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Developing a model to predict fraudulent financial reporting

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Abstract

This paper investigates how well the Beneish and Spathis models can predict fraudulent financial reporting. The coefficients of these two models were adjusted using the logistic regression and the newly adjusted models were investigated for the prediction of fraudulent financial reporting. This research seeks to design a suitable native model to predict possible fraud in financial statements. The statistical population included 99 manufacturing companies listed on the Tehran Stock Exchange (1089 observations) during the years 2009-2019. The results show that the Beneish and Spathis models are not good at predicting fraudulent financial reporting, but their adjusted versions can predict it with an accuracy of 72% and 64%, respectively. The prediction accuracy rate of the extracted model based on the best explanatory variables is 79%, which shows that it is possible to predict and discover fraudulent financial reporting.

Keywords: Fraudulent financial reporting, Beneish model, Spathis model, fraud, financial ratios
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1 Introduction

Nowadays, one of the most important tools to make the right decisions, get the expected benefit and use optimally the financial resources is access to accurate and timely information as well as their accurate and realistic analysis [17]. Financial statements are tools to present the company's performance to others during a given period. Managers with poor performance use available loopholes and opportunities to commit fraud and increase their reward as well as the company's stock market price [16]. Some other financial frauds are a kind of tax avoidance [31].

Fraud in financial statements misleads the users of financial statements in the decision-making process [12]. Fraud is an unethical behavior. Unethical behaviors may affect public trust and confidence [34]. Recent accounting scandals indicate audit failures, which in turn led to serious implications for the business community. Some examples in the United States are Enron, WorldCom, Tyco, Quest and Global Crossing, which caused great turmoil in the capital market [3]. In 2017, about three million people in the United States were victims of financial fraud [**?**]. In recent years, distortions of financial statements by companies listed on the Tehran Stock Exchange and the Iran OSE led to turmoil in the capital market and losses to shareholders. Consequently, regulatory bodies such as the Iran Securities and Exchange Organization, Iran Central Bank, Central Bank of the Islamic Republic of Iran, and the Iranian Association of Certified Public Accountants faced serious challenges [7]. As a result, investors, legislators and auditors have always been concerned with the prediction and detection of fraud in financial reporting. In addition, the increased ability of

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auditors in the prediction and detection of fraud reduces the gap between various expectations of audit performance and the risk of lawsuits against auditors [28].

According to the literature, most of the developed countries have an official organization to report fraud statistics and introduce fraudulent companies. The results of previous research show the positive impact of these reports on the prevention and detection of future frauds. Unfortunately, there is no such organization in Iran to provide official statistics on fraud. However, unofficial statistics found in some newspapers indicate the high volume of financial corruption in the country, which has led to society's sensitivity to the issue of predicting financial fraud by managers. A more accurate prediction of the fraud risk in financial reporting increases the possibility of fraud prediction and discovery and helps us to reduce the heavy costs caused by fraud [37]. Therefore, the large damages caused by fraudulent financial reporting will indicate the importance of the present article, aiming to propose a comprehensive model for predicting and detecting fraud. In addition, the new proposed model enables us to identify fraudulent and non-fraudulent companies more accurately. Many researchers have used Beneish's financial indicators to provide a model to detect fraud. All of these researches have used adjusting coefficients of the Beneish model to introduce a native fraud detection model, but the present research combines and adjusts the financial indicators of the Beneish model and uses potential financial ratios introduced by Spathis to develop a native model for fraud detection.

2 The research theoretical foundations

One of the particularly important items in external financial reporting is the earnings figure because earnings is one of the performance evaluation criteria used to determine the economic value of enterprises [15]. Therefore, sometimes managers manipulate earnings or even do fraud. Fraud is known as an effective factor causing severe financial crises. Frequent financial crimes in the private and public sectors remind us that fraud and its negative consequences cripple economic units around the world. Understanding the multidimensional nature of fraud is the key to its prevention and detection [18].

Association of Certified Fraud Examiners of the United States defines fraud as illegal acts intentionally committed for specific purposes (i.e. manipulating or providing false reports to other parties) by individuals inside or outside the organization for personal or group gain, which directly or indirectly hurts other parties. The Auditing Standard Statement No. 99 defines fraud as an intentional act to make significant misstatements in financial statements [33].

