionary accrual adjustments. In these models, the non-discretionary accruals adjustments are estimated as a linear function of the model's explanatory variables. The accruals models are typically estimated by industry and year, and the remainder of the model for the total accruals is used to estimate the discretionary accruals adjustments (Artienwicz et al., 2020). On the other hand, the Dechow model (F-Score model) requires the calculation of the index and then the probability value. The probability value is divided by the overall probability of fraud in a given population of companies. The result shows how many times a certain company has a greater probability of falsifying financial statements than a randomly selected company from the entire surveyed population (Wyrobek et al., 2020). However, the accrual models have a poor ability to actually measure the value of the discretionary accruals, because the information about which financial data was manipulated by directors is strictly confidential (Piasecki, 2015). Moreover, the M-Score models can use an overall benchmark of 1.78 or 2.76 to determine whether the financial statement suggests earnings manipulation or an attempt to conceal embezzlement funds. In addition, by decomposing the M-Score model into its components, a researcher can determine whether each calculation may contain unusual variances or anomalies that require further investigation (Mantone, 2013).

3. THE POLISH SCENARIO

In the Polish legal system, no legal acts refer to the definition of financial statement fraud. In such a case, the only clear evidence that the financial statements have been manipulated may be serious reservations of auditors or proceedings initiated by various regulators resulting in the imposition of penalties. The KNF Board is one of the bodies ensuring the proper functioning, stability, security, transparency and confidence in the financial market and ensures that the interests of market participants are protected. The KNF Board also imposes financial or legal sanctions in connection with non-compliance with the International Financial Reporting Standards (IFRS) guidelines.

Due to the lack of an appropriate legal definition of financial statement fraud, a few studies have adopted one of the two possibilities of defining a company as a manipulator. Golec (2019) assumed that the companies that had received an adverse or disclaimer opinion by the auditors could be involved in earning management practices. In this way, the author identified 24 companies listed on Warsaw Stock Exchange (WSE) from 2014 to 2017. For each fraud company, a control company conducting as similar a type of activity as possible was assigned based on the sector. The M-Score model correctly identified 67% of manipulators and 75% of non-manipulators. The research showed that SGI, SGAI, LEVI and TATA were significant in detection of earnings management. Comporek (2020) analyzed 27 companies listed on the WSE that received a monetary fine from the KNF Board in the context of compliance with IFRS principles in the period 2006–2018. The author did not include a control sample to the analysis, because he noted that it is not always possible to choose a company similar enough to reflect all the features that may affect the scope of manipulation. The Beneish model correctly classified 41% observations in the year for which accounting manipulations were detected, and 63% in

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the two previous years for which no accounting manipulations were detected. Hołda (2020) assumed that companies that been fined by the KNF Board for irregularities related to financial statements and received a disclaimer opinion by the auditors or notoriously qualified opinions due to irregularities identified in the statements could be classified as manipulators. Hołda used a sample of eight companies listed on the WSE in the period 2009–2010, in which four firms were identified as manipulators using the 5-variable and 8-variable M-Score models. The author chose only this period because he noticed that it was known what had happened with these companies, and based on their history, it was possible to correctly classify them as a group of manipulators and non-manipulators. The 5-variable model correctly identified only five firms; however, the 8-variable model correctly classified all companies.

4. DATA AND HYPOTHESES

The present empirical research on the Beneish model includes 55 companies listed on the main market of WSE that have received an adverse or disclaimer opinion by the auditors, are established in the territory of Poland and have not received a monetary fine from the KNF Board for violation of IAS/IFRS principles related to financial statements in the period 2015–2020. Table 2 shows the most important reasons for the company's receiving an adverse or disclaimer opinion by the auditors. A matched pair of samples were used in this study, whereby each company is matched with a corresponding control firm based on the industry (according to the Standard Industry Classification code) and financial year, with minimizing the difference in the size of total assets. Each control firm was required to have an unqualified opinion by the auditors. In addition, three companies that received a monetary fine from the KNF Board in the period 2015–2020 related to non-compliance with IAS 1, IAS 24, IAS 34, IAS 36, IAS 39, IFRS 3, IFRS 7 or IFRS 8 (in each case, it was a violation of four IAS/IFRS guidelines) and three control firms were included in the empirical research as a separate sample. The data were collected for these two samples from the annual reports of the companies. In some cases, the denominator of the variables was equal to zero. This study adopted two solutions: first, setting the value of the indicator equal to one, which is the solution used by Beneish (1999), Paolone and Magazzino (2014), Repousis (2016), Feruleva and Shtefan (2017), Golec (2019), Comporek (2020), and second, removing the observation from the sample.

