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A Model Recommendation On Determination Of Manipulation Risk In Financial Statements: BIST Application*

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ABSTRACT

Aim of this study is investigate whether is there a specific set of financial information that signals manipulation in the financial statements. The paper aims to develop a model for detecting manipulation risk in financial statements with high level of significance and explanatory. Ratio analysis based mixed models were tested with the financial statement data of BIST companies and powerful indicators selected by logistic regression. For classifying risk and control groups Benford analysis is used. The model proposed in the study was formed by examining the strengths and weaknesses of the three models - Altman (1978), Beneish (1999) and Spathis (2002)- frequently used in the literature to determine the risks in financial statements with adding Benford analyse step. Model has the highest explanatory power, with 10.4% among the compared models. The model predicts companies that have manipulated correctly by 16.7%. Moreover, all variables in the model are significant at the 95% significance level. This research limited by 184 companies which traded BIST real sector and period of 2008-2017. This paper recommends an original model for alternative to mixed models, which can be used for manipulation risk detection. The implication of the recommended model that has highest explanation power and all variables are significant comparing with previous common use models. Also model presents a new approach by using Benford Analysis for classifying risk and control groups. Evaluated that this model could be useful for audit targets to auditors, professionals and researchers.

Keywords: *Financial Manipulation, Financial Statement Anaylsis, Ratio Analysis*

Jel Classification: *M40, M41, M42.*

Finansal Tablolarda Hile Riskinin Belirlenmesi Üzerine Bir Model Önerisi: BIST Uygulaması

ÖZET

Bu çalışmanın amacı, finansal tablolarda manipülasyona işaret eden belirli bir finansal bilgi kümesinin olup olmadığını araştırmaktır. Rapor, finansal tablolarda manipülasyon riskini tespit etmede anlamlı ve yüksek açıklama gücüne sahip bir model geliştirmeyi amaçlamaktadır. Oran analizine dayalı karma modeller, BIST şirketlerinin finansal tablo verileri ve lojistik regresyon tarafından seçilen güçlü göstergelerle test edilmiştir. Risk ve kontrol gruplarını sınıflandırmak için Benford analizi kullanılmıştır. Araştırmada önerilen model, finansal tablolardaki riskleri belirlemek için literatürde sıkça kullanılan üç modelin - Altman (1978), Beneish (1999) ve Spathis (2002) - güçlü ve zayıf yönlerinin incelenmesiyle oluşturulmuştur. Model, diğer modellerle karşılaştırıldığında modeller arasında% 10,4 ile en yüksek açıklayıcı güce sahiptir. Model, finansal tablolarda manipülasyon riski yüksek şirketleri % 16,7 oranında doğru tahmin etmektedir. Ayrıca, modeldeki tüm değişkenler % 95 anlamlılık düzeyinde anlamlıdır. Bu araştırma, BIST reel sektörünü ve 2008-2017 dönemini ticaret yapan 184 firma ile sınırlandırılmıştır. Bu makale, manipülasyon riski tespiti için kullanılabilecek karma modellere alternatif olarak original bir model önermektedir. Ayrıca model, risk ve kontrol gruplarını sınıflandırmak için Benford Analizini kullanarak yeni bir yaklaşım sunmaktadır. Bu modelin denetçilere, uzmanlara ve araştırmacılara denetim hedefleri için yararlı olabileceği değerlendirilmektedir.

Anahtar Kelimeler: *Finansal Manipülasyon, Financial Tablolar Analizi, Oran Analizi.*

JEL Sınıflandırması: *M40, M41, M42.*

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1. INTRODUCTION

The determination of the financial statement and financial health of the company is appropriate to be analyzed by financial ratios. Agencies have been set up to create a qualitative type of information that assesses the credibility of businesses, even in periods prior to the development of quantitative measures of company performance (Altman,2000:8). There are many methods using at detecting manipulation of financial information called profit management, profit stabilization, creative accounting practices, aggressive accounting etc. The common feature of these methods is that they are based on changing the numbers subject to accounting data. Methods of manipulating financial information according to Mulford and Comiskey (2011) are:

-Aggressive Accounting: In order to achieve the desired results, accounting policies and practices are carried out without consideration of accounting principles for intentional selection and typically higher current earnings, regardless of compliance with generally accepted accounting principles.

- Earnings Management: Earnings management is differentiated earnings by interfering with the financial statements. The goal is usually to keep the profit at a certain level, to keep analysts estimates or to display a stable profit trend.

- Income Smoothing: It is aimed to make the financial appearance of the company less risky in order to ensure stability in profit distribution. For this reason, profit is reduced during periods when the profit is high, and the profit is increased during the periods when the profit is low, and the period adjustment is made on the profit.

-Fraudulent Financial Reporting: Financial information is deliberately or intentionally misappropriated and declared, which is considered administrative and judicial forgery.

