# Modification of the Beneish Model for Earnings Management Prediction using Logit and Probit Analysis

### Nahid Maleki Nia\*

Dept. of Management, Science and Research Branch, Islamic Azad University, Tehran, Iran

#### Abstract

This study aimed to modify the Beneish model (1999) by incorporating two environmental variables, namely information asymmetry and product market competition. Data of 184 firms listed on the Tehran Stock Exchange for 2007-2017 were collected. The model coefficients were estimated using Logit and Probit logistic regression. Given the absence of lagged dependent variables on the right side of the equations of both original and modified Beneish models, the prediction was made by the static method. In the Probit approach, the best accuracy of the original and modified Beneish models at the optimal cut-off points (0.5215 and 0.5450) was 56.18% and 68.83%, respectively. In the Logit approach, the best accuracy of the original and modified Beneish models at the optimal cut-off points (0.5216 and 0.5450) was 56.18% and 68.83%, respectively. In the Logit approach, the best accuracy of the original and modified Beneish models at the optimal cut-off points (0.5216 and 0.5450) was 56.18% and 68.83%, respectively. In the Logit approach, the best accuracy of the original and modified Beneish models at the optimal cut-off points (0.5216 and 0.5508) was 56.43% and 69.12%, respectively. There is a significant difference between the prediction accuracy of the Beneish model and the modified Beneish model. The Logit approach is more effective than the probit approach in identifying earnings management levels. The results of the Wilcoxon test show a significant difference at the 5% significance level between the two models and the two approaches.

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Corresponding author: nahid.malekiniya@iaubsm.ac.ir

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# Introduction

Over the years, there have been many studies on the quality of earnings statements and the possibility of earnings manipulation. In 1999, Beneish proposed a model for detecting earnings manipulation based on eight accounting variables. He showed that abnormal changes in demand, gross profit margin, asset quality, sales, and accruals may very well be the signs of earn ings manipulation. However, the Beneish model ignores the incentivizing effects of the environment in which firms operate. According to studies in the field of earnings management and manipulation, factors that can incentivize and impact earnings manipulation can be divided into two groups of factors inside the accounting data and those outside it. In other words, external and environmental factors can also incentivize earnings manipulation, and can, therefore, be useful in predicting this phenomenon.

In a study, they showed that the Beneish model has at best 70% predictive power, or in other words, a 30% error in detecting earnings manipulation in the Iranian capital market. Therefore, it may be possible to improve the predictive power of the model through more attention to external and environmental factors that incentivize earnings manipulation; factors that have not received enough attention in the original Beneish model (1).

The Beneish model is based on a study of a group of firms in the United States and research in other countries has shown that it may not have the same performance in all countries and capital markets. According to a study (2), since accounting valuations are done differently in different markets, it is impossible to make a judgment based on these valuations simply by studying a specific market. Therefore, in a world where there are many different countries with different financial institutions and structures, it is important to consider the nuances of accounting figures for different countries as much as possible. A fraud detection model, however effective, may not necessarily be accurate for all countries and must be localized according to the economic situation of each nation. Considering the unsatisfactory accuracy of the original Beneish model for the economic situation of Iran, it has been modified into a localized model for this country based on its economic structure (3).

It has been suggested that fierce market competition can act as an incentivizing factor for earnings management and manipulation. According to the signaling hypothesis, in firms operating in highly competitive markets, managers are incentivized to manipulate accounting information, including earnings, to send positive signals about the firm's future performance. However, less competitive markets are more prone to earnings manipulation because of less oversight over management activities. In contrast, there is always more control and oversight over firms that operate in competitive industries and environments, which means they have less opportunity to engage in earnings manipulation (4). In general, there is a significant direct relationship between competition indicators in a product market and the quality of financial data published by the firms operating in that market (5). Therefore, in the present study, product market competition is considered as one of the environmental variables that need to be taken into account in the localization of the Beneish model.

Information asymmetry and conflict of interest between managers and shareholders may allow or even incentivize the firm's management to manipulate the firm's information as they wish. When firms perform poorly in providing transparent information and there is no serious oversight or pressure to increase transparency, the situation is ripe for earnings manipulation and publishing of false information (6). Therefore, in places where there are enough incentives for managers to manipulate earnings, it is necessary to examine the relationship between information asymmetry and earnings management in order to give the users of financial statements a better insight into the reliability of published information (7). Considering the impact of information asymmetry on agency costs, the present study considers information asymmetry as another environmental variable that should be taken into account in the localization of the Beneish model.

In this study, the objective is to improve the accuracy and predictive power of the model of Beneish (1999) through modification (localization) with emphasis on environmental incentivizing factors, including information asymmetry and product market competition. Unlike previous modifications of the Beneish model, which have been based solely on accounting data and have neglected the impacts and consequences of nonaccounting variables, this study tries to consider and examine the concurrent effects of both accounting and non-accounting variables. To achieve the research objective, the following hypotheses are considered:

- 1- The Beneish model can predict earnings manipulations.
- 2- The modified Beneish model has more predictive power than the original Beneish model.