Iran's Auditing Standard No. 240 defines fraud as any deliberate or deceptive action by one or more managers, employees or third parties to get unfair or illegal advantages. However, fraud with the meaning of "cheating" differs from "mistake". The distinguishing factor between fraud and mistake is whether the underlying act aiming at misstatement of the financial statements is intentional or inadvertent.

2.1 The fraud types

Fraudulent acts vary depending on the industry type [13]. However, in general, the Association of Certified Fraud Examiners classifies professional fraud into three categories: financial corruption, misappropriation of assets, and fraudulent financial reporting (i.e. manipulating the financial statements).

Financial corruption: it refers to the employees' abuse of their position and influence to get direct or indirect benefits, such as receiving commissions and bribery.

Abusing assets: it includes theft of assets or misusing the company resources by employees, management or third parties. According to a global study on occupational fraud and abuse conducted by the Association of Official Fraud Examiners (2020), abusing assets is the most common type of fraud [22].

Fraudulent financial reporting: it means deliberate distortion of the financial statements results to present a false image of the company (e.g. overstating assets and incomes, and understating debts and expenses [26]. Overstatement of assets and incomes means for example including fictitious costs as assets or reporting incorrect incomes to show a better company financial status. In contrast, understatement of debts and expenses means not recognizing the expenses or neglecting financial obligations. Both of these methods increase the ownership rights and net wealth of the company.

3 Research background

Many researches are conducted on fraud in financial reporting in Iran. Shakoori et al. [29] proposed a comprehensive model to predict, prevent and detect fraud in financial reporting using the adjusted Beneish model and concluded that adjusting some coefficients of the Beneish model variables improves the detection of fraudulent companies. AskarAlooj et al. [4] added two variables of the product market competition and the company information asymmetry to the Beneish model and observed that the area under the rocking curve in Beneish's generalized model is increased, which indicates the greater strength of Beneish generalized model compared to the original model. Rahimian and HajiHeydari [24] attempted to detect fraud using the adjusted Beneish model and identify the financial ratios sensitive to fraud. Three iterations of the regression model showed that the ratio of sales to total assets and the ratio of equity to total assets are sensitive to fraud and the adjusted Beneish model is very effective in the detection of fraud in financial statements. Khorasani [19] presented a model to predict the fraud risk in financial reporting and found that the adjusted Beneish model as well as the model introduced in this research are able to measure the fraud index.

She'ri Anaqiz et al. [30] used the original and adjusted Beneish models to investigate the accuracy of the results on detecting and disclosing fraudulent financial reporting in Iran's economic environment. They concluded that the adjusted Beneish model more accurately detects fraud in the financial statements of companies.

Kordestani and Tatli [20] used the Beneish model to predict earnings manipulation. To this purpose, they adjusted the Beneish model's coefficients and developed a native model to predict earnings manipulation based on the best predictor variables. Their results showed that the adjusted Beneish model and the models developed by them based on the discriminant analysis and the Logit approach are able to distinguish between companies manipulating and those not manipulating earnings with an overall accuracy of 72%, 75% and 81%, respectively. Etemadi and Zalghi [9] used logistic regression along with nine financial ratios to identify fraudulent financial reporting. They introduced several signs of fraud, including unacceptable audit opinion, the existence of tax disputes, the existence of important annual adjustments, and restated financial statements. They concluded that a high ratio of debt to equity and a high ratio of long-term debt to assets are among the most important predictors of fraud.

Aqilah et al. [2] examined how well the Beneish model can detect the possibility of earnings manipulation in Malaysia. They concluded that the Beneish model is an early detection tool to alert enforcement agencies about the need for further investigations or legal actions. In addition, they also recognized that three indicators of sales growth, the total accruals to total assets index and the days' sales in receivables index are significantly different between earnings manipulator and non-manipulator companies. Lehenchuk et al. [21] used the Beneish model to detect fraudulent financial statements in Ukrainian companies. They also investigated the ability of the Roxas model in detecting fraudulent financial statements and concluded that both models are able to detect fraudulent financial statements in Ukrainian companies.

In order to predict fraud in financial statements, Hariri et al. [11] analyzed two anonymous fraudulent companies using the Beneish model and found that these two companies are also classified as earnings manipulator companies according to the Beneish model. Zainudin and Hashim [36] used the financial ratios of the Spathis model to detect fraudulent financial reporting during 2007-2013. Fraudulent companies were selected based on their actions' non-compliance with stock exchange requirements. They examined 30 companies (15 fraudulent and 15 non-fraudulent companies) during 2007-2013 in the Malaysian Stock Exchange and found that these ratios are important factors in detecting fraud in financial reporting.

