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Redefining Financial Manipulation Detection: A New Model's Performance Against the M-Score *

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Abstract

Financial manipulation negatively affects market participants. Therefore, various techniques are developed to detect manipulation. One of the most widely used techniques in the literature is the M-score. The study investigates whether the M-score is an effective model across different periods and aims to provide perspective to researchers and market players. In this study, we developed a model to detect financial manipulation. We compared our model results with the M-score results. In the study, we first scanned the US Securities and Exchange Commission's "Accounting and Auditing Practice Bulletins" and identified fifty-one companies (red flags) from the reports. Then, we calculated some ratios from the financial reports of these companies (red flags) and companies with control variables and created the prediction model. The results show that the success of the created manipulation prediction model is eighty-three per cent. The M-score results are lower. The model in the study is the most up-to-date model with many explanatory variables to detect financial manipulation. The study showed that established manipulation detection models may lose effectiveness over time, and the effects of the variables in the model may change. Therefore, the study offers a novel perspective to the literature. In future studies, researchers could investigate how imbalances in the proportion of "1" versus "0" observations affect the detection model.

Keywords: Financial statements, Financial fraud, USA, Logistic regression analysis, M-score.

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1. INTRODUCTION

Financial statements are prepared to fairly present a company's financial position, operational performance, and cash flows. These reports play a critical role in the financial decision-making process. Shareholders, investors, creditors, and government agencies base their financial decisions on the information in these statements. Therefore, ensuring the reliability of financial reporting standards is of great importance.

Accounting fraud involves intentionally misrepresenting financial statements or illegal acts that directly affect financial disclosures. It is usually committed by corporate executives who fraudulently present financial information (Guy & Pany, 1997). Beasley et al. (2010) define accounting fraud as intentionally misrepresenting financial statements or disclosures. These fraudulent activities may have different motivations but always lead to significant negative consequences (Brennan & Hennessey, 2001).

According to the Association of Certified Fraud Examiners (ACFE), financial statement fraud is the least common globally, accounting for only 10% of detected cases. However, it is the costliest form of fraud when it does occur. Financial fraud is often complex and challenging to detect in advance. Notable examples include fraudulent financial reporting by companies such as Enron, WorldCom, Xerox, Qwest, Tyco, HealthSouth, and Cendant (Kedia & Philippon, 2009).

Since the late 20th century, various methods have been developed to detect such fraudulent activities. Pioneering studies in this area include Healy's (1985) study of manipulations used by corporate executives to obtain incentive bonuses, DeAngelo's (1986) examination of financial manipulations through discretionary accruals during stock buybacks, and Jones's (1991) analysis of profit manipulations by companies seeking to benefit from import discounts. Additionally, Barton and Simko (2002) analyzed changes in net operating items to detect balance sheet manipulations, while Beneish (1997, 1999) used accruals and financial ratios (known collectively as the M-score) to detect fraudulent reporting.

Many studies have developed financial fraud detection models (Beasley, 1996; Persons, 1995; Spathis, 2002; Küçükkocaoğlu & Küçüksözen, 2005; Aprillia, 2011; Dechow et al., 2011; Perols & Lougee, 2011; Ujal et al. 2012; Amara et al., 2013; Kanapickiene & Grundiene, 2015; Lin et al., 2015; Zainuddin & Hashim, 2016; Hajek & Henriques, 2017; Hung et al., 2017; Ravenda et al., 2018; Song et al., 2018; Tran et al., 2018; Situngkir & Triyanto, 2020; Çağlak & Çakır, 2024). However, the model results in these studies have not been compared with the M-score results. Some studies in the literature aim to detect firms that engage in manipulation by using the M-score equation rather than developing a new detection model (Matsumura & Tucker, 1992; Küçükkocaoğlu et al., 2007; Bekçi & Avğarlıgil 2011, Aris et al., 2013; Kara et al., 2015; Mahama, 2015; Hasan et al., 2017; Herawati & Tarjo, 2017; Erdoğan & Erdoğan, 2020; Halilbegovic et al., 2020; Lehenchuk et al., 2020; Demetriades & Owusu-

Agyei, 2022). This study developed a financial fraud detection model using financial statement data of companies traded on the US stock exchanges. The estimation results of this model were compared with the M-score results to fill a gap in the literature. The findings provide insights to investors, creditors, and researchers in detecting financial statement fraud.