According to Logit and Probit methods, the modified Beneish model is more accurate in identifying earnings manipulations than the original Beneish model.

### **Research Methodology**

This study was performed on the data of 184 firms (1840 firm-year observatories) for the period 2008-2017. After separating the samples into two groups with high and low levels of earnings management, first, the accuracy of the Beneish model was examined by probit and logit regression. Then the proposed variables (product competition market and information asymmetry) were used to modify the Beneish model for better prediction of earnings management. Next, the accuracy and error of the modified model were investigated by probit and logit regression. And finally, the accuracy of the modified model was compared with that of the original Beneish model with the help of ROC analysis and the Wilcoxon test.

The cut-off point was determined through three methods: the shortest distance from the upper left corner, the intersection of this point with Youden index and the point giving maximum precision. The cutoff point resulting in the highest model accuracy was selected for use

in subsequent analyses. In ROC analysis, one can predict the group to which each sample belongs based on its characteristics through comparison with the optimal cutoff point. The daily ask and bid prices and the financial statements and information were collected from the Rahavard software, the Bourse View website, and Mofid Securities database, and the Codal website. The analyses were carried out using Excel, Eviews, and MatlabR2014b. Since there is no specific body or institution in Iran for publishing the names of firms that commit earnings management, manipulating firms were identified based on Beneish's theory (1999), which defines earnings manipulation as any violation of generally accepted accounting principles (GAAP) to shed a positive light on financial performance. This identification was performed by the use of audit reports and specifically the clauses of these reports that are related to earnings management. Accordingly, the firms were classified into two groups: earnings managing firms and non-earnings managing firms. The variables of the original Beneish model are listed in Table 1.

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Indicator	Indicator components	Equation
1- Days' Sales in Receiva- bles Index (DSRI)	REC: net receivables	$DSRI = \frac{REC_{t} / SALES_{t}}{REC_{t-1} / SALES_{t-1}}$
2- Gross Margin Index (GMI)	SALES: annual sales COG: cost of goods sold	$GMI = \frac{(SALES_{t-1} - COG_{t-1}) / SALES_{t-1}}{(SALES_t - COG_t) / SALES_t}$
3- Asset Quality Index (AQI)	CA: current assets PPE: property, plant, and equipment ASSETS: total assets	$AQI = \frac{1 - (CA_{t} + PPE_{t}) / TotalASSETS_{t}}{1 - (CA_{t-1} + PPE_{t-1}) / TotalASSETS_{t}}$
4- Sales Growth Index (SGI)	SALES: annual sales	$SGI = \frac{SALES_t}{SALES_{t-1}}$
5- Depreciation index (DEPI)	DEP: depreciation of fixed tangible assets PPE: property, plant, and equipment	$DEP = \frac{\frac{DEP_{t-1}}{t-1} + PPE_{t-1}}{\frac{SEP_{t}}{DEP_{t}} + PPE_{t}}$
6- Sales, General, and Ad- ministrative Expenses In- dex (SGAI)	SGA.EXP: sales, general and administrative expenses SALES: annual sales	$SGAI = \frac{(SGA, EXP) / TotalASSETS}{(SGA, EXP) / TotalASSETS}_{t-1} / TotalASSETS}_{t-1}$
7- Total Accruals to Total Assets Index (TATA)	ACC: accruals (the difference between oper- ating income and operating cash flow) ASSETS: total assets of the year	$ATA = \frac{ACC}{t}_{t}_{t}$
8- Leverage Index (LVGI)	LTD: long-term debt CL: current liabilities ASSETS: total assets of the year	$LVGI = \frac{(LTD_{t} + CL_{t}) / TotalASSETS_{t}}{(LTD_{t-1} + CL_{t}) / TotalASSETS_{t-1}}$

Table 1. varia	bles of the	original	Beneish	model

In addition to the above variables, the modified Beneish model makes use of two other variables: product market competition and information asymmetry. These two variables and their measures are described below.

1- Product market competition

$$HHI_{jt} = \sum_{i=1}^{n} S_{i,t}^{n} \sum_{i=1}^{n} \left( \frac{sale_{i,j,t}}{SALE_{j,t}} \right)^{2} \qquad \text{Eq.}$$

Herfindahl-Hirschman Index (HHI): This index is used to measure competition in the market and specifically the concentration of the industry. The higher the HHI value, the higher the concentration, and the less competitive is the market and vice versa. As in the studies of Dhaliwal 30, Huang, Khurana, and Pereira (2008), and Hi (2009), HHI was used as a measure of competition. In Eq. (1), HHI is the Herfindahl-Hirschman index, *sales*<sub>*i*,*j*,*t*</sub> is sales of firm i in industry j at the end of year t, *SALE*<sub>*j*,*t*</sub> is the total sales of all firms in industry j at the end of year t, and *S*<sub>*i*,*j*,*t*</sub> is the market share of firm i in industry j at the end of year t.