Dani [8] investigated the ability of the financial ratios of the Spathis model and the Beneish model in detecting fraudulent financial reporting on a statistical sample of 122 fraudulent and non-fraudulent companies during 2003-2010 in the Malaysian Stock Exchange. Fraudulent companies were selected based on the stock exchange disclosures. To adjust the models and test the hypotheses, the backward logistic regression method was used. The results showed that all these financial ratios were able to detect fraud. In addition, two variables of the debt-to-equity ratio and the sales-to-assets ratio from the Spathis model and indicators such as the Days Sales in Receivables Index, the asset quality index, the sales growth index, the depreciation index, the Sales, General, and Administrative Expenses Index, and Total Accruals to Total Assets Index from the Beneish model have a significant relationship with the fraudulent financial reporting.

Sezgin [27] used financial ratios of the Spathis model to predict manipulation of financial statements and succeeded to detect manipulation in financial statements, aiming at providing false signals to investors and forcing them to buy or sell securities.

4 Research hypotheses

Choosing the right model for financial information users with respect to their needs and environmental, economic and social conditions is a complex task. As a result, this paper uses the Beneish and Spathis model along with the adjustment and combination of their variables to examine how well they can detect fraudulent financial reporting among companies listed on the Tehran Stock Exchange. In addition, we investigate whether adjusting coefficients of Beneish and Spathis models enables us to predict fraudulent financial reporting in Iran's economic environment. Can we design a simple but strong model based on the best explanatory variables of fraud to distinguish fraudulent and non-fraudulent companies in Tehran Stock Exchange?

According to the above, five hypotheses were formulated:

- First hypothesis: the Beneish model can predict financial fraud in companies.
- Second hypothesis: the Adjusted Beneish model is better than the Beneish model predicts financial frauds.
- Third hypothesis: the Spathis model can predict financial fraud in companies.
- Fourth hypothesis: the Adjusted Spathis model better than the Spathis model predicts financial frauds.
- Fifth hypothesis: combining the financial variables of the Beneish and Spathis models results in a model to predict the financial fraud of companies.

5 Research methodology

This study seeks to determine the right financial indicators and financial ratios for the prediction of fraudulent financial reporting. Therefore, this research is applied in terms of purpose and is descriptive in terms of nature, because on the one hand, it examines the current situation and on the other hand, it uses the Logit regression analysis and composite data to explain the relationship between different variables. In addition, it is an Ex-Post Facto study and is based on the financial statements of manufacturing companies listed on the Tehran Stock Exchange. Excel software and logistic regression were used to test the hypotheses.

6 Sample and statistical population

This study uses the systematic elimination method to select a statistical sample from the companies listed on either the Tehran Stock Exchange or Iran Fara Bourse Securities Exchange, which must have the following conditions:

- For the sake of comparability, their finances must be ended with Iran's calendar year and all the required information must be available.
- In order to control the effect of all variables at the same time horizon as well as their similar effect on the statistical sample and in or order to better analyze data, the sample companies should not have changed their financial year during the research period.
- Banks, credit institutions and other monetary institutions, financial intermediaries and financial investments with other industries must be excluded from the sample.
- In order to avoid choosing inactive and low-circulation companies, the companies with a trading break of more than three months must be excluded.

With respect to the above limitations, 99 companies were selected as the statistical sample of the research and the study period was between 2009 and 2019.

7 Research variables and their measurement

The dependent variable of the research is fraud in financial statements. The independent variables, which predict and affect fraud in financial statements, are the financial ratios of the Spathis model and the financial indicators of the Beneish model.

7.1 Dependent variable

The research-dependent variable is fraud in financial statements, which has a qualitative nature and a nominal measurement scale. An unacceptable auditing report is used to detect fraudulent companies. Companies with (without) fraudulent signs in their financial reporting are assigned the fraud probability 1 (0), and they are considered as the dependent variables.

The companies whose audit reports were rejected, uncommented or conditional during the study period than the companies with an acceptable audit report were more subjected to fraud, thus, first, the former companies were identified. Then, among the identified cases, the companies whose auditing reports had referred to some kinds of fraud were identified as companies suspected of fraud [1, 10, 14, 23, 35].