- Creative Accounting Practices: All the steps used to play the game of financial numbers, the application of aggressive election and accounting principles, fraudulent financial reporting and earnings management, or transactions related to income management can be evaluated within this scope (Fındık ve Öztürk,2008:487).

Last decades, financial ratio analysis has become extremely useful for knowing the financial situation of the enterprises. Indicators selected at these ratios are also used to measure the health of the financial statements and to detect signals of performance, bankruptcy, fraud or manipulation. Although these studies constitute some important generalizations about the performance and trends of certain measures, it is necessary to discuss the adaptation of the results to assess the financial health potential of firms both theoretically and practically. The ratio analysis presented in this way is open to misinterpretation and potentially confusing. For example, a company with a profitability and / or insufficient solvency may be considered a potential bankruptcy risk. However the average liquidity may be at an acceptable level due to some reasons not to be seen in the proportions. The potential uncertainty regarding the relative performance of several firms is evident. The essence of the deficiencies that exist in any univariate analysis is found here. For this reason, it is necessary to incorporate the various criteria that will build upon the findings for healthy analysis and interpretation into a meaningful prediction model. In doing so, the use of ratio analysis as an analytical technique should pay attention to the potential for some questions to be answered. Questions; (1) what rates are most important to determine the potential of fraud, (2) what weights should be added to the selected ratios, and (3) how the weights will be established objectively (Altman,2000:8).

Aim of this study is to investigate whether is there a specific set of financial information that signals manipulation in the financial statements. There are different models developed in the literature on this subject. Most frequently use of these can be count; Altman Z-score (1968), Beneish (1999), and Spathis (2002) models. These models have determined various financial ratios that can be effective in the performance or manipulation of financial statements and tested the determination of financial manipulation by regression analysis. Financial ratios which may be effective in financial statements manipulation, including the ratios included in the three different models mentioned in the study, were investigated by logistic regression analysis and a new model has created by selecting the rates with the highest and meaningful explanation of manipulation.

The literature contribution of this study can be summarized as follows. It is often not possible to identify fraudulent companies to implement the model. In this study, its first time, BDS (Benford Digit Score) method was used in the selection of companies with high risk of manipulation for the formation of risk group. BDS method is an additional tool of Benford analysis which recommended by author of this article. This method is an effective model that can be used when there is no exact data about manipulation. At the other hand this paper recommends an original model alternatively to mixed models, which used for fraud detection. The implication of the recommended model that has highest explanation power and all variables are significant comparing with previous common use models.

2. LITERATURE REVIEW

Ratio analysis is a frequently used method of interpretation and audit of financial statements. For manipulation research different models have been developed and implemented on a set of ratios derived from financial statements. These models can sort as; accrual based models, mixed models and alternative models.

Some of the accrual-based models developed to measure manipulation in the literature are; Healy (1985), DeAngelo (1986), McNichols and Wilson (1988), Jones (1991), Dechow, et al. (1995) and Kothari, Leone and Wasley (2005). Focusing on a specific accrual models tries to separate intentional and non-intentional parts by following a single attitude rather than total accrual. McNichols and Wilson (1988) attempted to determine whether earnings management was made through the provision for doubtful trade receivables. Jackson et all. (2002) attempted to determine whether earnings management was made through doubtful trade receivables in their work. Philips at all. (2003) used deferred tax expense as a measure of accrual management and argued that the difference between tax profit and accounting profit was due to intentional accruals.

Models that measure income around a threshold usually come from the assumption that earnings management is the goal of catching a targeted threshold level or trying to stay there. In the literature, these thresholds are in the form of zero profit (avoiding harm) instead of net loss, catching the previous years profit (avoiding profit loss), keeping analysts profit forecasts or catching sectoral averages (Burgstahler and Dichev 1997; Degeorge et all 1999; Matsumoto 2002; Burgstahler and Eames 2006; Roy Chowdhury 2006).

Mixed models are probit models developed to estimate earnings manipulation using various variables in financial statements. These models can be used to determine not only the accruals that are desired but also the earnings management (Fındık ve Öztürk,2016:489). The most common of these are the Altman Z-Score model, Beneish model and Spathis model which is also the subject of this study. Summary information of similar studies is given in Table1.