2- Information asymmetry: This variable is calculated based on the difference between the asking price and the bid price:

$$BAS_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{d_{i,t}} \frac{Ask_{i,d} - Bid_{i,d}}{\left(\frac{Ask_{i,d} + Bid_{i,\underline{r}}}{2}\right)}$$

The information environment can be evaluated using information asymmetry indicators, one of which is the bid-ask spread. Following the approach of Cormier, Sylvain, and Marie (2013), this indicator was used to measure information asymmetry. The larger the bidask spread, the greater the information asymmetry and, consequently, the weaker the information environment (Setayesh, Mehtari, and Mohammadian, 2015). In Eq. (2),  $BAS_{i.t}$  is the bid-ask spread,  $Ask_{id}$  the best (lowest) daily ask price for stocks of firm i, and  $Bid_{id}$  is the best (highest) daily bid price for the same stocks.

Statistical population and sample

The statistical population of this study comprised of the firms listed on the Tehran Stock Exchange (TSE). The time-domain of the research was a 10-year time period from 2008 to 2017. However, since the data of 2007 were also needed for calculations, this year's data were also collected. The sampling was done systematically under the following condition:

- 1- Availability of the information required for the research.
- 2- No long pause (longer than six months) in the exchange of the firm's shares (to make sure that the firm has been active during the research period).
- 3- Availability of the firm's ask prices and bid prices.
- 4- The firm being first listed on the stock exchange before the fiscal year 2007.
- 5- Not being a bank or financial institution (investment firm, financial intermediary, holding firm, or leasing firm), as they follow different financial disclosure rules and have different corporate governance structure.

The total number of firms listed on the stock exchange during the years of interest was 312 (according to the Codal website and the Rahavard software). Based on the availability of data, 219 firms were eligible for analysis with the original Beneish model, and of these, 184 firms (1840 firm-year observations) were also eligible for analysis with the modified Beneish model. Of the 1840 firm-year observations, 900 firm-years were categorized as having a low level of earnings management and 940 firm-years were categorized as having a high level of earnings management

### Research models

1- The Beneish model

The model of Beneish (1999) is based on a survey of 74 earnings manipulating firms during 1982-1992. This model was developed by the probit analysis of

the explanatory variables of both earnings manipulating and non-earnings manipulating firms. He assigned the value 1 to manipulating firms and 0 to non-manipulating companies and calculated the coefficients of the independent variables accordingly. The cutoff point of this model is -1.78. Therefore, if the calculated score (M-Score) is greater than -1.78, the company is likely to have committed earnings manipulation. The overall accuracy of this model is approximately 76%. The formulation of Beneish's earnings management model (1999) is as follows:

$$EM - Score = \alpha_0 + \beta_1 DSRI_{it} + \beta_2 GMI_{it} + \beta_3 AQI_{it} + \beta_4 SGI_{it} + \beta_5 DEPI_{it} + \beta_6 SGAI_{it} + \beta_7 TATA_{it} + \beta_8 LVGI_{it}$$
(3)

Where M-Score is the score of earnings manipulation.

#### 2- The modified Beneish model

This study attempted to modify the Beneish model so that it takes into account the product market competition and the information environment of the firms listed on TSE. The purpose of this effort was to determine whether combined models such as the Beneish model (1999) can identify earnings manipulation in the Iranian economic environment; is it possible to increase the earnings manipulation prediction accuracy of this model; and is it possible to design a model for detecting earnings manipulation in Iran's information and competitive environment by incorporating the variables that represent information environment and product market competition into the original Beneish model? Presented below is the modification made in the Beneish model to incorporate information asymmetry and product market competition variables:

$$\begin{split} \mathrm{EM}_{\mathrm{ANN-BBO}} &= \alpha_0 + \beta_1 \mathrm{DSRI}_{\mathrm{it}} + \beta_2 \mathrm{GMI}_{\mathrm{it}} \\ &+ \beta_3 \mathrm{AQI}_{\mathrm{it}} + \beta_4 \mathrm{SGI}_{\mathrm{it}} \\ &+ \beta_5 \mathrm{DEPI}_{\mathrm{it}} + \beta_6 \mathrm{SGAI}_{\mathrm{it}} \\ &+ \beta_7 \mathrm{TATA}_{\mathrm{it}} + \beta_8 \mathrm{LVGI}_{\mathrm{it}} \\ &+ \beta_9 \mathrm{HHI}_{\mathrm{it}} \\ &+ \beta_{10} \mathrm{BAS}_{\mathrm{it}} \end{split} \end{split}$$

In this equation, BAS is the indicator of the firm's information environment and HHI is the indicator of product market competition.