The contribution of this study to the literature is that it includes more financial variables than existing models and compares the model results with the M-score results. Therefore, this research brings a new perspective to the field. Future studies can be conducted with an alternative dataset that includes the financial ratios of bankrupt companies withdrawn from the stock exchange or traded in the OTC market. In this way, it will contribute to the literature by eliminating the limitations stated in the dataset.

2. METHODOLOGY

2.1. Econometric Model

Classical regression techniques are not appropriate when the dependent variable is categorical (e.g., 0 or 1). Instead, the Logistic regression method should be used. The logistic regression method is a decision-making tool in many fields, such as medicine, engineering and social sciences. This technique is a regression method that allows for the separation and assigning of sample groups. The fact that it is an analysis that does not require normal distribution and continuity assumptions increases the ease of application of this technique. The accumulated model reveals which class the data groups should belong to according to specific probabilities. The coefficient obtained by the model is classified using the threshold value. If the company's coefficient accumulated with the help of the model is greater than the threshold value, that company is considered a company that has been manipulated. If the coefficient is less than the threshold value, it is concluded that the company does not manipulate.

In the logistic regression equation, the odds ratio is calculated as follows:

$$\frac{P_i}{1-P_i} = \frac{1+e^{Z_i}}{1+e^{-Z_i}} = e^{\beta_1+\beta_2 X_i} \tag{1}$$

In logistic regression, the probability of an event not occurring (0) and the probability of it occurring (1) must be calculated. In order to obtain a linear equation, its logarithm must be taken. (that is why it is called the logit model) The final form of the equation is created as follows:

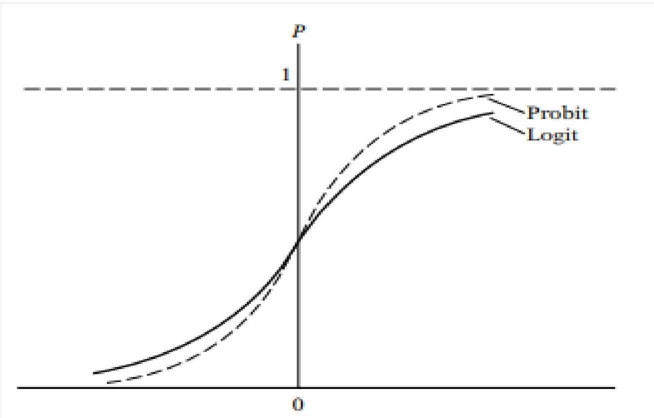
$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i \rightarrow \beta_1 + \beta_2 X_i \tag{2}$$

The log of the odds ratio, L, is linear in X and (in terms of prediction) linear in the parameters. L is called logit. Therefore, models such as L_i L_i are called the logit models (Gujarati & Porter, 2009).

As P goes from 0 to 1 (Z changes from −∞ to +∞), the logit L goes from −∞ to +∞. Although the probabilities are (necessarily) between 0 and 1, logits are not that limited. Although L is linear in X, the probabilities themselves are nonlinear. This contrasts with the Linear Probability Model (LPM) model as probabilities move linearly with X. However, we only included a single X variable or regressor in the previous model as many regressors as required by the underlying theory can be added. Let us assume that L (logit) is optimistic. In this case, this means that the probability of the regressor being equal to 1 (meaning a relevant event has occurred) increases as the value of the regressor/regressor increases. If L is negative, the probability of the regressor equaling one decreases as the value of X increases. In other words, as the odds ratio decreases from 1 to 0, the logit becomes negative and gradually increases. As the odds ratio increases from 1 to infinity, the logit becomes increasingly significant and positive (Hosmer & Lemeshow, 1989). For the logit model in L_i: β2, the slope measures the change in L for one unit change in X. While LPM is linearly related to Pi and Xi, in the logit model, it is assumed that the log of the odds ratio is linearly related to Xi (Gujarati & Porter, 2009).