Table 1. Ratio Analysis Used in Manipulation Detection

Author	Year	Term	Method	Manip. Risk Yes	No	Data Selection	Variables
Altman	1968	1946-1965	Discriminant analysis	33	33	Bankrupt risk	5
Beneish M.D	1997	1987-1993	Logistic Regression	64	1989	SEC report, Media	12
Fanning K.M ve Cogger K.O.	1998		Artificial neural networks	102	102		
Beneish M.D	1999	1982-1992	Logistic Regression	74	2332	AAER report	8
Spathis C.T.	2002	2000	Logistikc Regression	38	38	Audit report	10
Carvello ve Nagy	2004	1990-2001	Logistic Regression	104	10	AAERs Bulletin	10
Küçüksözen ve Küçükkocaoğlu	2005	1992-2002	Logistic Regression	27	99	SPK Bulletin	9
Kirkos E., Spathis C., Manolopoulos Y.	2007	2000	Bayesian	38	38	Audit report	10
Suyanto S.	2009	2001-2006	Logistic Regression	55	88	Audit analytics	30
Amara I vd	2013	2001-2009	Logistic Regression	40	40	Beasley (1996) criterias	5
Huang S.Y vd	2014		Discriminant analysis	58	58	Judicial Data	25
Tekin	2017	2010-2014	Logistic Regression	8	65	SPK Bulletin	9
Fındık H. Ve Öztürk	2014	2013-2014	Logistic Regression	45	46	-	8
Pustyıck I.	2009	1999-2001	Logistic Regression	29	0	Accounting scandals	15
Dechow, Sloan ve Sweeney	1996	1950-1991	Logistic Regression	32		SEC report	6
Kara, Uğurlu ve Körpi	2015	2010-2012	Logistic Regression		132	-	10
Beasley	1996	1980-1991	Logistic Regression	75	75	AAERs Bulletin, WSJ Index	8

3. METHODOLOGY

In this study, a new model is proposed to compare the accrual-based and mixed models using the financial ratios in determining the risk of manipulation in the financial statements and to explain the risk of fraud manipulation. The proposed model is based on the combined use of digital analysis and ratio analysis in the detection of financial statement manipulations. The fundamental problem with the probit and logit models based on the ratio analysis method is to distinguish the companies which estimated as manipulators and non-manipulators in the data set and the groups. Manipulators and honest companies do not have a definite criterion for separation. Benford analysis results were used in the classification of the companies as high risk for manipulation and low risk for manipulation in this study, and the group of companies thus separated was tested with the logistic regression analysis model.

In the study, theoretical sampling technique known as theoretical saturation sampling or 'sequential sampling' was used. Theoretical sampling is to maximize the sample as much as possible and to provide the optimal conditions for constructing the theory so that as much data as possible can be collected (Guba and Lincoln,1982). These data consist of detailed balance sheets and detailed income statements, which are publicly disclosed and independently audited by the companies.

In the prediction of financial statement manipulation risk, used Benford analysis digit tests results based on the BDS value derived from the MAD values that show the mean deviation from expected frequencies according to the Benford’s law. MAD is calculates as below:

$$= \frac{\sum_{i=1}^{K} |AP - EP|}{K}$$

AP: Actual distribution, EP: Benford distribution, K: 9 (for fisrt digit test), 90 (for first 2 digit)

BDS calculate as below:

BDS = Average (1.Digit MAD, 2.Digit MAD, First 2 Digit MAD)

Table 2. Ratio Analysis Used in Manipulation Detection

BDS Value	Result
0,000 - 0,0095	Comformity
0,0095 - 0,0157	Accaptable Comformity
>0,157	Nonconformity

Companies with a lower BDS value are more compatible, while those with a higher BDS value are considered more incompatible with Benford’s law. The compliance of the financial statements of the company with Benford's law is interpreted as the indication of the accuracy of the financial statements.

In the study, balance sheets and income statements set between 2008-2017 of 184 companies which traded at BIST real sector were used as data. The financial ratios determined as an independent variable and the probability of manipulation risk in the financial statements as a result of the analysis of financial statements of these companies are accepted as dependent variables. The data are dictated as (1) if there is high manipulation risk and (0) if there is low manipulation risk in the predictive financial statement based on the BDS values obtained at the end of the Benford analysis. Logistic regression analysis was applied to the data set consisting of 1840 observations classified as this type. Sensitivity test applied to the data set and removed from observations which found close to 10% to critical value. Then logistic regression analysis was performed for the remaining 1421 observations.

In this study, all variables were analysed by Logistic Regression Analysis and the companies are categorized on an annual basis. The main focus of the logistic regression analysis is to form a regression equation without guessing which group of individuals is a member. In this study, Binary Logistic Regression Analysis was used to determine the combination of independent variables that best explain the membership of certain groups expressed as two categorical (dichotomous / binary) dependent variables. The purpose of the logistic regression analysis is to estimate the value of the categorical dependent variable, in fact the "membership" estimate for two or more groups attempted to be done here. According to this, it can be said that one of the aims of the analysis is the classification, and the other is to investigate the relations between dependent and independent variables (Çokluk, 2010: 1362).

Altman Z-score, Beneish and Spathis models were tested in BIST companies, provided that Benford’s law compliance was used first as a manipulation risk estimator. The most effective financial ratios were selected for the detection of manipulation and a new model was created by traying 38 different financial ratios, which were used in previous studies and recommended in the literature, to detect manipulation risk on financial statements. The t-test was used for comparison of the groups. The analyses were performed in SPSS 22 program. The data are taken from the FINNET database and www.kap.org.tr web site.