Table 2 presents the descriptive statistics of the firms divided by the level of earnings management. According to Beneish (1999), the larger the indicators are, the higher is the likelihood of earnings manipulation. According to the average of the indicators, among the indicators of the Beneish model, DSRI, GMI, AQI, SGI, and ATA are higher for the firms with a high level of earnings management than those with a low level of earnings management. However, contrary to Beneish's theory (1999), firms with a low level of earnings management have lower DEPI, SGAI, and LVGI. For the modified model, the firms with a high level of earnings management have higher HHI and lower BAS (8).

Low level of earnings management									
Variable (indicator)	Firm-year	Minimum	Maximum	Mean	Standard deviation				
Days' Sales in Receivables Index (DSRI)	900	0.01	9.43	1.285	1.22				
Gross Margin Index (GMI)	900	-5.95	8.29	1.012	0.75				
Asset Quality Index (AQI)	900	0.01	9.91	1.077	0.84				
Sales Growth Index (SGI)	900	0.46	3.42	1.147	0.25				
Depreciation index (DEPI)	900	0.00	9.33	1.134	0.71				
Sales, General, and Admin- istrative Expenses Index (SGAI)	900	0.06	9.65	1.158	0.65				

Table 2. descriptive statistics of model variables divided by the level of earnings management

			1	1	
Total Accruals to Total As- sets (TATA)	900	-0.75	0.49	0.008	0.12
Leverage Index (LVGI)	900	0.34	3.83	1.018	0.24
Herfindahl-Hirschman In- dex-HHI (product market competition)	900	1.3e+01	1.3e+04	9.0e+02	1.2e+03
Bid-Ask Spread-BAS (infor- mation asymmetry)	900	0.00	0.64	0.025	0.03
Earnings management	900	0	0	0	0
High level of earnings mana	agement				
Variable (indicator)	Firm-year	Minimum	Maximum	Mean	Standard deviation
Days' Sales in Receivables Index (DSRI)	940	0.00	9.99	1.332	1.22
Gross Margin Index (GMI)	940	-6.36	8.64	1.013	0.85
Asset Quality Index (AQI)	940	0.00	8.66	1.096	0.78
Sales Growth Index (SGI)	940	0.51	4.25	1.178	0.26
Depreciation index (DEPI)	940	0.00	9.82	1.090	0.81
Sales, General, and Admin- istrative Expenses Index (SGAI)	940	0.02	9.60	1.107	0.72
Total Accruals to Total Assets (TATA)	940	-0.85	0.98	0.028	0.13
Leverage Index (LVGI)	940	0.27	2.99	1.013	0.23
Herfindahl-Hirschman In- dex-HHI (product market competition)	940	9.9e+00	9.9e+03	1.3e+03	1.5e+03
Bid-Ask Spread-BAS (infor- mation asymmetry)	940	0.00	0.11	0.023	1.01
Earnings management	940	1	1	1	1

In this study, the likelihood-ratio (LR) statistic was used to evaluate logistic logit and probit regression models. The Wilcoxon test was then performed to determine the best model. Table 3 shows the results of the unit root tests for stationarity. The presence of non-stationary variables in the model causes false regression and undermines the reliability of T and F tests. Therefore, before estimating the regression

model, it was necessary to make sure of the stationarity of the variables. This was done using the augmented Dickey-Fuller test and the Phillips-Perron test. As the results presented in Table 3 demonstrate, the significance levels obtained for both tests are less than 0.05, indicating that there is no unit root (nonstationarity) among the model variables.

Table 5. Results of stationarry tests									
Test	Augmented Dickey-Fu	Iller	Phillips-Perron						
Indicator	Fischer's chi-square	Significance level	Fischer's chi-	Significance level					
	statistic	-	square statistic						
Days' Sales in Receivables In-	1174.18	0.000	1480.66	0.000					
dex (DSRI)									
Gross Margin Index (GMI)	1052.7	0.000	1342.60	0.000					
Asset Quality Index (AQI)	1199.65	0.000	1488.025	0.000					
Sales Growth Index (SGI)	977.362	0.000	1148.68	0.000					
Depreciation index (DEPI)	1110.44	0.000	1352.47	0.000					
Sales, General, and Adminis-	1268.20	0.000	1600.68	0.000					
trative Expenses Index (SGAI)									

Table 3. Results of stationarity tests

Total Accruals to Total Assets (TATA)	814.778	0.000	988.865	0.000
Leverage Index (LVGI)	1113.26	0.000	1415.32	0.000
Herfindahl-Hirschman Index- HHI (product market competi- tion)	593.295	0.000	803.432	0.000
Bid-Ask Spread-BAS (infor- mation asymmetry)	42.063	0.000	449.067	0.000
Earnings management	304.141	0.000	343.744	0.000

According to both augmented Dickey-Fuller and Phillips-Perron tests, the earnings management variable is also stationary.

