DETECTING FALSIFIED FINANCIAL STATEMENTS USING DATA MINING: EMPIRICAL RESEARCH ON FINANCE SECTOR IN TURKEY

İlker Kıymetli ŞEN *

Serkan TERZİ **

* *Corresponding Author*, Assist. Prof. Dr., Okan University, e-mail: ilkerkiymet-lisen@yahoo.com

ABSTRACT

The purpose of this paper is to develop a reliable model in order to determine the falsified financial statements (FFSs) of finance sector listed on the Istanbul Stock Exchange (ISE). In this paper, we conducted our research on financial statements of financial services companies for FFSs in ISE based on the auditor's opinion. The results of this paper are compatible with previous studies and represent the indication of falsification risks of listed companies' financial statements. In addition, we identified that some of the selected variables represent appropriate indication of FFSs.

Keywords: Falsification, Financial Statements, Data Mining, Finance Sector

GERÇEĞE AYKIRI FİNANSAL TABLOLARIN TESPİTİNDE VERİ MADENCİLİĞİNİN KULLANIMI: TÜRKİYE'DE FİNANS SEKTÖRÜ ÜZERİNE AMPİRİK BİR ARAŞTIRMA

ÖZ

Bu çalışmanın amacı, İstanbul Menkul Kıymetler Borsası (İMKB) finans sektöründe işlem gören şirketler için gerçeğe aykı-

** Assist. Prof. Dr., Cankiri Karatekin University, Yaprakli Vocational School, VIC 18100, Turkey. Tel: +90 376 213 2626 Fax: +90 376 212 0422; e-mail: serkanterzi@karatekin.edu.tr

rı finansal tabloları belirlemek amacıyla güvenilir bir model geliştirmektir. Çalışmada kullanılan veriler, İMKB finans sektörüne kote olan şirketlerin denetlenmiş finansal tablolarından elde dilmiştir. Yapılan çalışmada elde edilen bulgular, önceki çalışmalarla uyumlu olup, yayınlanan finansal tabloların tahrif edilme riski taşıdığını göstermektedir. Ayrıca seçilen değişkenlerden bazılarının gerçeğe aykırı finansal tablolarının belirlenmesinde iyi bir gösterge olduğu sonucuna ulaşılmıştır.

Anahtar Kelimeler: Tahrif Etme, Finansal Tablolar, Veri Madenciliği, Finans Sektörü

1. Introduction

Falsified financial statements can arise from either fraud or error. However, concepts of fraud and error have different characteristics. The difference between fraud and error is the underlying action that results in the FFSs is whether intentional or unintentional (Terzi, 2012).

Definitions of fraud were made by various organizations. According to Turkish Language Association, fraud is defined as: "to deceive someone, in order to mislead, act and intrigue" (http://www.tdk.gov.tr/). According to International Federation of Accountants (IFAC), fraud is defined as: "An intentional act by one or more individuals among management, those charged with governance, employees, or third parties, involving the use of deception to obtain an unjust or illegal advantage" (Erol, 2008). American Institute of CPAs (AICPA) issued SAS no.99 "Consideration of Fraud in a Financial Statement Audit", fraud is defined as: "Intentional act that results in a material misstatement in financial statements that are the subject of an audit" (http://www.aicpa.org/).

According to commonly accepted classification, fraud falls into two groups. The first group covers frauds of the employees, and it contains the misappropriation of assets. The misappropriation of assets involves such things as outright theft, embezzlement, payment for the unclaimed goods, and peculation. The peculation of the money materializes in the organization's records, inventory theft, and personal usage of the company assets can be given as examples of employee's frauds. And the second group is the financial statement frauds which compose of the irregularities deriving from reporting, deliberate mistakes to deceive the users of the related statements or ignorance of various amounts (of money). Financial statement frauds are kind of frauds of the top management (Ata and Seyrek, 2004).

According to 2010 and 2012 reports of Association of Certified Fraud Examiners (ACFE), the companies all over the world lose 5% of their income due to fraud. The 2010 report stated that the companies suffer losses over 4 million dollars (1 million dollars in the 2012 report) on average annually, due to the FFSs (http://www.acfe.com/).