1. Incorrect identification of incomes and incorrect measurement of realized incomes.
2. Overstatement of assets and balances at the end of the period
3. Incorrect cost identification and failure to measure realized costs
4. Understatement of debts and incorrect and fraudulent use of reserve accounts
5. Failure to prepare financial statements with the assumption of cessation of activity in companies whose assumption of continued activity is disrupted fundamentally and reflected in the auditing reports.
6. Mistakes in collecting and processing information underlying the prepared financial reports
7. Incorrect accounting estimates due to ignoring or misinterpreting the facts
8. Mistake in applying accounting standards related to measuring, identifying, classifying, presenting or disclosing information.

After the fraudulent company years were determined based on the above-mentioned criteria, the rest of the company years were identified as non-fraudulent company years.

7.2 Independent variables of the Beneish model

The variables of the Beneish model are the day's sales in receivables index, gross earnings margin index, asset quality index, sales growth index, depreciation cost index, total accruals to total assets index, financial leverage index, and the sales, general, and administrative expenses index.

The Beneish model uses explanatory variables belonging to both groups of earnings manipulator and non-manipulator companies based on the Probit analysis. It assigns number 1 (0) to the manipulator (non-manipulator) companies and calculated the coefficients of the independent variables. The Beneish model succeeded to detect three-quarters of the U.S. manipulator companies. The cutoff point of this model is -1.78. If the calculated score is more than -1.78, it is more likely that the company manipulates earnings [5, 6].

$$\begin{aligned} M-Score =& -4.84 + 0.92DSRI + 0.528GMI + 0.404AQI + 0.892SGI \\ &+ 0.115DEPI - 0.172SGAI + 4.679TATA - 0.327LVGI \qquad (Model1) \end{aligned}$$

where

M-Score: earnings manipulation score

DSRI: days' sales in receivables index

GMI: gross margin index

AQI: asset quality index

SGI: sales growth index

SGAI: sales, general, and administrative expenses index

TATA: total accruals to total assets index, and

LVGI: leverage index

In this model, DSRI is obtained from equation (7.1) as follows:

$$DSRI = \frac{REC_t/SALES_t}{REC_{t-1}/SALES_{t-1}} \tag{7.1}$$

The GMI is calculated using Equation (7.2):

$$GMI = \frac{SALES_{t-1} - COG_{t-1}/SALES_{t-1}}{SALES_t - COG_t/SALES_t} \tag{7.2}$$

The AQI is calculated using Equation (7.3):

$$AQI = \frac{1 - (CA_t + PPE_t)/ASSETS_t}{1 - (CA_{t-1} + PPE_{t-1})/ASSETS_{t-1}} \tag{7.3}$$

The SGI is calculated using Equation (7.4):

$$SGI = \frac{SALES_t}{SALES_{t-1}} \tag{7.4}$$

The DEPI is calculated using Equation (7.5):

$$DEPI = \frac{DEP_{t-1}/PPE_{t-1}}{DEP_t/PPE_t} \tag{7.5}$$

The SGAI is calculated using Equation (7.6):

$$SGAI = \frac{SGA, EXP_t/SALES_t}{SGA, EXP_{t-1}/SALES_{t-1}} \tag{7.6}$$

The TATA is calculated using Equation (7.7):

$$TATA = \frac{ACC_t}{ASSETS_t} \tag{7.7}$$

The LVGI is calculated using Equation (7.8):

$$LVGI = \frac{LTD_t + CL_t/ASSETS_t}{LTD_{t-1} + CL_{t-1}/ASSETS_{t-1}} \tag{7.8}$$

7.3 The Spathis model variables

Spathis used the financial ratios of 76 companies listed on the Athens Stock Exchange and the logistic regression method to analyze and predict fraud in financial information. The explanatory variables of the Spathis model were as follows: Debt to equity ratio (D/E), Sales to total assets ratio (Sales/TA), Net profit to sales ratio (NP/Sales), Receivable accounts to sales ratio (REC/Sales), Net profit to total assets ratio (NP/TA), Working capital to assets ratio (WC/TA), Gross profit to total assets ratio (GP/TA), inventories to sales ratio (INV/Sales), total debt to total assets ratio (TD/TA), and the Altman Z-score. Spathis considered the cutoff point of his model equal to 0.5. The accuracy of the Spathis model in distinguishing between earnings manipulator and non-manipulator companies is equal to 84% [32].