4. RESULTS AND DISCUSSION

4.1. Classification of Companies According to Manipulation Risk

In this section, financial ratios of companies which divided into two groups are examined according to their BDS values: those compatible and incompatible with Benford’s law. The purpose here is to determine the power of the classification made according to the BDS values in terms of compliance with Benford’s law and to investigate whether the financial ratios of companies that are compatible and incompatible with Benford's law are significantly differentiated.

Table 3. Comparing Financial Ratios According to Financial Ratios

Ratios	Manip. risk	N	Mean	Std. Deviation	T-Test sig.
CUR	Low	1097	2,0156	1,85320	0,000
	High	743	2,8988	7,15669	
ROA	Low	1097	3,7074	11,61525	0,000
	High	743	1,3847	14,26725	
CASH	Low	1097	52,7268	114,18748	0,000
	High	743	108,1372	456,94454	
TA	Low	1093	8,7431	,73259	0,000
	High	738	8,2736	,69114	
MV/BV	Low	1097	1,9824	2,75010	0,006
	High	743	2,5237	5,65912	
DBT/TA	Low	1097	53,1549	31,09933	0,019
	High	743	49,5285	34,64499	
EPS	Low	1097	,8768	2,56430	0,008
	High	743	,5831	1,93607	

"CUR" The current ratio represents the ability of a firm to meet its short-term debt and is measured by the ratio of current assets to short-term debt. As a result of the analysis, current ratio was 2,89 in companies incompatible and 2,01 in companies compatible with Benford’s law. That seems the ratio is significantly different between group of companies.

“CASH" Cash ratio shows the power of money and similar values to meet short-term foreign resources. This rate calculates by dividing Liquid Assets and Securities to Short-term Liabilities. As a result of the analysis, CASH ratio was found to be 108 for incompatible companies, and 52 for compatible companies. The ratio is significantly different.

"ROA" Assets Profit ratio shows how effective the company assets are in generating profit. The ratio calculated by dividing Net profit by total assets. The average of this ratio appears to be split between those high manipulation risk companies and low manipulation risk companies. ROA, on average, was 1.38 for incompatible companies, and 3.7 for compatible companies.

Looking at the asset size, which represents the sum of the balance sheet in a certain period, it is seen that the companies conformity to Benford’s law a have higher assets than the that nonconformity companies. In other words, the conformity for large companies financial statements appears to be higher.

The "MV / BV" Market Value / Book. The price of a stock is part of a shareholder value. According to the analysis result, the average MV/BV ratio was 1.98 when there was conformity, whereas it was 2.52 when there was nonconformity.

"DEBT/ASSETS ratio shows how much of a companys assets are financed by debt, with Total Debt divided by total assets. According to the results of the analysis, the ratio was 53 in the companies which compatible to Benford’s law, 49 in the incompatibles.

"EPS" earning per share is cheaper, on average, lower than those incompatible companies. All these ratios are different between those high manipulation risk and low manipulation risk companies according to the expectation. Benford analysis can be interpreted that the estimation is appropriate for the classification of companies.

4.2. Application Of Models

4.2.1. Altman Z-Score Model

The aim of Altman model is to determine the risk of bankruptcy in financial statements using 5 variables. The variables used in the model are;

X1 = working capital/total assets,

X2 = retained earnings/total assets,

X3 = earnings before interest and taxes/total assets,

X4 = market value equity/book value of total liabilities,

X5 = sales/total assets

The descriptive statistics for the model are given in Table 4. The number of observations analyzed in the model is 1421 in all variables.

Table 4. Altman Model Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Dvt.
X1	1421	-7,98	,99	,1289	,40633
X2	1421	-,46	1492,77	6,6340	47,30199
X3	1421	-1,07	1,27	,0606	,11621
X4	1421	,00	1492,77	7,0281	48,52442
X5	1421	,00	136,70	1,1872	6,10112

According to Table 5, which shows the logistic regression results, R^2 value of the model was realized as 0,101. This means that the variables in the model explain for 10% of the effective rates of manipulation.

Table 5. Altman Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1732,362[a]	,074	,101

Looking at the classification table for the model in Table 6, the model accurately predicts 17.6% that companies with high manipulation risk and 95% of companies with low manipulation risk.

Table 6. Altman Model Classification Table

		Observed	Predictal		
		Manipulation Risk	Low	High	Percentage Correct
Step 1		Low	822	43	95,0
		High	431	92	17,6
	Overall Percentage				65,9

When the statistical significance of the variables in the model examined, the variables X1 and X5 with p value over 0.005 are insignificant and other variables are significant. Accordingly, the ratio of sales to Total Assets (X1) and the ratio of working capital to assets (X5) are not effective in the financial statements.