The increasing trend of FFSs in the world not only intimidates investors and adversely affects their investment decisions, but also damages the credibility of capital markets around the world. Due to the high costs arising from the financial statement fraud, various countries establish regulations in order to combat fraud. In 2002, the US Congress passed the Sarbanes-Oxley Act to improve the accuracy and reliability of corporate financial reporting and disclosures. In addition, auditing standards have been issued by the IFAC and the AICPA. IFAC issued ISA 11 (1982) "Fraud and Error" and ISA 240 "The Auditor's Responsibilities Relating to Fraud in AN Audit of Financial Statements" (http://www.ifac.org/). IACPA issued SAS 47 (1983), SAS 82 (1997) and SAS 99 (2002).

ISA 240 lists various categories of material misstatements in the auditing process. These can be explained as follows (Gaganis, 2009):

- falsification or alteration of accounting statements;
- misappropriation of assets or theft;
- suppression or omission of recording transaction or operation in accounting statements;
- recording of operations or transactions without written proof;
- intentional misapplication of accounting regulations and policies;
- willful misrepresentation of transactions.

This paper uses a sample of 113 financial statements of listed companies on ISE, 12 of which were assigned qualified or adverse audit opinion. Two well-known data mining algorithms were applied to build detection/prediction models for this paper: artificial neural networks (ANN), and classification/decision trees (DT).

2. Literature Review

The data mining methods are used in the literature for FFSs. Some important researches on data mining methods are used for the detection FFSs in the literature are as follows:

Fanning and Cogger (1998) developed a model using ANN for detecting management fraud. The study offers an in-depth examination of publicly available important predictors of FFSs. The result of the study concludes that ANN offers superior ability to standard statistical methods in detecting FFSs.

Atiya (2001) developed a model to determine financial failure using ANN method. Financial ratios were used in the model and the selected variables are tested with the help of ANN method. The researcher found that the prediction accuracy from 81.46% to 85.5% for a three-year-ahead forecast.

Spathis et al. (2002) examined the effectiveness of an innovative classification methodology in order to detect companies' FFSs and the identification of the factors associated to FFSs. The methodology is based on the concepts of multi criteria decision aid (MCDA) and the application of the UTADIS classification method (UTilite´s Additives DIScriminantes). Financial ratios were determined as the fraud risk factors. The researchers found that the proposed MCDA methodology outperforms traditional statistical techniques which are widely used for FFSs detection purposes. In addition, the researcher detected that some financial ratios hold potential risk of FFSs.

Cerullo and Cerullo (2006) examined ANN methods to detect FFSs. The researchers accessed financial data of 30 companies (15 FFS and 15 non-FFSs) and analyzed with selected financial ratios. As a result, the researchers detected that some financial ratios are important in detecting the FFSs.

Kirkos et al. (2007) explored the effectiveness of data mining classification methods in detecting firms that issue FFSs and deals with the identification of factors associated to FFSs. In addition, this study investigates the usefulness of DT, ANN and Bayesian Belief Networks in the identification of FFSs. In this study, the used variables were used in previous studies. As results, the researchers are detected data mining methods and the Bayesian Belief Network method achieved the best performance managing to appropriately classify FFSs.

Kotsiantis et al. (2007) used Athens Stock Exchange registered financial statements of 164 companies in Greece. According to auditors' views, the financial statements were classified as fraudulent and non-fraudulent. In this study, there were 41 FFSs and 123 non-FFSs identified. The researchers used a method of data mining and selected financial ratios for fraud risk factors in financial statements. As a result of their research, the researchers, using data mining, classified the fraudulent financial statements with 90% accuracy. In addition, they claimed that certain financial ratios were important variables for detecting fraud.

Liou (2008) examined the similarities and differences of the models that determine the business failure prediction and FFSs using logistic regression, DT and ANN methods. The results of the study indicated that many variables affected the determination of FFSs and financial failures. Logistic regression and DT methods were stated as the most efficient methods in FFSs and failure prediction.

Ata and Seyrek (2009) used ANN and DT methods in order to determine FFSs. The researchers accessed financial data of 100 listed companies on ISE. As a result, the researchers detected that some financial ratios are important in detecting the FFSs.

Gaganis (2009) developed 10 alternative classification models using logit analysis, discriminant analysis, support vector machines, ANN, probabilistic neural networks, nearest neighbors, UTADIS and MHDIS for the detection of FFSs. The results are used to derive conclusions on the performance of the methods and to investigate the potential of developing models that will assist auditors in identifying FFSs. In addition, the researcher detected that some financial ratios hold potential risk of FFSs.