$$E(y) = \frac{\exp(b_0 + b_1x_1 + b_2x_2 + ... + b_nx_n)}{1 + \exp(b_0 + b_1x_1 + b_2x_2 + ... + b_nx_n)} \qquad (Model2)$$

where $E(y)$ is the dependent variable, which is 1 for fraudulent companies and otherwise 0. In addition, b_0 is constant value, b_1 to b_n are coefficients of the independent variables, and X_1 to X_n are the independent variables. He found that the inventories to sales ratio, the total debt to total assets ratio, and the Altman's Z-score can explain the financial information fraud methods.

8 Descriptive statistics

Tables 1 and 2 present some descriptive statistics concepts. Out of 1089 observations, 520 observations were classified as possibly fraudulent companies and 569 observations were classified as possibly non-fraudulent companies. It should be noted, according to the research classification criteria, some companies might be classified as fraudulent in some years and as non-fraudulent in some other years. In other words, classification is done based on the company's status in each year separately.

One of the most important dispersion parameters is the standard deviation. In this research, this parameter for the receivables to sales index and the asset quality index is equal to 4.894 (0.089), respectively. These values show the greatest and lowest standard deviation in the Beneish model, respectively. In the Spathis model, the debt-to-equity ratio has the greatest standard deviation (15.352) and the working capital to total assets has the lowest standard deviation. The minimum ratio of inventories to sales is zero because the inventory level in Sepanta Company (2009) and Bahman Group (2013) is zero.

Table 1: Descriptive statistics of the Beneish model variables

Variables	Observation	Average	Mean	SD	Min.	Max.
(DSRI)	1089	1.359	1.012	4.894	0.005	156.8
(GMI)	1089	1.161	0.989	2.054	−7.28	37.1
(AQI)	1089	1.006	1.001	0.089	0.577	2.53
(SGI)	1089	1.279	1.174	0.927	0.013	23.5
(DEPI)	1089	1.420	0.965	3.404	0.02	89.71
(SGAI)	1089	1.117	1.001	0.763	0.113	18.91
(TATA)	1089	0.022	0.020	0.191	−3.499	1.12
(LVGI)	1089	1.006	0.004	0.216	0.064	3.304

Table 2: Descriptive statistics of the Beneish model variables

Variables	Observation	Average	Mean	SD	Min.	Max.
(Z-score)	1089	2.60	2.305	1.875	−5.19	12.9
(D/E)	1089	2.65	1.546	15.352	−82.08	303.8
(Sales/TA)	1089	1.00	0.776	3.011	0.005	97.6
(NP/Sales)	1089	0.14	0.119	0.354	−2.202	7.80
(NP/TA)	1089	0.084	0.096	0.593	−15.42	0.626
(REC/Sales)	1089	0.54	0.343	1.714	0.003	52.00
(WC/TA)	1089	0.120	0.148	0.271	−3.11	0.836
(GP/TA)	1089	0.196	0.189	0.463	−14.33	0.703
(INV/Sales)	1089	0.343	0.277	0.416	0.000	11.42
(TD/TA)	1089	0.632	0.625	0.276	0.047	4.002

9 Testing hypotheses

9.1 First hypothesis

The first hypothesis is as follows: the Beneish model can predict financial fraud in companies.

To test the first hypothesis, the accuracy and error of the Beneish model were investigated in both groups. The results showed that eight independent variables of the Beneish model and their coefficients remained unchanged. In cases where the M–score of the Beneish model is greater than -1.78, the company's financial statements may be fraudulent. As shown in Table 3, the correct prediction of the model in fraudulent and non-fraudulent groups is 44.4% and 67.3%, respectively. In addition, the incorrect prediction of the Beneish model in fraudulent and non-fraudulent groups is 55.6% and 32.7%, respectively. Furthermore, the overall accuracy and error of the Beneish model are 56.4% and 43.6%, respectively. Since the accuracy of the Beneish model for distinguishing between fraudulent and non-fraudulent companies is low, the first hypothesis is not confirmed.