# **Findings**

Using the coefficients of the original Beneish model (1999), the overall accuracy and error of this model in

detecting high and low levels of earnings management were estimated. As shown in Table 4, the overall accuracy of the original model for firm-year observations of this study is 46.7%, which means quite low precision in identifying earnings management levels. In other words, the original Beneish model has a fairly high error in detecting earnings management in the area of interest.

			Accurac	y und ch		Singiniai De			
M - Score =	= -4.84 +0.92	20DSRI +0	).528GMI +0	).404AQI +	0.892SGI +0	).115DEPI -0	.172SGAI +	4.479ATA -0	.327LEVI
Model	ment	Ū	s manage-	ment	el of earning	is manage-			
	M-Score<-	1.78	1	M-Score	>-1.78	1			
	Firm-years	Accuracy	Error	Firm-years	Accuracy	Error	Total firm-years	Total accuracy	Total error
Original Beneish model	1057	648	409	1123	371	752	2180	46.7	53.3

 Table 4. Accuracy and error of the original Beneish model

To calculate the probability value for a certain level of independent variable(s) in the logit model, one should first calculate the fit value of the dependent variable and then use the following formula to obtain the corresponding probability value.

$$P(DI = I) = \frac{1}{1 + e^{-z}}$$
 Eq. (5)

In this equation, Z is the fit value of the dependent variable at level Y and E is the base of the natural logarithm.

In the Probit model, the fit value of the dependent variable for a certain value of the independent variable must be calculated, and then the corresponding probability must be obtained from the standard normal table. Then, the obtained probability must be interpreted according to the research topic. In this study, the results obtained from both Logit and Probit models were almost similar to the results of linear regression. These results are presented in Tables 5 and 6.

Table 5. Summary of the results of the original Beneish model based on Logit and Probit regression	Table 5.	. Summary	of the results	of the origina	al Beneish mode	el based on Log	it and Probit regression
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	Probit regression	5			Logit regression		
Variable	Coefficient	Z statistic	Significance level	Coefficient	Z statistic	Significance level	

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Intercept	-0.288	-1.618	0.106	-0.467	-1.612	0.107
Days' Sales in Re- ceivables Index (DSRI)	-0.003	-0.136	0.892	-0.006	-0.135	0.892
Gross Margin Index (GMI)	0.014	0.391	0.696	0.023	0.392	0.695
Asset Quality Index (AQI)	-0.031	-0.781	0.435	-0.050	-0.781	0.435
Sales Growth Index (SGI)	0.097	2.117	0.034*	0.158	2.081	0.037
Depreciation index (DEPI)	0.059	1.507	0.132	0.096	1.492	0.136
Sales, General, and Administrative Ex- penses Index (SGAI)	0.086	1.800	0.072	0.143	1.779	0.075
Total Accruals to To- tal Assets (TATA)	-0.814	-3.379	0.001*	-1.310	-3.355	0.001
Leverage Index (LVGI)	0.070	0.540	0.589	0.110	0.530	0.596
likelihood-ratio (LR) statistic	21.22103		0.006583	21.25703		0.006495
McFadden's coeffi- cient of determina- tion (R2)	0.008322			0.008336		

The Beneish model was tested by Probit and Logit regression. As reported in Table 5, in the Probit and Logit model, only SGI and TATA have significance values lower than 0.05. Therefore, these are the only that are statistically significant at the 0.95 confidence level. The LR statistic and McFadden's R2 measure the regression's total validity and explanatory power, respectively. The significance values obtained for LR and McFadden's R2 in the Logit model are somewhat higher than those in the Probit model. This shows that Logit regression has higher validity and explanatory power than Probit regression, although their difference is not statistically significant.

#### Table 6. Summary of the results of the modified Beneish model based on Logit and Probit regression

	Probit regression			Logit regression		
Variable	Coefficient	Z statis- tic	Significance level	Coefficient	Z statistic	Significance level
Intercept	-0.620	-3.330	0.001	-1.114	-3.581	0.000
Days' Sales in Re- ceivables Index (DSRI)	0.005	0.204	0.838	0.006	0.152	0.879
Gross Margin Index (GMI)	0.003	0.083	0.934	0.018	0.292	0.770
Asset Quality Index (AQI)	-0.029	-0.727	0.467	-0.041	-0.621	0.535
Sales Growth Index (SGI)	0.093	2.053	0.040*	0.144	1.952	0.051
Depreciation index (DEPI)	0.055	1.362	0.173	0.089	1.343	0.179