Ravisankar et al. (2011) used data mining and logistic regression analysis methods in order to determine falsified financial statements. The researchers analyzed financial data of listed companies on Chinese stock exchange. Financial ratios were determined as the fraud risk factor. In this research, logistic regression method and various data mining methods results compared with t-test analysis. As a result, the researchers identified that profitability ratios were important parameters in the detection of FFSs.

In literature, studies of falsified financial statements generally include companies operate outside of the finance industry. In particular, companies operate in manufacturing industry are analyzed for FFSs. Ata and Seyrek (2009) conducted a research of FFSs of manufacturing industry in Turkey. Therefore, our study is the first research to identify FFSs of finance sector in Turkey.

3. Research Methodology

3.1. Sample Selection

The purpose of this paper is to develop a reliable model in order to determine the FFSs of finance sector listed on ISE. In this paper, the used variables were obtained from the quoted 113 companies' audited financial statements in ISE. Accordingly, 12 of 113 selected financial services companies' financial statements include signs of falsification. The remaining 101 companies' financial statements were determined as non-falsified.

We used auditors' opinions in order to classify non-falsified financial statements; therefore, there is no definite decision that these financial statements are non-FFSs.

An auditor uses audit samples in accordance with certain methods. Therefore, an auditor's opinion is assumed to be correct until proven otherwise. Also, auditor's opinion types of qualified and disclaimer of opinion represent that financial statements may include important or very important errors, or inhibitions; accordingly, an auditor may not able to check the accuracy of some accounts in financial statements.

In literature, few empirical studies help to understand financial statements of public companies include whether falsified information (Persons 1995, Spathis 2002, Spathis et al. 2002, Kotsiantis et al. 2007, Ata ve Seyrek 2009).

The following auditors' opinions were used in order to determine the FFSs:

- Qualified opinion
- Disclaimer of opinion

3.2. Variables

In this research, the used variables were obtained from the companies' balance sheets and income statements for the period between 2010 and 2009. The selected variables were used in previous studies. The selected variables include ratios of companies' liquidity, operating efficiency, financial structure and profitably. These variables and their characteristics are shown in Table 1.

Table 1. Selected Variables and Characteristics

	Mean		Standard Deviation	
Variables	**Non-FFSs**	**FFSs**	**Non-FFSs**	**FFSs**
Asset Turnover (AST) *Fanning and Cogger (1998); Spathis et al. (2002)*	11.13	0.35	30.09	0.38
Return on Asset (ROA) *Spathis et al. (2002); Kirkos et al. (2007); Liou (2008); Ata and Seyrek(2009);Gaganis(2009);Ravisankar et al.(2011)*	0.04	0.00	0.06	0.08

Receivables to Sales. net (RE/SAL) *Fanning and Cogger (1998); Gaganis (2009)*	2.71	1.44	5.57	2.90
Receivables to Total Assest (RE/TA) *Fanning and Cogger (1998);Liou (2008); Gaganis(2009)*	0.21	0.18	0.28	0.22
Gross Margin (GM) *Fanning and Cogger (1998); Gaganis (2009); Ata and Seyrek (2009)*	47.40	62.95	229.91	213.07
Gross Profit to Total Asset (GP/TA) *Spathis et al.(2002);Kirkos et al.(2007); Ravisankar et al.(2011)*	0.07	0.05	0.07	0.08
Fixed Asset to Lon-term Liabilities (FA/LTL) *Cerullo and Cerullo (2006)*	1,772.82	17.71	17,205.61	42.78
Operating Profit Margin (OPM) *Atiya (2001); Ata and Seyrek (2009)*	104.31	0.78	1,518.44	9.34
Financial Leverage Ratio (FLR) *Spathis et al. (2002); Gaganis (2009); Ata and Seyrek (2009)*	0.39	0.71	0.35	0.38
Cash Flow to Total Asset (CF/TA) *Liou (2008)*	0.01	0.05	0.18	0.08
Cash Flow to Total Liabilities (CF/TL) Cerullo and Cerullo (2006); Liou (2008)	-1.02	0.55	16.38	1.63
Cash Ratio (CAR) *Liou (2008); Gaganis (2009); Ata and Seyrek (2009)*	55.37	9.65	154.65	32.39
Cash and Equivalent to Total Asset (CE/TA) *Liou (2008); Gaganis (2009); Ravisankar et al. (2011)*	0.20	0.09	0.20	0.11
Net Profit Margin (NPM) *Spathis vd (2002); Kirkos et al. (2007) Ata and Seyrek(2009)*	101.27	-18.33	1,518.02	65.50
Equity Turnover (EQT) *Cerullo and Cerullo (2006); Gaganis (2009)*	4.63	0.11	20.39	2.04
Return on Equity (ROE) *Fanning and Cogger (1998); Liou (2008)*	0.07	-0.12	0.12	0.36
Equity to Total Asset (EQ/TA) *Cerullo and Cerullo (2006); Liou (2008)*	0.61	0.31	0.35	0.37
Total Liabilities to Equity (TL/EQ) *Fanning and Cogger (1998); Spathis et al.(2002); Cerullo and Cerullo (2006); Kirkos et al. (2007); Ravisankar et al. (2011)*	1.94	1.57	4.00	2.71