Table 3: The Beneish model results (first hypothesis)

$M - Score = -4.84 + 0.920DSRI + 0.528GMI + 0.404AQI + 0.892SGI + 0.115DEPI – 0.172SGAI + 4.679TATA – 0.327LEVI$

Group	Observations	The model prediction result		Correct prediction	Incorrect prediction
		Accuracy	Error		
Possibly fraudulent companies	520	231	289	44.4%	55.6%
Probably non-fraudulent companies	569	383	186	67.3%	32.7%
Overall accuracy of the model	$(383 + 213)/1089 \times 100 = 56.4\%$				
Overall error of the model	$(186 + 289)/1089 \times 100 = 43.6\%$				

$Total\ accuracy = (fraudulent\ accuracy + non - fraudulent\ accuracy)/(number\ of\ fraudulent\ companies + number\ of\ non - fraudulent\ companies) \times 100$

$Total\ error = (fraudulent\ error + non - fraudulent\ error)/(number\ of\ fraudulent\ companies + number\ of\ non - fraudulent\ companies) \times 100$

9.2 Second hypothesis

The second hypothesis is as follows: the Adjusted Beneish model better than the Beneish model predicts financial frauds. To test the second hypothesis based on the Adjusted Beneish model, the coefficients of the Beneish model were adjusted by using the logistic regression. The new developed model is called the Adjusted Beneish model. Since the odds ratios corresponding to all the variables is less than 1, it can be said that increasing these variables decreases the fraud probability in financial reporting.

Table 4: The results of estimating the coefficients of the Adjusted Beneish model (second hypothesis)

Variables	Dependent variables: fraudulent and non-fraudulent			
	β	S.E	Error level	Odds ratio
Intercept	8.809	1.000	0.000	1.007
DSRI	−1.601	0.000	0.000	0.092
AQI	−2.015	1.000	0.031	0.040
SGI	−1.166	0.000	0.000	0.077
TATA	−2.776	1.001	0.000	0.064
LVGI	−1.966	1.001	0.006	0.062

The classification results in Table 5 show that the overall accuracy of the Adjusted Beneish model is 72% in correctly detection of fraudulent companies. The cutoff point of the Adjusted Beneish model is set 0.5 [24, 20].

Table 5: Classification results of the Adjusted Beneish model (second hypothesis)

$Adjusted–M - Score–Beneish = 8.809 - 1.601(DSRI) - 2.015(AQI) - 1.166(SGI) - 2.776(TATA) - 1.966(LVGI)$

Group	Observations	The prediction model results		Correct prediction percentage
		Accuracy	Error	
Possibly fraudulent companies	520 years-company	400	169	70
Probably non-fraudulent companies	569 years-company	387	133	74
Total correct prediction percentage				72

The Wilcoxon test was used to compare the prediction accuracy of the Beneish model and the adjusted Beneish model and the pairwise comparison test was performed to select the best prediction model. Since the significance level of the z-score and the pairwise comparison test is less than 0.05, there is a significant difference between the prediction accuracy of the original and adjusted Beneish models. In other words, the adjusted model is more promising and the second hypothesis is confirmed.

9.3 Third hypothesis

The third hypothesis is as follows: the Spathis model can predict financial fraud in companies.

To test the third hypothesis, the accuracy and error of the Spathis model were investigated in two groups of fraudulent and non-fraudulent companies. The cutoff point of the Spathis model is 0.5 [32]. As shown in Table 6, the correct predictions of the model in fraudulent and non-fraudulent groups are 55% and 49%, respectively. In addition, the incorrect predictions of the Spathis model in fraudulent and non-fraudulent groups are 44% and 50%, respectively. The overall accuracy and error of the Spathis model are estimated to be 52% and 47%, respectively. Therefore, the accuracy of the model is low and the prediction error is high, and the third hypothesis is not confirmed.

Table 6: Results of the Spathis model (third hypothesis)

$FFS_{spathis} = 0.23 + 2.659(INV/SAL) + 6.685(TD/TA) - 3.327(Z - Score)$					
Group	**Observations**	**The model prediction result**		**Correct prediction**	**Incorrect prediction**
		Accuracy	Error		
Possibly fraudulent companies	520	288	232	55.3%	44.6%
Probably non-fraudulent companies	569	281	288	49.4%	50.6%
Overall accuracy of the model	$(281 + 288)/1089 \times 100 = 52.2\%$				
Overall error of the model	$(148 + 214)/980 \times 100 = 47.8\%$				
$Total\ accuracy = (fraudulent\ accuracy + non-fraudulent\ accuracy)/(number\ of\ fraudulent\ companies + number\ of\ non-fraudulent\ companies) \times 100$					
$Total\ error = (fraudulent\ error + non-fraudulent\ error)/(number\ of\ fraudulent\ companies + number\ of\ non-fraudulent\ companies) \times 100$					

9.4 Fourth hypothesis

The fourth hypothesis is as follows: the adjusted Spathis model better than the Spathis model predicts the financial fraud.