Logit and probit are similar for most practical applications. The main difference is that Pi approaches zero or one more slowly in the logit model than in the probit model, as seen in Figure 1. That is, the logistic distribution has slightly thicker tails. Many researchers choose the logit model in practice due to its mathematical simplicity.

Figure 1. Logit and Probit Cumulative Distributions



Source: Authors' own creation.

In this study, the Binary Logistic Regression method was used to test the presence (coded as "1") or absence (coded as "0") of financial manipulation.

2.2. Sample Selection and Data Processing

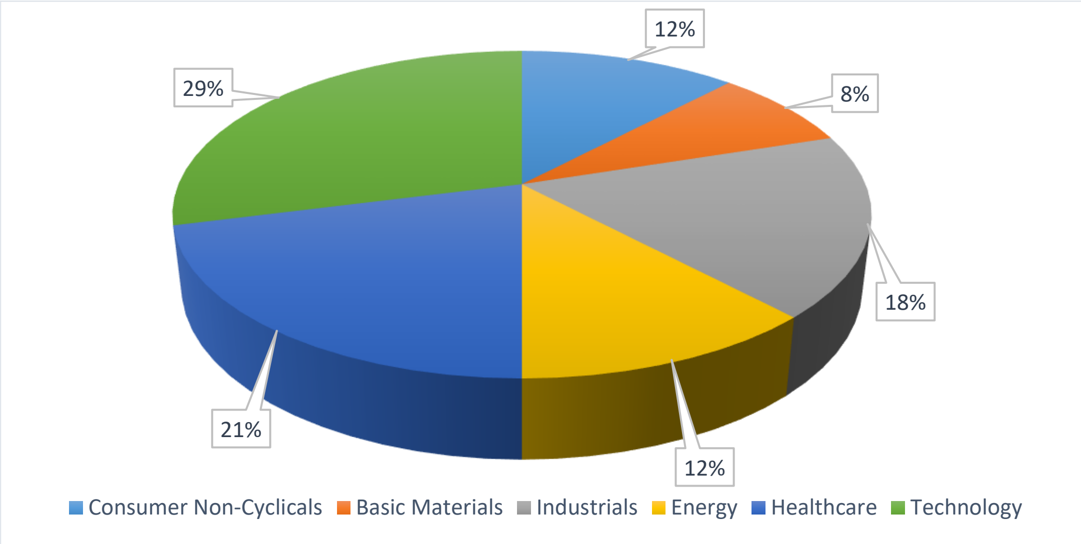
Bulletins of companies on the US stock exchanges published between 2009 and 2019 were scanned to select the companies. Subsequently, errors, frauds and irregularities in previous financial reports were identified through detailed examination.

The bulletins (from AAER_3094 to AAER_4200) of companies subject to accounting enforcement actions by the Securities and Exchange Commission (SEC) using Accounting and Auditing Enforcement Releases (AAERs) published between 2009 and 2019 were scanned in the USA. Subsequently, errors, frauds and irregularities in previous financial reports were tried to be detected through detailed examination. 180 bulletins containing manipulation were identified. 159 of the releases included manipulations regarding financial reports. Among the companies that engage in financial manipulation, 51 companies whose financial statements can be accessed and are not included in Over the Counter Markets (OTC) were included in the sample. Financial reports of 51 companies in the same sector and with similar asset sizes were used as a control group for these companies.

In the analysis, companies that manipulate the dependent variable will be included as "1" (red flag), and companies selected as control variables will be included as "0" (green flag). Companies that should have been included in the sample but whose financial statements needed to be improved (bankruptcy, delisting, being placed in the custody market, etc.) were excluded from the analysis. In addition, although there are studies on the financial manipulations of banks (Fratrič et al., 2022; Li et al., 2022), banks, insurance companies, and intermediary institutions were excluded from the sample due to different financial reporting techniques. Financial reports of the companies in the sample were obtained from ROIC.ai. (n.d.) and Securities and Exchange Commission (2009) 10-K reports. Independent variable ratios were calculated from these reports.