Table 7. Logistic Regression Results of the variables in the Altman Model

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	X1	-,291	,159	3,375	1	,066	,747
	X2	-,174	,060	8,367	1	,004	,841
	X3	-3,556	,616	33,323	1	,000	,029
	X4	,210	,060	12,220	1	,000	1,234
	X5	,033	,052	,417	1	,518	1,034
	Sabit	-,484	,083	33,706	1	,000	,616

According to the results shown in Table 7, the X1 ratios p value is 0.004, which means that the ratio is effective in manipulation. If the variable X2 is negative in the model, it can be said that reducing this ratio will increase the risk of manipulation. The variable X3, which shows the ratio of interest to pre-tax profits, is significant with p = 0,000. However, the fact that the two variables in the model are 95% insignificant can be interpreted as not being useful in predicting the risk of manipulation in BIST companies.

4.2.2. Beneish (1999) Model

Beneish (1999) attempted to detect manipulation through 8 different variables in the model. The variables used in the model are;

DSRI =(Receivables /Sales)$_{t}$ / (Receivablest_/Sales)$_{t-1}$

GMI =[(Sales - Cost of goods sold)/ Sales]$_{t}$ / [(Sales - Cost of goods sold)$_{t-1}$ /Sales]$_{t-1}$

AQI = [(1 - Current assets + PP&E) /Total assets]$_{t}$ / [(1 - Current assets+ PP&E) /Total assets]$_{t-1}$

SGI =Sales$_{t}$ / Sales$_{t-1}$

DEPI = [Depreciation / (Depreciation + PP&E)]$_{t-1}$ / [Depreciation /(Depreciation + PP&E)]$_{t}$

SGAI =(Sales, general, and administrative expense /Sales)t / (Sales, general, and administrative expense/Sales)$_{t-1}$

LVGI = [(LTD + Current liabilitiest) /Total assets]$_t$ / [(LTD + Current liabilitiest)/Total assets]$_{t-1}$

TATA =(ΔCurrent assets - ΔCash - ΔCurrent liabilities - ΔCurrent maturities of LTD - Δlncome tax payable -Depreciation and amortizationt)$_t$ / Total assets$_t$

Table 8. Beneish Modeli Descriptive Statsitics

	N	Minimum	Maximum	Mean	Std. Deviation
DSRI	1421	,00	68,27	1,2233	2,42893
GMI	1421	-27,05	2641,52	2,9699	71,49733
AQI	1421	,03	23,35	1,0088	,62889
SGI	1421	,00	143,46	1,2977	4,17011
DEPI	1421	-1,78	57,51	1,4318	3,03699
LVGI	1421	,00	11,07	1,0672	,56111
TATA	1421	-6,91	47,01	,0279	1,36554
SGAI	1421	-,30	231,80	1,3178	6,91723

The number of data analyzed in the model is 1421. Other descriptive statistics are given in Table 8.

Table 9. Beneish Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1768,894[a]	,009	,012

According to the summary outputs of the model given in Table 9, the R2 value of the Beneish model found 0,012. This rate shows that the variables in the model are 1,2% effective in manipulation. The low R2 value indicates that the model is weak.

Table 10. Beneish Modeli Classification Table

	Observed	Predicted		
	Manipulation Risk	Low	High	Percentage Correct
Step 1	Low	856	2	99,8
	High	486	11	2,2
	Overall Percentage			64,0

Table 10 shows classification of companies that model accurately predicts 2,2% that companies with high manipulation risk and 99,8% of companies with low manipulation risk.

Looking at Table 11, which shows the significance of the variables in the model, the p value of all the variables is greater than 0.005, so the model is not significant.

Table 11. Logistic Regression Results of the variables in the Beneish model

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	DSRI	,095	,049	3,776	1	,052	1,100
	GMI	-,002	,004	,173	1	,677	,998
	AQI	,117	,136	,733	1	,392	1,124
	SGI	-,003	,016	,029	1	,866	,997
	DEPI	,009	,021	,171	1	,679	1,009
	LVGI	-,047	,124	,142	1	,707	,954
	TATA	,118	,102	1,348	1	,246	1,125
	SGAI	-,011	,011	,956	1	,328	,989
	Sabit	-,720	,206	12,216	1	,000	,487

Beneish model studies on BIST have similar results. Küçüksözen and Küçükkocaoğlu (2004) found that AQI, SGAI, TATA and LVGI variables were insignificant in another study which made on BIST. Tekin (2017) found that, the AQI, DSRI, LVGI and TATA variables in the model were not significant. In this light, it can be said that Beneish model is not a model enough to make manipulation prediction on BIST companies.

Küçüksözen and Küçükkocaoğlu (2004) developed the model by adding new variables to Beneish model. In this context, the "growth index on sales (SGI)" was removed from the model and the "stocks to sales ratio" (SSE) and "financing expenditure to sales ratio (FGE)" models were added as independent variables. In this study, these variables were tested by logistic regression analysis. While SSE was insignificant and FGE was found significant at 95% level.

4.2.3. Spathis (2002) Model

Spathis (2002) used 9 variables to detect manipulation in financial statements.