Table 2
The most important reasons for receiving an adverse or disclaimer opinion by the auditors

Reason	No. of cases
Disclaimer regarding adoption of going concern principle by the company	40
related to:	
insufficient audit evidence to evaluate the assumptions made in the notes and financial statements	28
negative equity	11
negative net working capital	8
irregularities or lack of test fixed asset for impairment	5
Not all accounting documents/information are available to the auditor	17
The auditor's report was not made available	7
Tax and audit proceedings conducted against the company	6
Valuation of some of the company's assets in violation of the regulations	5

Note: The auditor could indicate more than one reason for receiving an adverse or disclaimer opinion.

Source: Author's own elaboration.

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Several authors have used the 5- and 8-variable M-Score models in their research. To investigate which of these two models is better for the listed companies on the WSE, the first hypothesis was formulated as follows:

Hypothesis 1: *The 8-variable model will have greater accuracy than the 5-factor model on the sample of companies that have received an adverse or disclaimer opinion from the auditors.*

Several authors have adapted the Beneish model to the conditions of their own country (Paolone & Magazzino, 2014; Repousis, 2016; Feruleva & Shtefan, 2017; Hasan et al., 2017; Ozcan, 2018; Halilbegovic et al., 2020; Kramarova & Valaskova, 2020; Svabova et al., 2020; Vetoshkina et al., 2020; Shakouri et al., 2021; Sabău et al., 2021). This leads to the second hypothesis that:

Hypothesis 2: *The modified M-Score model based on logistic regression results will be more accurate than the 8-variable (5-variable) M-Score model for companies fined by the KNF Board.*

5. RESULTS

Table 3 shows the descriptive statistics for the M-Score variables for the sample of companies that received an adverse or disclaimer opinion by the auditors and have not received a monetary fine from the KNF Board and control firms. The Mann-Whitney U-test showed that there was a significant difference between the variables SGI, DEPI, SGAI, LEVI and TATA for companies that had received an adverse or disclaimer opinion compared to the control group firms. The high SGI ratio can raise expectations, many of which are not sustainable for the company's management but do not yet imply financial statement fraud. A high value of DEPI ratio indicates that fraudulent firms revise the useful life of their assets upwards or adopt a new depreciation method that boosts corporate earnings. The high SGAI ratio may signal deteriorating sales and administrative efficiency that may induce the firm's management to commit financial statement fraud. A high value for the LEVI ratio indicates that firms may become more prone to financial statement fraud. The high level of the TATA ratio may increase the likelihood of the manipulation of corporate earnings.

Table 3
Descriptive statistics

	Minimum		Maximum		Mean		Std deviation	
	Adverse	**Control**	**Adverse**	**Control**	**Adverse**	**Control**	**Adverse**	**Control**
DSRI	-0.58	0.00	3527.86	15.12	89.33	1.60	520.86	2.32
GMI	-18.87	-351.76	4.87	2.09	-0.10	-5.72	3.38	47.98
AQI	-0.63	0.00	19.86	5.60	1.74	1.03	3.24	0.72
SGI***	-0.72	0.22	1.59	257.43	0.51	5.83	0.45	34.89
DEPI**	0.10	0.04	9.42	4.43	1.03	1.13	1.34	0.68
SGAI**	-3.48	0.00	699.23	9.80	27.71	1.19	118.26	1.26
LEVI***	0.00	0.13	60.69	26.19	3.87	1.54	9.14	3.50
TATA***	-27.69	-25.61	8.33	0.32	-1.88	-0.51	5.00	3.45

Note: *** indicates Mann-Whitney U-test significant at the 1 percent level, ** at the 5 percent level and * at the 10 percent level.

Source: Author's own elaboration.

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Table 4 illustrates the classification scheme of the full sample, where it is assumed that the value of the indicator is equal to one when the denominator is equal to zero. The results from the Beneish model reveal that 12 out of the 55 firms (27.9%) are found to have a total M-Score higher than (−1.78) and were classified as earnings manipulators, while 38 control firms (69.1%) are classified as non-manipulators. In contrast, using the Roxas model, the results showed that 23 firms with adverse or disclaimer opinions (41.8%) and 34 control companies (61.8%) are prone to financial statement fraud. The Roxas model approach increases accuracy by 6.3 percentage points.