Of the companies that engage in financial manipulation (red flag), 29% are technology companies, and 21% are healthcare sector companies. Some examples in AAER bulletins are as follows: He committed irregularities by paying bribes to the authorities of the countries in question while obtaining operating permits for health sector companies and recording these bribes as education expenses. Companies such as technology and energy make fictitious sales through subsidiaries in different countries or make manipulations through bribes in tender purchases, which frequently encounter manipulations. Supervisory authorities took penal actions for these manipulations.

Figure 2. Sectoral Distribution of Manipulating Companies (Red Flag)



Source: Authors' own creation.

3. EMPIRICAL RESULTS AND DISCUSSION

Eight of the ratios in the analysis (DSRI, GMI, AQI, DEPI, SGAI, ACR, SGI, LVGI) are the variables used by Beneish (1999). In addition, twenty-one different ratios are independent variables with the ratios added from the literature.

For analysis, the data set consists of the ratios calculated from the companies' financial reports using the formulas in Table 1. This data set is divided into "training data" and "test data".

Table 1. Ratios and Formulas to Be Used in the Analysis

Days' sales in receivables index (DSRI)	$\dfrac{Account\ Receivable_t / Sales_t}{Account\ Receivable_{t-1} / Sales_{t-1}}$
Gross margin index (GMI)	$\dfrac{Sales - Cost\ of\ goods\ sold_{t-1} / Sales_{t-1}}{Sales - Cost\ of\ goods\ sold_t / Sales_t}$
Asset quality index (AQI)	$\dfrac{(1 - Current\ assets. + PP\text{and}E)_t / Total\ assets_t}{(1 - Current\ assets. + PP\&E)_{t-1} / Total\ assets_{t-1}}$
Depreciation index (DEPI)	$\dfrac{Depreciation_{t-1} / (Depreciation + PP\&E)_{t-1}}{Depreciation_t / (Depreciation + PP\&E)_t}$
Sales, general, and administrative expenses index (SGAI)	$\dfrac{(Sales, general, and\ administrative\ expense)_{t-1} / Sales_{t-1}}{(Sales, general, and\ administrative\ expense)_t / Sales_t}$
Total accruals to total asset (TATA)	$\dfrac{Operation\ income - Cash\ Provided\ by\ Operating\ Activities}{Total\ assets}$
Sales growth index (SGI)	$\dfrac{Sales_t}{Sales_{t-1}}$
Leverage index (LVGI)	$\dfrac{Current\ Liabilities + non - Current\ Liabilities_t / Total\ assets_t}{Current\ Liabilities + non - Current\ Liabilities_{t-1} / Total\ assets_{t-1}}$
Financial Expenses/ Operating Expenses	$\dfrac{Financial\ Expense}{Total\ operation\ expense}$
EBIDTA/Financial Expenses	$\dfrac{EBIDTA}{Financial\ expenses}$
Current Ratio	$\dfrac{Total\ current\ assets}{Total\ current\ liabilities}$
Acid-Test ratio	$\dfrac{Total\ current\ assets - Inventory}{Total\ current\ liabilities}$
Leverage ratio	$\dfrac{Current\ Liabilities + non - Current\ Liabilities}{Total\ assets}$

Table 1 (cont.)

Equity to Dept (E/D)	$\frac{Total\ Shareholders\ Equity}{Total\ Dept}$
ROA	$\frac{Net\ Profit}{Total\ Assets}$
ROE	$\frac{Net\ Profit}{Equity}$
Commercial receivable/net sales	$\frac{\text{Commercial receivable}}{Net\ Sales}$
Gross Profit/ Net Sales Ratio	$\frac{Gross\ Profit}{Net\ Sales}$
Other Assets/Total Assets	$\frac{Other\ \ Assets}{Total\ Assets}$
Accumulated Depreciation ratio (ADR)	$\frac{Depreciation}{(Depreciation + PP\&E)}$
Operating Expenses/Revenue	$\frac{Operating\ Expenses}{Revenue}$

Source: Authors' own creation.