Sales, General, and Administrative Ex- penses Index (SGAI)	0.084	1.741	0.082	0.143	1.752	0.080
Total Accruals to To- tal Assets (TATA)	-0.787	-3.213	0.001*	-1.244	-3.115	0.002
Leverage Index (LVGI)	0.053	0.401	0.689	0.079	0.365	0.715
Herfindahl-Hirsch- man Index-HHI (product market competition)	0.0002	8.301	0.000*	0.0003	7.934	0.000
Bid-Ask Spread- BAS (information asymmetry)	5.890	3.355	0.001*	12.436	3.201	0.001
likelihood-ratio (LR) statistic	108.038		1.33e-18	115.321	4.49e-20	
McFadden's coeffi- cient of determina- tion (R2)	0.042369			0.045225		

The developed Beneish model was also tested by Probit and Logit regression. As shown in Table 6, for the developed Beneish model, the significance values for SGI and TATA, HHI, and BAS are lower than 0.05, which means they are statistically significant at the 0.95 confidence level. As before, the significance values obtained for LR and McFadden's R2 in the Logit model are slightly higher than those in the Probit model, but again this difference is not statistically significant. After estimating the coefficients of the variables using logistic regression with Probit and Logit methods, the models were constructed accordingly. After estimating the coefficients and obtaining the equations of all models using the software Eviews, the results were used to predict the variable earnings management for the same period. Since there was no

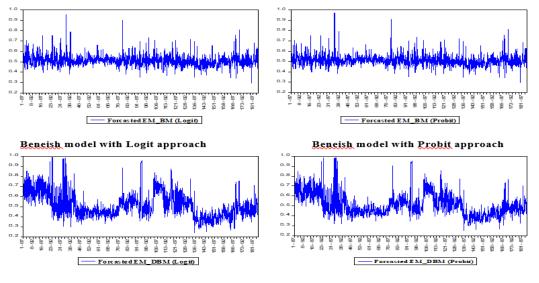
lagged dependent variable on the right side of the equations of both original and modified Beneish models, the prediction was made by the static method. As shown in Table 7, although the modification of the Beneish model by environmental variables has reduced the prediction error, this decrease is not remarkable. According to RMSE, MAE, and MAPE calculations, while the modification of the Beneish model has improved these error criteria in both Probit and Logit regression approaches, this reduction is not statistically significant. Comparing the results obtained by Probit and Logit regression shows that for both original and modified Beneish models, the Logit approach has yielded better results with less prediction error than the Probit approach, but their differences are not statistically significant.

statistic	Beneish model	· ·	modified Beneish model		
SIGUSUC	Probit	Logit	Probit	Logit	
Percentage bias	0.0000	0.0000	8.0e6-0	0.0000	
Percentage variance	0.809120	0.808297	0.644103	0.61420	
Percentage covariance	0.190880	0.191703	0.355889	0.385793	
Thiele coefficient	0.404638	0.404628	0.390889	0.389043	
RMSE	0.497043	0.497031	0.483306	0.482393	
MAE	0.494147	0.494110	0.470950	0.467743	
MAPE	130.5916	130.5907	129.2611	128.9969	

Table 7. Results	(statistics)	of prediction evaluation
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The results of the earnings management prediction by Probit and Logit regression are plotted in Figure 1. As this figure, the original Beneish model's predictions of earnings management with both regression methods are mostly random and fall in the range of 0.4-0.6. This model is unsuccessful in identifying earnings managing firms (i.e. X=1) and non-earnings managing firms (i.e. X=0). With the modification, this range has increased to 0.3-0.8 and has fluctuated and the model has performed better in identifying the earnings managing and non-earnings managing firms. However, the modified model is still unable to fully detect earnings management.



Modified Beneish model with Logit approach Modified Beneish model with Probit approach

Figure 1. Prediction of earnings management with Probit and Logit approaches

#### Model validity and performance

To assess the validity of model predictions, it was checked whether the model can identify earnings management in listed firms and assign the samples to one of the two groups (earnings managing firms or non-earnings managing firms). For this assessment, earnings management was measured discretely on a sample of firms listed on TSE. After selecting a suitable cutoff point, the earnings managing firms or nonearnings managing firms were identified using the receiver operating characteristic (ROC) curve based on sensitivity and specificity at that point and also the loss function.

The area under the ROC curve (AUC) is approximated by the Mann-Whitney test statistic. The higher the AUC is, the better is the performance of the developed model.

Table 8 provides a summary of the results of the ROC analysis. In both models, AUC is larger than 0.5. For the Beneish model, AUC is between 0.5 and 0.6, indicating that the Beneish model's differentiation of earnings managing or non-earnings managing firms is not significantly different from random allocation. This

means the Beneish model has performed this differentiation completely randomly. For the modified Beneish model, AUC is between 0.6 and 0.7-0.6, which although better than in the original model, is still quite poor and suggests that this differentiation too is almost random. Comparing the results obtained using Logit and Probit regressions shows that the former method has resulted in higher AUC, which means better performance, but the difference is not statistically significant.