3.3. A Brief Description of the Methods

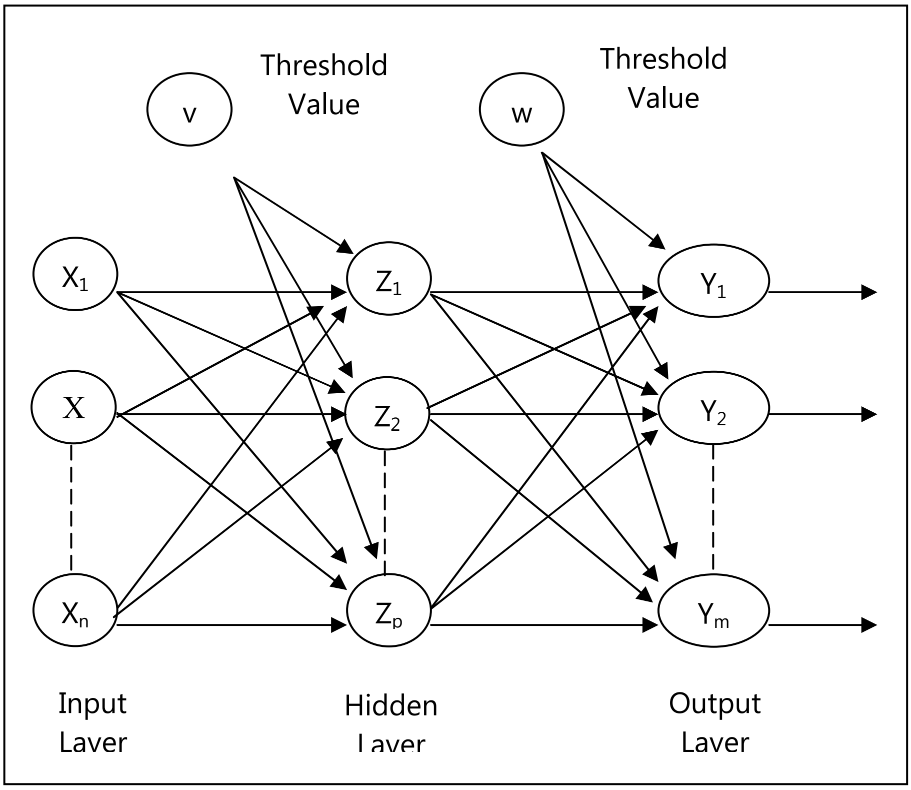
In this paper, we used two well-known data mining algorithms, ANN and DT for detecting FFSs. (Spathis vd. 2002; Liou 2008; Ata and Seyrek 2009).

ANN is a data processing system that operates similar to the biological neural networks' characteristics. In other words, the ANN is the computer systems which are developed for automatically and unaided carrying out the talents such as exploring and performing new information. The ANN is an artificial intelligence technology which gives out accomplished outputs in such cases at which there are multivariate, complicated and correlated interactions between the variables, or there is not only one solution set (Kurtaran Celik, 2010).

The structure of an artificial neural network, where the nerves connected with each other in the input layer, hidden layer and the output layer are basically three layers. The input layer is the first level and provides entry of the external data into the model. These data, while considered statistically, correspond to the independent variables. The last layer is the output layer and it functions for transmitting the data outwards. The output variables also correspond to the dependent variables when considered statistically. The other layer in the model is the hidden layer in-between the input layer and output layer. The neurons in the hidden layer have no relationship with the external environment; they only get signals that were sent from the input layer and they send signals to the output layer. Besides the layers, one of the most important elements is the connection that implements data transmission between the neurons. A connection transmitting information from any (i) neuron to a (j) neuron also has a weight value (wji). There are different weight values of all the connections within the artificial nerve net. These weight values are generated coincidentally in SPSS package. The net is tested by using these values (Kıcıkkocaoglu et al, 2007). The most common form of ANN structures (which we utilized in our study) is the multi-layered artificial neural network (MLP).