For analysis, it is necessary to look at the data structure and whether there is a correlation between the data. In this respect, firstly, the descriptive statistics of the independent variables were calculated for the companies that manipulated the data set and the control variables. In this context, the descriptive statistics of the data set are in Table 2.

Table 2. Descriptive Statistics

		Mean	Median	Std Dev.	Min.	Max.	Total	Number
DSRI	1	1.19	1.03	0.71	0.34	4.37	60.46	51
	0	3.81	1.02	19.32	139.03	0.12	194.31	51
GMI	1	1.07	1.01	0.42	-0.26	3.40	54.32	51
	0	1.18	1.01	0.75	5.89	0.50	60.20	51
AQI	1	1.33	1.00	1.55	0.14	11.38	68.05	51
	0	1.04	1.01	0.41	2.49	-0.72	52.98	51
SGI	1	1.13	1.07	0.41	0.49	3.22	57.46	51
	0	1.08	1.05	0.42	3.07	0.02	54.96	51
DEPI	1	1.06	0.99	0.49	0.29	3.63	54.22	51
	0	1.95	1.02	5.14	37.11	0.61	99.40	51
SGAI	1	0.95	1.01	1.03	-5.63	2.57	48.51	51
	0	1.28	1.02	1.84	13.87	0.06	65.48	51
LVGI	1	1.12	1.01	0.61	0.12	5.04	56.93	51
	0	1.10	0.98	0.48	4.00	0.73	56.33	51
ACR(TATA)	1	-0.03	0.00	0.18	-1.19	0.23	-1.50	51
	0	-0.02	-0.01	0.09	0.17	-0.48	-0.89	51

Table 2 (cont.)

		Mean	Median	Std Dev.	Min.	Max.	Total	Number
Current Ratio	1	2.48	2.12	1.42	0.30	6.27	126.53	51
	0	2.63	2.38	1.55	6.67	0.76	133.99	51
Acid-Test Ratio	1	1.85	1.48	1.30	0.28	6.24	94.24	51
	0	2.07	1.78	1.34	6.04	0.07	105.42	51
Leverage Ratio	1	0.57	0.53	0.35	0.14	2.44	28.83	51
	0	0.49	0.48	0.25	1.17	0.08	24.99	51
Equity to Dept (E/D)	1	1.29	0.90	1.37	-0.59	6.16	65.92	51
	0	1.96	1.07	2.50	11.04	-0.19	99.73	51
EBITDA/Financial Expenses	1	453577.74	15.31	3230043	-246.58	23068387	23132465	51
	0	16.28	13.34	250.20	632.01	-1381.00	830.05	51
Financial Expense Ratio	1	0.16	0.04	0.46	-1.25	1.98	8.12	51
	0	0.14	0.08	0.16	0.56	-0.10	7.39	51
ROA	1	-0.02	0.06	0.41	-2.80	0.28	-1.02	51
	0	0.06	0.07	0.12	0.33	-0.49	3.04	51
ROE	1	0.15	0.12	0.36	-0.70	1.94	7.73	51
	0	0.23	0.13	0.66	3.48	-1.77	11.48	51
Account Receivable/Revenue	1	0.69	0.19	3.52	0.01	25.33	35.33	51
	0	0.45	0.15	2.16	15.58	0.00	22.91	51
Gross profit/net income	1	1.02	0.12	6.78	-1.93	48.47	52.25	51
	0	0.18	0.19	0.22	0.73	-0.81	9.43	51
Other assets/total assets	1	0.29	0.26	0.18	0.01	0.61	14.62	51
	0	0.28	0.21	0.21	0.80	0.02	14.24	51
Accumulated Depreciation ratio (ADR)	1	0.18	0.14	0.19	0.00	1.00	9.40	51
	0	0.22	0.18	0.22	0.99	0.00	11.14	51
Operation expense/Revenue	1	0.18	0.18	0.38	-2.18	1.03	9.01	51
	0	0.44	0.17	1.56	11.23	0.01	22.60	51

Source: Authors' own creation.