In order to test the fourth hypothesis and develop the adjusted Spathis model, the coefficients of the Spathis model were adjusted using the logistic regression. The new developed model is called the adjusted Spathis model. If the odds ratio is less than 1, it can be said that as the REC/Sales ratio increases, the probability of fraud in financial reporting decreases. If the odds ratio is greater than 1, it can be said that as the TD/TA ratio increase, the probability of fraud in financial reporting increases.

Table 7: The results of estimated coefficients of the adjusted Spathis model (fourth hypothesis)

Variables	**Dependent variables: fraudulent and non-fraudulent**			
	β	S.E	Error level	Odds ratio
Intercept	2.027	0.000	0.000	1.938
(REC/Sales)	0.001	0.000	0.000	1.963
(TD/TA)	−2.001	0.000	0.000	0.060

The classification results in Table 8 show that the overall accuracy of the adjusted Spathis model in correctly detection of fraudulent companies is 64%.

Table 8: The classification table for the adjusted Spathis model (fourth hypothesis)

$Adjusted\text{–}Spathis = 2.027 + 0.001(REC/Sales) - 2.001(TD/TA)$				
Group	**Observations**	**The prediction model results**		**Correct prediction percentage**
		Accuracy	Error	
Possibly fraudulent companies	520 years-company	310	210	59%
Probably non-fraudulent companies	569 years-company	387	182	68%
Total correct prediction percentage				64%

Since the significance level of the z-score and pairwise comparison test is less than 0.05, therefore, there is a significant difference between the prediction accuracy of the original and the adjusted Spathis model. In other words, efficiency of adjusted model is higher and, thus, the fourth hypothesis is confirmed.

9.5 Fifth hypothesis

The fourth hypothesis is as follows: combining the financial variables of the Beneish and Spathis models results in a model to predict the financial fraud of companies.

To test the fifth hypothesis, the potentially related to financial fraud variables from the Beneish and Spathis models, which had a significant relationship with the dependent variable, were selected and then estimated using the Logit model. In cases where the odds ratio is less than 1, increase of (TD/TA), (TATA), (SGI), (AQI) and (DSRI) ratios will decrease the probability of fraud in financial reporting. On the contrary, if the odds ratio is greater than 1, increase of (NP/Sale), (NP/TA) and (WC/TA) ratios will increase the probability of fraud in financial reporting.

Table 9: The results of estimating the coefficients of the developed model (the fifth hypothesis)

Variables	**Dependent variables: fraudulent and non-fraudulent**			
	β	S.E	Error level	Odds ratio
Intercept	12.092	1.001	0.000	1.840
(NP/Sale)	2.057	1.001	0.000	1.262
(NP/TA)	5.058	1.001	0.000	1.400
(WC/TA)	2.000	0.001	0.000	1.089
(TD/TA)	−4.850	0.001	0.000	0.095
(TATA)	−7.089	0.001	0.000	0.084
(SGI)	−2.079	0.001	0.000	0.060
(AQI)	−2.025	1.001	0.047	0.259
(DSRI)	−2.170	0.001	0.000	0.096

The classification results in Table 10 show that the overall accuracy of the introduced model in correctly detection of fraudulent companies is 79%. Since the classification accuracy is high, the fifth hypothesis is confirmed.