Model		Approach	AUC	Standard devi- ation	Confidence interval	Standard AUC	p-value
Original	Be-	Probit	0.54846*	0.01338	0.5224 - 0.57469	3.6221	1.4612e-04
neish		Logit	0.54855*	0.013379	0.52233 - 0.57477	3.6287	1.4245e-04
Modified	Be-	Probit	0.64565**	0.012732	0.62069 - 0.6706	11.44	0
neish		Logit	0.64776**	0.012711	0.62274 - 0.67257	11.616	0

#### Table 8. Result of ROC analysis

The optimal cut-off point was determined through three methods: the shortest distance from the upper left corner, the intersection of this point with the Youden index and the point giving maximum precision using the software MATLAB. As shown in Table 9, the best accuracy of the original Beneish model with the Probit approach at the optimal cut-off point (i.e. 0.5215) is 56.18%, and the best accuracy of the original Beneish model with the Logit approach at the optimal cut-off point (i.e. 0.5216) is 56.43%. These results show that for the original Beneish model, using Logit regression results in higher accuracy (56.43%) than using Probit regression (56.18%). For the modified Beneish model, the best accuracy achieved with the Probit approach at the optimal cut-off point (i.e. 0.5450) is 68.83%, and the best accuracy achieved with the Logit approach at the optimal cut-off point (i.e. 0.5508) is 69.12%. This means that for the modified Beneish model, too, using Logit regression leads to higher accuracy (69.12%) than using Probit regression 68.83%). Therefore, it can be stated that there is a significant difference between the prediction accuracies that can be achieved with Probit and Logit approaches, as Logit regression is more effective in identifying levels of earnings management.

Model	Regression Approach	Parameter	Method 1	Method 2	Method 3
Original Beneish	Probit	Optimal cut-off point	0.5048	0.5215	0.5048
		Best precision	55.60	56.18	55.60
	Logit	Optimal cut-off point	0.5052	0.5216	0.5051
		Best precision	55.8	56.43	55.54
Modified Beneish	Probit	Optimal cut-off point	0.4828	0.5450	0.4628
		Best precision	62.43	68.83	60.68
	Logit	Optimal cut-off point	0.4794	0.5508	0.4753
		Best precision	62.30	69.12	62.00

#### Table 9. Optimal cut-off points obtained for the two models

According to Derrac, García, Molina, and Herrera (2011), the performance of heuristic models should be evaluated using statistical tests, as mean and stand-

ard deviation are not good enough measures for comparing these models. A statistical test should be able to prove that a new model significantly outperforms the existing models in solving a specific problem. To test whether there is a significant difference between the original Beneish model and the modified Beneish model, and also between Probit and Logit regression approaches in predicting earnings management, the nonparametric Wilcoxon test was performed at the 5% significance level. Obtaining a statistic value lower than 5% in this test means that the null hypothesis is rejected and the opposite hypothesis (research hypothesis) is confirmed. The results of the nonparametric Wilcoxon test are presented in Table 10

Comparison of the two mo	odels		,						
	Frequer	icies	Sum of ranks		Mean rank		Frequency of ranks		
Comparison of the two models	Nega- tive	Posi- tive	Negative	Positive	Nega- tive	Positive	Tied	Total	
Probit	1142	698	652653	1041067	571.5	1491.5	0	1840	
Logit	1115	725	622170	1071550	558	1478	0	1840	
	Distribut proxima		z-value	One-way p-value	Two-way p-value Test result		lt		
Probit	Normal		36.0408	0				Rejection of the null hypothesis	
Logit	Normal		36.2914	0	0		Rejection of the null hypothesis		
Comparison of the two reg	gression a	pproache	S						
	Frequer	requencies Sum of ranks		(S	Mean rank		Frequency of ranks		
Comparison of the two regression approaches	Nega- tive	Posi- tive	Negative	Positive	Nega- tive	Positive	Tied	Total	
Original Beneish	1072	768	575128	1118592	536.5	1456.5	0	1840	
Modified Beneish	915	925	419070	1274650	458	1378	0	1840	
	Distribution ap- proximation		z-value	One-way p-value	Two-way p-value		Test result		
Original Beneish	Normal		36.6278	0	0		Rejection of the null hypothesis		
Modified Beneish	Normal		37.1377	0	0		Rejection of the null hypothesis		