Table 2 shows that there are extreme values in the interest-earning variable. This situation is because the ratio is calculated as EBITDA/financing expenses. The interest earned reaches high values in companies with very low or no financing expenses.

In addition to descriptive statistics, the correlation relationship between variables before building the model is in the correlation table in Table 3.

Table 3. Correlation Matrix

	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	ACR	CR	ATR	LR	E/D	EBITDA/Fin. Exp.	FER	ROA	ROE	Acc. Rec./Rev.	G. Profit/ Net Inc.	Other Assets/Tot. Assets	ADR	Oper. Exp./ Revenue
DSRI	1																				
GMI	0.79	1																			
AQI	-0.17	-0.16	1																		
SGI	-0.27	-0.19	0.20	1																	
DEPI	0.19	0.12	-0.08	-0.04	1																
SGAI	0.85	0.66	-0.13	-0.21	0.18	1															
LVGI	0.55	0.37	-0.08	-0.32	0.09	0.16	1														
ACR	0.02	-0.10	-0.06	-0.26	0.05	0.02	0.00	1													
Current Ratio(C/R)	0.28	0.21	-0.09	-0.03	0.14	0.31	0.13	0.13	1												
Acid-Test Ratio (ATR)	0.26	0.23	-0.15	-0.03	0.07	0.28	0.16	0.05	0.90	1											
Leverage Ratio (LR)	0.01	0.09	-0.01	0.31	-0.02	-0.03	-0.07	-0.53	-0.47	-0.42	1										
Equity to Dept(E/D)	-0.04	0.00	0.00	-0.10	-0.03	0.00	0.08	0.04	0.54	0.54	-0.64	1									
EBITDA/ Financial Expenses	-0.01	-0.02	-0.02	0.00	-0.03	-0.01	0.03	0.04	0.15	0.16	-0.06	-0.03	1								
Financial Expense Ratio (FER)	-0.04	0.01	0.01	0.24	0.06	0.08	-0.39	0.08	0.07	0.15	0.08	0.05	-0.04	1							
ROA	0.00	-0.09	-0.10	-0.47	0.05	0.04	0.06	0.64	0.11	0.08	-0.66	0.18	0.03	-0.05	1						
ROE	-0.04	-0.10	0.04	0.21	0.01	-0.03	-0.04	-0.39	-0.10	-0.04	0.42	0.00	0.00	0.00	-0.29	1					
Account Receivable/ Revenue	0.53	0.34	-0.13	-0.26	0.10	0.06	0.89	0.00	0.08	0.08	0.01	-0.01	-0.01	-0.36	0.02	-0.02	1				
Gross Profit/ Net Income	0.00	-0.09	-0.04	-0.16	0.00	-0.46	0.72	-0.01	-0.09	-0.08	-0.01	0.00	-0.01	-0.40	0.05	0.00	0.85	1			
Other Assets/ Total Assets	-0.11	0.04	-0.03	-0.04	-0.12	-0.07	-0.09	0.08	-0.16	-0.07	-0.08	0.14	-0.03	-0.07	0.12	-0.04	-0.13	-0.08	1		
ADR	-0.10	0.01	-0.10	-0.01	-0.13	-0.06	-0.01	-0.09	0.09	0.15	0.11	-0.08	-0.07	-0.09	-0.11	0.22	-0.12	-0.08	0.21	1	
Operation Expense/ Revenue	0.96	0.77	-0.18	-0.20	0.17	0.93	0.36	-0.02	0.32	0.30	0.03	-0.04	0.01	0.00	-0.05	0.02	0.32	-0.23	-0.07	-0.03	1

Source: Authors' own creation.

When the correlation table is examined, it is seen that there is a very high positive correlation between operation expense/revenue/revenue/revenue and SGAI and DSRI. In addition, there is a robust positive correlation between operating accounts receivable/revenue and LVGI and gross profit/net income and between operation expense/revenue/revenue and trade receivables index (DSRI) and operating expense index (SGAI). Therefore, while establishing the model, care was taken to ensure that these variables were not included in the model simultaneously.