S1: Debts / Equal
S2: Sales / Total Assets
S3: Net Profit / Sales
S4: Receivables / Sales
S5: Net Profit / Total Assets
S6: Working Capital / Total Assets
S7: Gross Profit / Total Assets
S8: Inventories / Total Assets
S9: Total Debt / Assets

The descriptive statistics for the model of Spathis (2002) are given in Table 12. The number of observations analysed in the model is 1421.

Table 12. Spathis Model Descriptive Statsitics

	N	Minimum	Maximum	Ortalama	Std. Sapma
S1	1421	-31,70	554,87	2,1105	16,23828
S2	1421	,00	6,57	,9372	,78798
S3	1421	-41,45	53,90	,0201	2,00199
S4	1421	,00	13,22	,2540	,64123
S5	1421	-140,16	130,77	2,7424	13,28291
S6	1421	-7,98	,99	,1290	,40635
S7	1421	-136,52	7,34	-,0467	6,11332
S8	1421	,00	,75	,1355	,12087
S9	1421	,00	4,48	,5065	,34373

Table 13 summarizes the model. Accordingly, the R2 value of the model is ,085 that means the model explain manipulation risk for 8.5%. The explanatory power of the model is relatively high, but the significance ratings of the variables must also be considered.

Table 13. Spathis Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1730,000[a]	,063	,085

According to Table 14, the model accurately predicts companies with high manipulation risk by 15.5% and companies with low manipulation risk by 96.1%. The average correct estimate percentage is 66.2%.

Table 14. Spathis Modeli Classification Table

Observed		Predicted		
	manipulation Risk	Low	High	Percentage Correct
Step 1	Low	835	34	96,1
	High	432	79	15,5
	Overall Percentage			66,2

Table 15. shows the logistic regression results for the model. Significant variables at the 95% level of significance in the model are S1, S2, S4, S5 and S6. Accordingly, the ratio of debt to capital (S1) increases the risk of manipulation by a factor of 1. A positive correlation was found between the volatility rate of the sales (S2) and the manipulation risk by 0.78. The ratio of receivables to sales (S4) is the ratio with the strongest effect according to coefficient B. This increase of 1 unit increases the risk of manipulation by 2,277 times.

Table 15. Logistic Regression Results of the variables in the Spathis model

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	S1	,021	,010	4,470	1	,034	1,021
	S2	,202	,098	4,264	1	,039	1,224
	S3	-,144	,110	1,713	1	,191	,866
	S4	,823	,344	5,705	1	,017	2,277
	S5	-,030	,007	19,407	1	,000	,970
	S6	-,659	,320	4,249	1	,039	,518
	S7	-,350	,219	2,560	1	,110	,705
	S8	1,010	,531	3,625	1	,057	2,746
	S9	-1,482	,279	28,255	1	,000	,227
	constant	-,097	,181	,290	1	,590	,907

Variables S3, S4 and S7 seem to be insignificant compared to p value. For this reason, it can be said that the model is insufficient in detecting manipulation in BIST companies.

4.2.4. Recommended Model

In the model, the existence of manipulation risk in the financial statements was determined according to the BDS scores of the bench tests conducted in Benford analysis. Corporate groups that detected the low manipulation risk based on the BBS score and high manipulation risk were combined in the model with high financial ratios selected by logistic regression analysis.

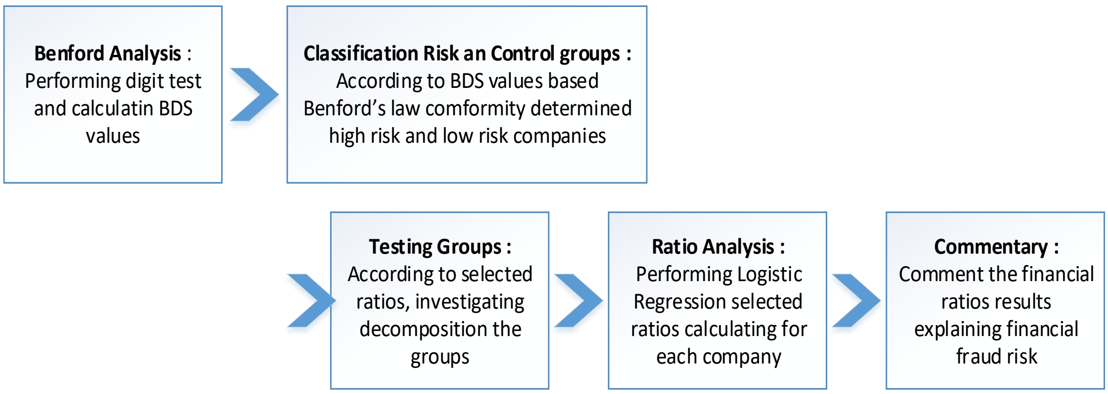

Figure 1. Recommended Model Flowchart

Altman (1968) Model, Beneish (1999) model and Spathis (2002) models, which are frequently used in predicting manipulation in the literature, were applied to the model formation, but no statistically significant results were obtained. 38 different financial ratios were tested, including the variables in the models tested for use in detecting manipulation risk in the financial statements, and a new model was created from the strongest ratios in terms of clarity and significance in fraud detection. For this reason, considering the parameter estimates of Logistic Regression Analysis and other related statistics; each independent variable was examined with respect to 0.05 significance level (p> 0.05), and those that were not statistically significant were discarded from the model and the analysis was repeated with statistically significant independent variables ($p < 0.05$). As a result, logistic regression analysis was performed by including 7 variables in all.