Table 10. Ranking and statistics	of the Wilcoxon test
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The statistic of the nonparametric Wilcoxon test was estimated using the normal approximation method. As the results of Table 13 show, because of the lack of equal values, there is no tied ranking for earnings management predictions. The higher average positive rank of the modified Beneish with Probit regression (1491.5) than the average negative rank of the original Beneish model with that regression (571.5) and also the higher average positive rank of the modified Beneish with Logit regression (1478) than the average negative rank of the original Beneish model with that regression (588) shows that the modification has made a significant change in the model performance. In other words, it can be claimed that the modification has improved the accuracy of the model in detecting earnings managing firms. Also

The higher average positive rank of the Logit regression (1456.5) for the Beneish model than the average negative rank of the Probit regression for that model (536.5) and the higher average positive rank of the Logit regression (1378) for the modified Beneish model than the average negative rank of the Probit regression for that model (458) shows that there are significant differences between the outcomes of using these two regression methods. Therefore, it can be concluded that the Logit regression method has been more suitable than Probit for use in the identification of earnings management. The z-statistic obtained for the models is higher than the critical value of 1.64, which indicates statistical significance at the 95% level. Therefore, the null hypothesis that there is no difference between the two models is rejected. From this, it can be concluded that there is a significant difference between the performance of the original Beneish model and the performance of the modified Beneish model in predicting and identifying earnings management. The z-statistic obtained for the two regression methods is also higher than the critical value of 1.64, which means the null hypothesis that there is no difference between the two methods is rejected and there is indeed a significant difference between Probit and Logit in terms of how effective they are in predicting earnings management.

### Discussion

This study investigated the ability of the Beneish model with logistic Probit and Logit regression to predict earnings management in Iranian firms. Considering the need to localize the Beneish model (as it has been designed based on the data of other countries) and also to add environmental variables to its main eight components, we also modified/localized this model by incorporating two variables representing product market competition and information asymmetry into its formulation. We then compared the capabilities of the original and modified Beneish models in identifying Iranian firms that commit earnings management. The findings showed that the original model has a fairly high error in earnings management detection in Iran. For the Beneish model, the area under the ROC curve (AUC) was estimated to be in the very low confidence range of 0.05-0.6, indicating that for the sample of this study, the Beneish model's differentiations of earnings managing firms and non-earnings managing firms are random. Therefore, the original Beneish model cannot be used to identify the firms listed on TSE that engage in earnings management.

The analyses of this study showed that modifying the model by introducing environmental variables that product market competition and information asymmetry increased AUC to 0.6-0.7 and improved the accuracy of the model to 68.83% when implemented with Probit regression and 69.12% when implemented

with Logit regression. Overall, this modification (adding e environmental variables) had limited impact on the Beneish model, as it only reduced the prediction error from 43.82% to 31.17% (i.e., 12.65% reduction) in the Probit approach and from 43.57% to 30.88% (i.e., 12.69% reduction) in the Logit approach, and only mildly improved the predictive power of the Beneish model. While the modified Beneish model was found to be more accurate than the original model and the Logit regression method was found to be more suitable than Probit for use in earnings management prediction, the findings from the ROC analysis showed that AUC will remain below the acceptable range (e.g., 0.7-0.8) and the model prediction error will still be above 30%.

The results showed that the best accuracy of the modified Beneish model (69.12%) was higher than that of the original model (56.43%). Despite this and the fact that the Wilcoxon test showed a significant difference between the two models in terms of performance, the ROC analysis, which involved finding the optimal cutoff point and measuring the best accuracy at this point, showed that both models are unable to reliably detect earnings managing firms. Since the modification of the Beneish model with the introduction of product market competition and information symmetry variables made a mild (insignificant) improvement in the predictive power of the Beneish model, it can be concluded that there is a weak (insignificant) relationship between these variables and earnings management. In this respect, the results of this study are consistent with the findings of other studies (4, 6, 9-12). The results of this study are also consistent with the finding of some studies (1) in that the original Beneish model did not perform well and was highly error-prone in identifying the levels of earnings management. However, our result contradicts the findings of studies (1, 8, 13) in that the modification did not make the method capable of differentiating the firms that engage and not engage in earnings management. A study has reported that their modification of the Beneish model has improved the model accuracy, but this study lacks ROC analysis and has not determined the optimal cut-off point and precision, which makes it impossible to comment on the ability of the model to identify earnings management or manipulation (3).

# Conclusion

To discover earnings manipulation, Iranian financial statement users are recommended to pay attention not only to accounting variables and items within financial statements, but also to non-accounting, motivational, and environmental factors that may stimulate this behavior. Although research findings are indicative of the not-so-significant impact of environmental variables such as product market competition and information asymmetry on the detection of earnings management, it may be beneficial to investigate whether other variables that affect information environment (stock turnover, illiquidity, firm size, firm growth opportunities, stock volatility, institutional ownership, number of shareholders, firm age, etc.) can be used to improve the performance of the Beneish model. Interested researchers are also encouraged to try using meta-heuristic algorithms such as particle swarm optimization to reduce the error in the model's prediction of earnings management.

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