A total of 51 manipulation companies in the sample and 51 non-manipulation companies were selected as a match for these companies, and they were separated as training and test data. 39 manipulation companies and their equivalent 39 control variable companies, a total of 78 companies (77% of the total data set), were determined as the training set. For the test data set, 24 companies (23% of the total data set) were chosen, including 12 manipulation companies and 12 matched control variable companies.

Table 4. Logistic Regression Results

Variable	Coefficient	Std. Error	z-Statistic	Prob.	Exp(B)
GMI	-2.233	1.037	2.558	0.031**	0.107
ACR(TATA)	5.347	4.199	3.275	0.203	210.052
Leverage Ratio (LR)	-2.008	1.178	3.907	0.088***	0.134
Equity to Dept(E/D)	-0.675	0.268	3.262	0.012**	0.509
EBITDA/Financial Expenses	0.003	0.001	5.833	0.016**	1.003
ROA	-5.101	2.407	3.159	0.034**	0.006
Account Receivable/Revenue	10.191	3.939	7.647	0.010*	266.090
Other Assets/Total Assets	4.489	1.799	6.231	0.013**	89.068
Constant	1.046	1.529	0.468	0.494	2.846
Prob (LR statistic)	0.0000	Obs with Dep=0 Obs with Dep=1 Total obs	39 39 78		

* Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level. (The "Backward: Conditional" method was used in logistic regression.)

Table 5. Model Fitting Information

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	66.431	0.414	0.552
13	72.016	0.371	0.494

The R^2 of the model created using the training data set is approximately 50%. As for the model variables, seven variables are significant, except the ratio of total accruals to total assets (ACR). The equation obtained from the analysis is as follows:

g(x) = 1.046 -2.233*GMI + 5.347*ACR - 2.008* LR -0.675*(E/D) + 0.003*(EBITDA/Financial Expenses) -5.101*ROA+10.191*(Account Receivable/Revenue) + 4.489*(Other Assets/Total Assets) (3)

The probability equation to be used to determine the possibility of financial manipulation is formulated as follows:

P(x) = 1/ 1+Exp (1.046 -2.233*GMI + 5.347*ACR -2.008*LR-0.675*(E/D) + 0.003*(EBITDA/Financial Expenses) -5.101*ROA+10.191*(Account Receivable/Revenue) + 4.489*(Other Assets/Total Assets)) (4)

P is the probability of fraud in financial statements (ranging from 0 to 1). The P value is interpreted according to a threshold value. Since a matched sample was used in the study, the threshold value is 50%. If P > 0.5, the financial statements are fraudulent; If P < 0.5, the financial statements are not fraudulent.

The companies were classified by typing the ratios of the companies selected for the probability equation training data. Using this classification, the model has predictive power for companies that engage in manipulation, as reported in Table 6.

Table 6. Strength of Models Used for Training Data

			Estimate			Success
			0	1	Total	%
New Model	Observation	0	31	8	39	79.5 %
		1	7	32	39	82.1 %
		Total	38	40	78	79.2%
M-Score	Observation	0	25	14	39	64.1 %
		1	22	17	39	43.5 %
		Total	47	31	78	53.8 %

Source: Authors' own creation.

The model's power to differentiate the training data set companies was tested. The results show that the power to distinguish companies that do or do not manipulate is around 80%. This rate is higher than the discrimination power of the M-score, which is widely used in literature. The model's power to discriminate the companies in the test data set is in Table 7.

Table 7. Strength of Models Used for Test Data

			Estimate			Success
			0	1	Total	%
New Model	Observation	0	11	1	12	91.6 %
		1	3	9	12	75 %
		Total	14	10	24	83.3%
M-Score	Observation	0	8	4	12	66.7 %
		1	8	4	12	33.3 %
		Total	16	8	24	50 %

Source: Authors' own creation.