Table 16. Descriptive Statsitics

	manipulation Risk	N	Mean	Std. Dvt	T-Test sig.
TATA	Low	1093	-,0140	,28108	0,042
	High	738	,1104	1,99326	
SGAI	Low	1074	1,2372	7,12498	0,850
	High	701	1,2936	4,15487	
FGE	Low	1092	1,2690	6,94300	0,194
	High	737	2,4739	29,46652	
X2	Low	1077	3,2506	7,87868	0,001
	High	727	10,2422	65,17480	
X3	Low	1093	,0717	,10288	0,137
	High	738	,0563	,31947	
X4	Low	1075	3,2199	7,52240	0,000
	High	727	11,1249	66,87705	
S6	Low	1093	,1460	,32679	0,033
	High	738	,1030	,53263	

The TATA and SGAI variables were taken from the model Beneish (1999), FGE taken from Beneish adaptation model by Küçüksözen (2004), X2, X3, X4 vareable taken from Altman (1968) and S6 variable taken from Spathis (2002) model.

Table 17. Recomended Model Veriables and T-Test Results

		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference
TATA	Equal variances assumed	12,483	,000	-2,033	1829	,042	-,12437
	Equal variances not assumed			-1,684	756,831	,093	-,12437
SGAI	Equal variances assumed	,214	,643	-,190	1773	,850	-,05645
	Equal variances not assumed			-,211	1752,951	,833	-,05645
FGE	Equal variances assumed	6,385	,012	-1,299	1827	,194	-1,20491
	Equal variances not assumed			-1,090	791,439	,276	-1,20491
X2	Equal variances assumed	34,664	,000	-3,483	1802	,001	-6,99168
	Equal variances not assumed			-2,878	740,345	,004	-6,99168
X3	Equal variances assumed	7,259	,007	1,488	1829	,137	,01544
	Equal variances not assumed			1,269	841,038	,205	,01544
X4	Equal variances assumed	40,169	,000	-3,840	1800	,000	-7,90506
	Equal variances not assumed			-3,174	738,440	,002	-7,90506
S6	Equal variances assumed	15,043	,000	2,139	1829	,033	,04301
	Equal variances not assumed			1,959	1110,825	,050	,04301

Table 17 shows the t-test results of the model. According to this, there is a significant difference between corporate groups low and high manipulation risk in the TATA variable. There was no significant difference between the groups when the p values of the SGAI, FGE, and X3 variables were greater than 0.005.

Table 18. Recomended Model Sumary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1659,570[a]	,076	,104

The R2 value of the model according to Table 18 is 0,104. This implies that the variables in the model account for 10.4% of the risk of manipulation in the financial statements.

Table 19. Recomneden Model Classification Table

Observed		Predicted		
	Manipulation Risk	Low	High	Percentage Correct
Step 1	Low	814	40	95,3
	High	409	82	16,7
	Overall Percentage			66,6

According to the classification table given in Table 19, 16.7% of companies that are likely to manipulate models correctly estimate 95.3% of non-manipulated companies. In the model as a whole, the correct estimate percentage is 66.6% on average.

Table 20. Logistic Regression Results of the variables in the Recomended model

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	TATA	,552	,244	5,112	1	,024	1,737
	SGAI	,579	,245	5,580	1	,018	1,785
	FGE	-,563	,248	5,182	1	,023	,569
	X2	-,212	,066	10,250	1	,001	,809
	X3	-3,314	,632	27,523	1	,000	,036
	X4	-,248	,066	14,001	1	,000	1,281
	S6	-,557	,199	7,877	1	,005	,573
	Sabit	-,466	,080	33,808	1	,000	,628

As can be seen from Table 20 where the values for the variables in the repeated logistic regression analysis are given, at 0,05 significance level, all independent variables in the model were found to be statistically significant. The B's given in the second column are used to construct the prediction function in multiple regression. In the logistic regression, they are used to determine the likelihood that companies will cheat or not. The sign of the coefficient B also indicates the direction of the relationship between the independent variable and the dependent variable (Çokluk, 2010: 1392).

It can be said that the coefficients of negative signs decrease the risk of manipulation in the financial statements and the coefficients of positive signs increase the possibility of manipulation. In other words, there is a high probability that manipulation will occur in companies with large proportions.

Since the manipulation risk position on the financial statements is "1" and the absence is coded "0"; it can be said that the independent variables with negative B coefficients reduce the risk of manipulation. The values in the column "Exp (B)" are odds ratios. The odds ratio in the study is the ratio of the likelihood of having a manipulation risk to the financial statements to the likelihood of not being present (Kamışlı ve Girginer, 2010: 18).