Table 4
M-Score model results for the full sample

	Beneish model		
	Manipulator	**Non manipulator**	**Correct (Percentage)**
Adverse	12	43	27.9%
Control	17	38	69.1%
Overall			45.5%
	Roxas model		
	Manipulator	**Non manipulator**	**Correct (Percentage)**
Adverse	23	32	41.8%
Control	21	34	61.8%
Overall			51.8%

Source: Author's own elaboration.

Table 5 presents the classification scheme for the companies for which it was possible to calculate all M-Score ratios. Based on the estimations, the Beneish model correctly classified 7 adverse firms (16.7%) and 30 control firms (71.4%); the accuracy of the model was 44.0%. The Roxas model correctly classified 17 adverse companies (40.5%) and 29 control firms (69.0%); and the Roxas model had greater accuracy than the Beneish model by 10.8 percentage points.

Table 5
M-Score model results for the sample with enumerated variables

	Beneish model		
	Manipulator	**Non manipulator**	**Correct (Percentage)**
Adverse	7	35	16.7%
Control	12	30	71.4%
Overall			44.0%
	Roxas model		
	Manipulator	**Non manipulator**	**Correct (Percentage)**
Adverse	17	25	40.5%
Control	13	29	69.0%
Overall			54.8%

Source: Author's own elaboration.

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Based on the results, Hypothesis 1 should be rejected. The Beneish model was less accurate than Roxas model. The goal of this research is not only to assess the differences between the two groups of companies but also to evaluate which of the eight ratios in the Beneish score individually influence the probability of identifying fraud for companies. Some authors have also modified the Beneish model to the conditions in their countries, primarily based on logistic regression (Ozcan, 2018; Erdogan & Erdogan, 2020; Papik & Papikova, 2020; Svabova et al., 2020). In this case, the logistic regression was used to analyze the interaction effects of the ratios in the Beneish model. The logistic regression model is selected to establish a model that can effectively predict the situation of firms with negative or adverse opinions. The results of estimating the research model by logistic regression and using data where it was possible to calculate all M-Score ratios are reported in Table 6.

Table 6
Logistic regression models for the sample with enumerated variables

	Beneish	**Roxas**	**Modified**
DSRI	-0.0126 (0.0285)	-0.0127 (0.0263)	
GMI	-0.5320 (0.2555)***	-0.8003 (0.2884)***	-0.4078 (0.2253)**
AQI	0.2892 (0.3463)	0.1896 (0.3142)	
SGI	-0.7401 (0.3513)***	-1.1068 (0.3967)***	-0.5693 (0.3101)**
DEPI	-0.7495 (0.5306)*	-0.9830 (0.5248)**	-0.8672 (0.6461)*
SGAI	-0.0045 (0.0050)		
LEVI	-1.0167 (0.6868)		
TATA	-2.2405 (1.4803)		-4.0402 (0.0023)***
Constant	2.1448 (1.0425)	2.2875 (0.9401)**	1.0181 (0.8805)
N	84	84	84
R-square	31.7%	22.1%	33.0%
Accuracy	75.0% (63)	76.2% (64)	79.8% (67)
Sensitivity	50.0% (21)	52.4% (22)	59.5% (25)
Specificity	100.0% (42)	100.0% (42)	100.0% (42)

Note: standard errors in parentheses: *** indicates variables significant at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Source: Author's own elaboration.

The results from the logistic regression indicate that the GMI, SGI and DEPI ratios are significant in both the Beneish and Roxas models. Based the regression results, the classification accuracy was 75.0% for the Beneish model and 76.2% for Roxas model. The GMI, SGI, DEPI and TATA have a direct and statistically significant effect on the Polish market in Table 6. The model correctly classified 59.5% of companies with adverse or negative opinions and 100% of

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the control companies. These findings align with the results of other studies in the literature. Shakouri et al. (2021) confirmed that there is a significant relationship between GMI, SGI, DEPI and TATA with financial statement fraud. Herawati (2015) in the conducted research also confirmed that GMI, DEPI and TATA ratios have a direct influence on identifying the presence of financial fraud. Sabău et al. (2021) also showed that GMI, DEPI and TATA ratio can signal the presence of financial fraud. In their study for the ratio TATA and SGI, Halilbegovic et al. (2020) ran tests that also showed they have a significant influence in detecting financial fraud.