In the test data, 20 out of 24 companies were correctly classified as manipulating or non-manipulating. Only four companies were incorrectly classified. These results show that the model has 83% correct classification power. With the M-score, for the same companies, 66.7% of the companies that did not manipulate were correctly predicted, while 33.3% of the companies that manipulated were correctly predicted. The probability of Type 1 error (i.e., falsely identifying manipulation) is high in the M-score results. Furthermore, the new model's predictive accuracy surpasses that reported in previous logistic regression studies (Beasley, 1996; Persons, 1995; Dechow et al., 2011; Ujal et al., 2012; Kanapickiene & Grundiene, 2015; Lin et al., 2015; Zainuddin & Hashim, 2016; Hajek & Henriques, 2017).

4. CONCLUSION

In the literature on financial manipulation, studies based on accrual and earnings management are concentrated. This study detected manipulation in accrual and earnings management ratios and bankruptcy and efficiency ratios.

In this study, the performance of a new logistic regression model developed to detect manipulation in financial statements was evaluated and compared with the M-score, which is widely used in the literature. The findings show that the model successfully distinguishes between manipulating and non-manipulating companies in the training and test data sets. The estimation model variables are AGMI, ACR (TATA), Leverage Ratio (LR), Equity/Debt (E/D), EBITDA/Financial Expenses, ROA, Account Receivables/Revenue, Other Assets/Total Assets. The model classified companies that did not manipulate the training data set at 79.5% accuracy and manipulating companies at 82.1%. The overall accuracy rate of the model was calculated as 79.2%. These results show that the model has a high discrimination power when detecting manipulation. Because the model is developed using the training dataset, evaluating its performance on a separate test dataset offers more objective validation. In the test dataset, the model classified non-manipulating companies with 91.6% accuracy and manipulating companies with 75% accuracy. The overall accuracy rate of the model was calculated as 83.3%. These results show that the model has a high generalization ability and performs consistently on different datasets. To understand the consistency of the model, we estimated the same dataset with the M-score. As a result, the training dataset classified non-manipulating companies with 64.1% accuracy and manipulating companies with 43.5% accuracy. The test dataset calculated the M-score accuracy rate as 66.7% for non-manipulating companies and 33.3% for manipulating companies. These results show that the M-score is particularly weak in detecting manipulating companies and that Type 1 errors (false positives) are high.

The new model in this study has a higher success rate than the M-score in detecting companies that do and do not engage in financial manipulation. Indeed, studies by Ramírez-Orellana et al., (2017), Mehta and Bhavani (2017), Lotfi and Chadegani (2017), Halilbegovic et al. (2020), Svabova et al. (2020) and Benligiray and Onay (2021) also show that the M-score is insufficient to detect manipulation in different country samples. In addition to these studies, the new model offers a more comprehensive analysis process instead of focusing only on the threshold value. In addition to providing higher accuracy rates on data sets, the model is more resistant and compatible with changing financial manipulation techniques. Hence, it eliminates the shortcomings of traditional methods and offers a more reliable and effective approach to detect manipulation.

The model could be a reliable tool for investors, creditors, and monetary authorities in assessing the risk of financial manipulation. In particular, the ability to detect manipulation using only two years of financial data (SEC 10-K reports) increases the practical applicability of the model. Limitations of the model include excluding companies from specific sectors, such as banks, insurance companies, and brokerage firms, from the analysis. In addition, the model did not use the financial ratios of bankrupt companies, companies that have exited the stock exchange, and companies in the OTC market. These limitations may affect the general validity of the model.

Future studies can be conducted with an alternative dataset that includes the financial ratios of bankrupt companies that have withdrawn from the stock exchange or are traded in the OTC market. It is also recommended that the model be tested on companies from different sectors and with other financial structures.

In conclusion, this study has significantly contributed to the literature on financial manipulation detection. The developed logistic regression model can be an effective tool in economic analysis and auditing processes with its high accuracy rate and practical applicability. However, future research should test and address the model's limitations using a more comprehensive dataset.

Ethics Committee approval was not required for this study.

The authors declare that the study was conducted in accordance with research and publication ethics.

The authors confirm that no part of the study was generated, either wholly or in part, using Artificial Intelligence (AI) tools.

The authors declare that there are no financial conflicts of interest involving any institution, organization, or individual associated with this article. Additionally, there are no conflicts of interest among the authors.

The authors affirm that they contributed equally to all aspects of the research.

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