As can be seen from Table 20; increasing the TATA ratio by 1 unit increases the risk of manipulation in the financial statement by 1.73 times. Likewise, in terms of manipulation risk effects on the financial statements, an increase in the SGI ratio by 1 unit is 1.78 times more effective in increasing the manipulation risk. Other ratios in the model are negatives. That is, the increase of X4 ratio by 1 unit reduces the risk of manipulation by 1.28 times. When the variables in the model are examined one by one;

"TATA" has a positive coefficient (0,552) as the ratio of total accruals to total assets and is significant at 95% confidence level. This can be interpreted as a 1-unit increase in total accruals that would increase the risk of manipulation in financial statements by 0.55 fold.

The coefficient of the ratio of the Operating Expenses to the Gross Sales is positive (0.579), excluding "SGAI" Rural Expenditures. It is significant at the 95% confidence level in the variable model. The coefficient B can be interpreted as a 1-unit increase in operating expenses, which will increase the risk of manipulation by 1.78 times in financial statements. This can be interpreted as an increase in activity that is not parallel to increases in sales will increase the risk of manipulation.

The "FGE" Financing Gains Index ratio has a negative coefficient (-0.563), and is significant at the 95% confidence level. It can be said that increasing the unit rate of finance expenses by 1 unit reduces the risk of manipulation by 0.56 times.

"X2" has an undistributed Profit / Loss ratio of negative coefficient (-0.212) and is significant at 95% confidence level. The drop of 1 unit in this area will increase the risk of manipulation by 0.8 times. This can be interpreted as the fact that relatively newly established companies are more prone to manipulation.

"X3" Interest Profit Before Tax / Profit ratio was negative (-3,314) as a result of the analysis. It is significant at the 95% level in the variable model. It can be said that the variable with B coefficient 0.036 is inversely related to the manipulation risk.

"X4" Market Value / Debt ratio has a negative coefficient (-0,248) and is significant at 95%. When evaluated according to the variable B coefficient, the decrease in 1 unit in the vicinity can be interpreted as the increase of the manipulation risk by 1.28 times.

"S6" Working Capital / Active ratio is negative coefficient (-0.557), meaning 95% level. Accordingly, there is an inverse relationship between rate and manipulation risk.

4.2.5.Comparison of Models

In the study, Altman (1978), Beneish (1999) and Spathis (2002) models tested on BIST data and a new model based on the strengths of these models were created. This new model applied to the BIST data to detect manipulation risk of financial statements. Comparisons of the models are given in Table 21.

Table 21. Comparision of Tested Models

Model	**R^2**	**Manipulation Risk Perc.Correct**	**Variables**		
			Significant	Insignificant	Total
Altman	0,101	%17,6	3	2	5
Beneish	0,012	%2,2	-	8	8
Spathis	0,08	%15,5	5	4	9
Recommended	0,104	%16,7	7	-	7

According to Table 21, Altman model has the highest detection rate of detecting manipulation risk, 17.6%, and the power of model R2 has the second highest values. However, the two variables in the model show no significance in the BIST implementation, indicating that manipulation risk of the model uses ineffective variables in the description.

As a result of the BIST application of the Beneish model, the R2 value of the model is low at 1% level. The accurate estimate of the risk of rape was also very low with 2.2%. Moreover, all of the variables in the model seem to be meaningless at the 95% significance level. This Beneish models due in the financial statements of Turkey said that the cause be useful in detecting manipulation risk.

The Spathis model has an explanatory power of 8%. In addition, model determined manipulation risk estimate 15.5% correctly. However, 4 of the 9 variables used in this model were not significant at the 95% significance level.

5. CONCLUSION

Benford analysis and ratio analysis based models used in manipulation detection of financial data in the study were applied to the financial statement data of the companies which traded in BIST and the manipulation risk on the financial statements was investigated. The aim of the study is to develop an alternative model in the determination of the fraud or manipulation risk in financial statements. In this direction, an alternative manipulation risk detection model was developed using Benford Analysis and ratio analysis based models.

As a result of the application of mixed models to the data set, no significant results could be obtained. For this reason, a new model has been created by selecting the most meaningful financial ratios from applied models. By the way this paper also recommends an original model alternatively to mixed models, which can be used for manipulation risk detection. The implication of the recommended model that has highest explanation power and all variables are significant comparing with previous common use models.

The model proposed in the study was formed by examining the strengths and weaknesses of the three models - Altman (1978), Beneish (1999) and Spathis (2002)- frequently used in the literature to determine the risks in financial statements with adding Benford analyse step. Model has the highest explanatory power, with 10.4% among the compared models. The model predicts companies that have manipulated correctly by 16.7%. Moreover, all variables in the model are significant at the 95% significance level. This is due to the superiority of the financial statements manipulation detected in Turkey is recommended to use this model.

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