The process of the ANN is shown in Figure 1 (Kaynar and Tastan, 2009).

Figure 1: Process of the ANN (Multi-Layered)



As it's evident from its name, it's a n estimator model looking like a tree. Each branch of the tree is a classification question and the leaves are the pieces' belonging to data set's that classification (Koyuncugil and Ozgulbas, 2008). A decision tree is a structure that applies small decision making steps and divides the high volume data into small data groups. By every division process, the members of the result group resemble each other much more. The decision trees with estimator and descriptive features are widely used classification models since they are easy to apply and interpret, easy to integrate to database systems and because they have a better reliability (Albayrak and Koltan Yilmaz, 2009). CART method as classification tree used in this paper (Kirkos et al. 2007).

There are two errors to detect the percent correct in classification of FFSs. Type I Error is the misclassification of FFSs as non-FFSs. Type II Error is the misclassification of non-FFSs as FFSs. Type I Error and Type II Error are shown in Table 2.

Table 2. Classification Errors

Observed	Predicted	
	FFSs	Non-FFSs
FFSs	Correct Classification	Type I Error
Non-FFSs	Type II Error	Correct Classification

Research Hypothesis:

H_o: Financial ratios are not significantly effective on detecting FFS for the finance sector.

H_1: Financial ratios are significantly effective on detecting FFS for the financial sector.

In this study we deployed the SPSS (Statistical Package for Social Science) in univariate and multivariate statistical analysis

3.4. Results and Discussion

In order to determine the statistical test for variables, the normality test is applied. For this, the Kolmogorov-Smirnov and Shapiro Wilks test (because there are few sample for FFSs) was performed. The selected variables are not compatible with the normal distribution ($p<0.05$). Therefore, we used Mann Whitney U test in our study whether there are significant differences of the selected variables. We selected the 18 financial ratios with using the Mann-Whitney U, financial ratio selection are shown in Table 3.

Table 3. The Result of Mann-Whitney U Test Analyses

Variables	Z-value	Sig. (2-tailed)	Variables	Z-value	Sig. (2-tailed)
AST	-1,305	0,192	CF/TA	-0,806	0,420
ROA	-2,041	(*) 0,041	CF/TL	-0,531	0,595
RE/SAL	-0,203	0,839	CAR	-2,330	(*) 0,020
RE/TA	-0,305	0,760	CE/TA	-2,307	(*) 0,021
GM	-0,682	0,495	NPM	-1,729	(**) 0,084
GP/TA	-1,216	0,224	EQT	-0,051	0,959
FA/LTL	-1,540	0,124	ROE	-1,626	(**) 0,100
OPM	-1,051	0,293	EQ/TA	-2,386	(*)0,017
FLR	-2,423	(*) 0,015	TL/EQ	-0,989	0,323

(*) Significant at 5% level

(**) Significant at 10% level

When examining of the financial ratios, we discovered that some variables are significant at 5% and 10% levels. And, this points out that there are important differences between FFSs and non-FFSs. These findings also indicate that the selected variables have a significant effect in the detection of FFSs in the finance sector.

The result of Mann-Whitney U test shows that if the CAR ($p<0.020$), CE/TA ($p<0.021$), FLR ($p<0.015$) variables have lower values and ROE ($p<0.100$) variable has an upper value; companies with FFSs may cause financial distress during the payment of debts. Furthermore, the lower levels of ROA ($p<0.041$) and EQT ($p<0.017$) indicate that the companies with FFSs provide financing from foreign sources. Therefore, the ratios are the main ratios for auditors to check for the detection of FFSs. In this case, an administration is exerted pressure for the management fraud. These results are consistent with the findings of prior studies which indicated that excessive debt usage increases the likelihood of FFSs (Spathis et al. 2002; Kirkos et al.

2007; Kotsiantis et al. 2007; Liou 2008; Gaganis 2009; Ata and Seyrek 2009). In these studies, liquidity ratios and financial structure ratios are important variables in determining FFSs risk factors.