Table 10: Classification table – the results of the introduced model (the fifth hypothesis)

$$FFS = 12.092+2.057(NP/Sale)+5.058(NP/TA)+2.000(WC/TA)-4.85(TD/TA)-7.089(TATA)-2.079(SGI)-2.025(AQI)-2.17(DSRI)$$

Group	**Observations**	**The prediction model results**		**Correct prediction percentage**
		Accuracy	Error	
Possibly fraudulent companies	520 years-company	101	419	80%
Probably non-fraudulent companies	569 years-company	449	120	78%
Total correct prediction percentage				79%

10 Conclusions and suggestions

Fraud is one of the most serious threats to the success of shareholders and corporate governance. It reflects the agency problem between management and shareholders [18]. The report containing incorrect information cause the users of those reports to make wrong decisions. According to the report of the Association of Certified Fraud Examiners in 2016, fraudulent financial reporting is less frequent than other types of fraud, but it has caused the greatest financial losses to companies [25]. In this research, the Beneish and Spathis models as well as their adjustments along with a new hybrid model are used to predict fraudulent financial reporting. The new proposed model is introduced to consider the necessity of localizing these models and increasing their predictive power. The findings showed that the prediction error of the Beneish and Spathis models is relatively high because their coefficients are calculated based on data obtained from different economic environments. The result of the first hypothesis test is consistent with results of Kordestani and Tatli [20], She'ri Anaqiz et al. [30], Khorasani [19], Shakoori et al. [29], but is not consistent with Lehenchuk et al. [21], and Aqilah et al. [2]. The result of the third hypothesis, which tested the ability of the Spathis model in predicting fraudulent financial reporting, is consistent with the results of Kordestani and Tatli [20], Etemadi and Zalghi [9], but not consistent with those of Spathis [32], Sezgin [27], and Zainudin and Hashim [36]. Therefore, Beneish and Spathis models are completely random models in the Tehran Stock Exchange market and, thus, cannot be used to detect companies publishing fraudulent financial reporting.

The analysis using the adjusted Beneish model increased the predictive power of the model so that the result of the Wilcoxon test shows a significant difference between the two models. Therefore, the accuracy of the adjusted Beneish model is more than the Beneish model in Iran's economic environment. Thus, the second hypothesis of the research is confirmed. The result of the second hypothesis is consistent with the results of Kordestani and Tatli [20], She'ri Anaqiz et al. [30], AskarAlooj et al. [4], Rahimian and HajiHeydari [24], and Shakoori et al. [29]. The accuracy of the adjusted Beneish model is more than the Beneish model in all the research conducted in Iran because this model is adjusted with respect to the Iranian companies. Similarly, Dani [8] reported that the accuracy of the adjusted Beneish model was more than the Beneish model in the Malaysian Stock Exchange.

The result of the fourth hypothesis shows that the accuracy of the adjusted Spathis model is higher than the Spathis model in detecting fraudulent financial reporting. The result of the Wilcoxon test also shows a significant difference between these two models so the accuracy of the model increased from 52% to 64%. The result of the fourth hypothesis is consistent with the results of Etemadi and Zalghi [9] and Dani [8].

To test the fifth hypothesis, the potential financial fraud variables of the Beneish and Spathis models, which had a significant relationship with the dependent variable, were selected and then estimated using the Logit model. The overall accuracy of the developed model was estimated at 79%. Results of comparing the accuracy and error of the developed model with the adjusted Beneish and Spathis models confirmed the fifth hypothesis. Therefore, it is possible to predict fraud in the financial statements of companies using financial ratios. The research findings showed evidence of the promising performance of the proposed model in predicting fraudulent financial reporting. The result of the fifth hypothesis is consistent with the results of Kordestani and Tatli [20], Etemadi and Zalghi [9], FarqhanDoost Haqiqi and Barwari [10], and Vakilifard et al. [35].

No institution in Iran is directly responsible for investigating and detecting possible cases of fraud. As a result, there is no database of reports on fraud in Iran, which is a limitation of the current research.

The results of the current research indicate that financial ratios such as the asset quality index, gross earnings margin index, days' sales in receivables index, and the total debt to total assets ratio, are effective in fraud detection when auditing the financial statements. As a result, auditors are suggested to focus on these variables, because they are more frequently observed in fraud prediction models. The honourable legislator is suggested to prevent fraud in financial reporting by amending the commercial law, embedding controlling and legally binding tools, considering appropriate punitive measures, and increasing the cost of committing fraud for the perpetrators, to cite a few. In addition to their analysis, financial analysts and investment advisors in the stock exchange are suggested to use the extracted model to predict possible frauds. Future research can investigate the use of other variables such as corporate governance, in addition to the current variables, to predict fraudulent financial reporting. Furthermore, financing methods and their impact on fraudulent financial reporting can be examined. Data mining methods such as artificial neural networks, decision trees, Bayesian networks, and ant-algorithms can be employed to develop a model to predict and detect fraudulent financial reporting.

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