Based on the results of logistic regression analysis, Equation 3 presents the following linear equation for the M-Score model for companies listed on the WSE:

$$\text{M-Score (Modified)} = 1.0181 - 0.4078*GMI - 0.5693*SGI - 0.8672*DEPI - 4.0402*TATA \quad (3)$$

The red flag values for these ratios were computed as the probability cutoffs that would minimize the expected costs of misclassification with relative costs of Type I to Type II errors equal to 1:1. The threshold values are as follows:

- Less than 0.7218 for GMI,
- Less than 0.9443 for SGI,
- Less than 0.7801 for DEPI and
- Less than (−0.1079) for TATA.

The marginal value of the modified M-Score was calculated based on the linear equation and the threshold values for the indicators and is equal to (–0.0544). It means a higher value indicates a higher probability that the company applied financial statement fraud techniques.

Table 7 reports the classification results of the modified M-Score model for companies that have received a monetary fine from the KNF Board for violation of IAS/IFRS principles. Both the Beneish and Roxas models accurately classified one out of three fined firms and all control firms, while the adapted model incorrectly classified only one fined company. The use of red flag values indicates that attention should be paid to all fined companies. The value for TATA was exceeded for all fined companies, SGI for two companies and GMI for one firm; however, for control companies, the red flag value for GMI identified one company and SGI two firms for further analysis. The classification results suggest that the adapted model has superior performance in the detection of firms that have received an adverse or disclaimer opinion by the auditors and received a monetary fine from the KNF Board.

Table 7
Modified M-Score model results for companies that have received a monetary fine from the KNF Board

	Beneish / Roxas		Modified	
	Manipulator	Non manipulator	Manipulator	Non manipulator
Fraud	1	2	2	1
Control	0	3	0	3
SUM	1	5	2	4

Note: Identical results were obtained for Beneish and Roxas models, therefore they were not separated in the table.

Source: Author’s own elaboration.

Based on the results, Hypothesis 2 cannot be rejected. The Modified M-Score model had better accuracy than the 8-variable (5-variable) M-Score models.

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6. CONCLUSION

Detecting financial statement fraud is extremely difficult for forensic accountants, especially if the firm's management is involved, although the methods used in forensic accounting make key contributions to the detection of financial statement fraud. Past experiences have played a critical role in the development of forensic accounting methods, but the rapidly changing global financial environment leads to the introduction of new methods.

The research sought to detect financial statement manipulation among 110 listed companies in Poland analyzed during a six-year period (2015–2020) using the Beneish and Roxas models. Based on the results, the Roxas model was more accurate than the Beneish model, and Hypothesis 1 should be rejected. The overall accuracy of the Roxas model was 51.8%. It is crucial to mention that Beneish or Roxas models do not present the perfect evaluation for earning manipulation in companies. That is why it is significant to detect the level of accuracy in the case of manipulation within firms, based on the models.

Also the modified M-Score model, based on the logistic regression approach, with 79.8% overall accuracy, allowed for correct identification of each control company and nearly 60% of companies that had received an adverse or disclaimer opinion from the auditors. For the Polish market, there are four significant ratios: GMI, SGI, DEPI and TATA. Based on the results for companies that have received a monetary fine from the KNF Board, Hypothesis 2 cannot be rejected. Researchers should remember that a single irregularity is not a sign of financial statement manipulation.

The results indicate that the Beneish and Roxas models should not be used for companies that have received an adverse or disclaimer opinion from auditors for public companies listed on the WSE. The logistic regression based on indicators from these models had greater accuracy. This paper found that the modified M-Score model for companies listed on the WSE has more powerful detection capacity than either the Beneish or Roxas models. The modified M-Score model can be used as a predictor in determining the risk of a negative opinion by an auditor. The data sample was prepared based on which companies had received an adverse or disclaimer opinion from the auditors; however, not all adverse or disclaimer opinions are a sign of fraud. The weakness of this study is the small sample size, which was dictated by data availability constraints. Future studies should investigate the detection capacity of the proposed model in other countries, because the methods for reporting financial indicators may differ significantly by country.

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