In the MLP analysis, we detected 4 hidden layers and 2 output layers. The results from the application of the ANN to the selected variables are summarized Table 4. The correct classification of the ANN on the sample is realized as 90.4% for the training set and 90.0% for the test set.

Table 4. Classification Performance of ANN

Classification	Training Set		Test Set	
	Number	Percent Correct	Number	Percent Correct
Non-FFSs	74	97.3%	26	96.2%
FFSs	8	25.0%	4	50.0%
Total	83	90.4%	30	90.0%

The results of the decision tree analysis are presented in Table 5. When the table below is examined, the success rate of the decision tree in correct classification can be stated as 89.4%.

Table 5. Classification Performance of Decision Tree

Classification	Number	Percent Correct
Non-FFSs	101	100.0%
FFSs	12	0%
Total	113	89.4%

We noticed that Type II Error is high in ANN and DT analysis. This situation carries the risk of classification of FFSs in non-FFSs. When we analyzed the models' success rates of correct financial statements classification, ANN achieves higher rate than DT. ANN model classifies FFSs with 50% accuracy rate and its overall success rate is 90%. This result occurred due to few samples of falsified financial statements. Increasing the sample size may reduce the Type II Error. In other words, the expansion of sample volume is required.

4. Conclusion

The main objective of this paper is to develop a reliable model to determine FFSs of public financial institutions of ISE. In order to achieve this objective, we have selected 113 companies' FFSs and non-FFSs as a sample group. We have used univariate and multivariate statistical analysis with selected financial ratios. In the paper, 7 of 18 ratios were selected as potential factors of identifying FFSs. The selected variables were used in previous studies.

The findings of this paper are compatible with previous studies and represent the indication of FFSs of published financial statements. In addition, some of the selected variables represent appropriate indication of FFSs.

Furthermore, according to the results of data mining application, we determined that ANN model is more effective in comparison with the decision tree model. In ANN model, we found a 90% accuracy rate. The literature regarding training set about the correct classification achievement of ANN in detecting FFSs states as following rates: Fanning and Cogger (1998) 75%, Atiya (2001) 85%, Kirkos et al. (2007) 100%, Kotsiantis et al. (2007) 56%, Liou (2008) 100%, Ata and Seyrek 91%, Gaganis (2009) 95% and Ravisankar et al. (2011) 78%. The literature, regarding test set about the correct classification achievement of ANN in detecting FFSs, states the following rates: Kirkos et al. (2007) 92%, Liou (2008) 91% and Ata and Seyrek 96%.

As a consequence of our study, we have discovered that some financial ratios hold potential risk of FFSs. These ratios are return on assets, financial leverage ratio, cash ratio, cash and equivalent to total asset, equity turnover, return on equity and equity to total asset. If the ROA ratio is lower than 0.02, the company is classified as falsified. This means that companies with ROA lower than 0.02 is very likely to commit falsification. The second important indicator is FLR. If FLR is greater than 0.55 than it is classified as falsified. The third important indicator is CE/TA. If CE/TA is greater than 0.15 than it is classified as non-falsified. Other important indicators are ROE, EQT and EQ/TA. If the EQT ratio is lower than 2.37, the ROE ratio is lower than 0.00, and the EQ/TA ratio is lower than 0.46, the company is classified as FFSs. The findings of this paper are compatible with previous studies and represent the indication of FFSs risks of published financial statements (Fanning and Cogger 1998; Spathis et al. 2002; Cerullo and Cerullo 2006; Liou 2008; Gaganis 2009).

The variables considered as meaningful in the study provide useful information about the financial situations of the financial institutions. The attained findings will be useful for the company management, auditors, tax authorities, financial analysts and other related parties. The auditors will be able to collect more effective proofs with the help of these findings and perform an auditing plan. Besides, the auditors will be able to analyze the companies' financial statements by adding these results to the software they use and they will also be able to determine the risk factors denoted as red flags. In addition, a company's management and financial analysts, using the identified financial statements' indicators, assess a company's financial statements are whether include falsified risk factors.

These results indicate that auditors need to devote extra time to liquidity and financial structure of companies in the planning stage of the audit. Auditors may develop additional audit procedures accordingly.

This study may provide an insight for future studies about the determination of FFSs. In the future studies:

- Including interim financial information of the companies together with the annual financial information in these analysis,

- Using data for longer time periods,
- Including qualitative factors together with financial (quantitative) data in the models

would increase the accuracy in the determination of FFSs.

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