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Application of Beneish M-Score Models and Data Mining to Detect Financial Fraud

Tarjo^{a*}, Nurul Herawati^b

^{a,b} *University of Trunojoyo Madura, Raya Telang Street PO BOX 2, Bangkalan Madura 60192 - Indonesia*

Abstract

This study aims to analyze the ability of m-score Beneish in detecting financial fraud. This research data refer to companies that commit fraud according to the fraud Database of Sanctions of Issuer Cases Public Companies that was released by the Financial Services Authority in the period of 2001-2014. The results showed that overall Beneish m-score model was capable to detect financial fraud. Gross margin index, depreciation index, index of sales and general administrative burden and total accruals were all significant in detecting financial fraud. Sales index, asset quality index, and leverage index was statistically not significant in detecting financial fraud.

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1. Introduction

Based on research conducted by the Association of Certified Fraud Examiners (ACFE) in 2014, the most disadvantage fraud in a row is statement of financial fraud by 73%, corruption by 18%, and asset misappropriation by 9%. Therefore, it can be stated that there are three (3) types of fraud. The financial statement fraud is the most harmful.

Various studies to detect financial fraud have often been committed by researchers with fraud triangle analysis. In the last few years, some researchers have been using Beneish m-score model (Beneish, 1999, 2012), Dimitriois (2014), data mining (Zaki & Theodoulidis, 2013), Ata & Seyrek (2009) on this problem.

* Corresponding author. Tel.: +6287853035508
E-mail address: tarjo@trunojoyo.ac.id

Research to detect financial fraud has been conducted by some researchers using financial ratios approach, data mining, and Beneish m-score model, but the method has drawbacks. First, there is a misclassification. Second, mistakes in data mining may lead to misclassification, this is due to the fact that different industries have different financial reporting requirements. Therefore, the research problem is “can the application of m-score model detect financial fraud?”

The results of this study will be very helpful for auditors in conducting audit anyone with an interest in company's financial statements. M-score models and data mining can be used as an early indication (red flags) for detecting financial fraud.

2. Detecting Financial Fraud

According to the ACFE (2014), financial statement fraud is a deliberate fraud performed by a manager or employee with no reports on actual financial statement information, for example, fictitious revenues, too low expenses report, and so forth. In financial reporting context, an audit is designed to provide assurance to interested parties that the company's financial statements are not influenced by a material misstatement and gives adequate confidence to the management accountability of the assets (Koroy, 2008). Public companies and private sector have an opportunity for profit manipulation. Tarjo (2008; 2010) confirms that the go public company, especially the manufacturing industry, can manipulate profits. While Pradana, Tarjo & Kompyurini (2013) show that there are various factors which can be used to detect fraud in the public sector organizations.

Who are in charge to perform financial fraud detection? Alleyne & Howard (2005) explores perceptions of auditors and users that it is auditor's responsibility to uncover fraud, performance-related audit procedures, the nature and extent of fraud in Barbados, as well as auditor's response since Enron's case came to light. The research findings of Alleyne & Howard (2005) show that there has been a big gap in expectations auditors perceive fraud detection as the responsibility of management, while users and management do not agree on this. Some research suggests that prevention and detection of fraud is management responsibilities, such as Beasley (1996) finding that companies with no fraud has board members from outside the company with a greater percentage than from inside the company. On the other hand, subsequent studies showed that auditors are the subject of analysis of studies on fraud detection (such as Owusu-Ansah, Moyes & Oyelere, 2002; Running (2009); Bishop 2004; Hutomo (2012); Mariana (2014); Rustiarini & Novitasari, 2014; Gamar, & Djamhuri 2015; Lisic, Silveri, Song & Wang, 2015). The role and demographic factors of auditors have become the subject in research on the detection of fraud.

How can we detect financial fraud? It has been a lot of research on fraud detection. The results of investigations by Bishop (2004) to 450 companies, which are victims of fraud in 2004 years since the ACFE report, on how fraud was initially detected, indicate that there are several ways of doing so, such as internal audit, tip from employees, by accident, internal control, external audit, tip from customers, tip from vendors, anonymous tip, and notified by police. Bishop (2004) states that fraud was most frequently detected by internal audit (23.8%) while the information of workers is the second most common detection method (23.6%). However, if all categories of information (employees, vendors, consumers, and anonymous) are combined, it becomes far and the most common detection method, 39.6%. These results indicate that the facilities / services to report violations provide the opportunity and encouragement to report the potential violation.

Other studies on reliability of financial ratios in detecting financial fraud are by Persons (1999); Spathis (2002); Kaminski, Wetzel & Guan (2004). Owusu-Ansah, Moyes & Oyelere (2002) does a study on fraud detection through effectiveness of audit procedures. The detection of fraud through control is conducted by Alleyne & Howard (2005); Bierstaker, Brody & Pacini (2006); Gottschalk (2011); Akbar, Tarjo & Carolina (2012) & Kummer, Sing & Best (2015). There are also financial fraud detection model approaches, such as by Spathis (2002), developing reliable models in the detection of False Financial Statements or FFS for the Greek company with ten financial variables chosen for testing as a predictor of potential FFS. Skousen & Twedt (2009) use a fraud score model, as determined by Dechow, to determine the possibility of manipulation on financial reports and found that the F-Score is an indicator of the risk of fraud, but not a direct signal that there is no fraud. Glancy & Yadav (2011) proposed fraud detection computational models / CFDM to detect fraud in financial reporting. CFDM uses a quantitative approach on textual data.

In its development, data mining can be used to detect financial fraud of companies. According to Turban, Aronson & Liang (2005), data mining is a semi-automatic process that uses statistical techniques, mathematics, artificial intelligence, and machine learning to extract and identify potential knowledge and useful information stored in a large database. There are several definitions of data mining.

3. Research Methodology

3.1 Data

This research data was company's fraud financial statements issued by the Capital Market Supervisory Agency or Services Authority Finance (FSA) in the period of 2001-2014. For comparison, the financial data of companies that committed no fraud of the period of the year and of the same industries was used.

3.2 Beneish M-Score

Beneish M-Score is a method that can be used to detect companies with a tendency to commit fraud on their financial statements (Beneish, 2012). Empirically, companies with higher M-Score have higher tendency to commit fraud. Beneish M-Score is a probabilistic model, so that one of the limitations is that the ability to detect fraud is not with 100% accuracy. The formula of Beneish M-Score is as follows:

$$M = -4.840 + 0,920XDSRI + 0,528XGMI + 0,0404XAQI + 0,892XSIGI + 0,115XDEPI - 0,172XSGAI + 4,679X \backslash TATA - 0,327XLVGI$$

If the M-score > -2.22, it shows indications of financial fraud within companies.

3.3 Data Mining

Beneish Model M-Score is used for data mining of fraud-committed companies. According to Turban et al. (2005), data mining is the semi-automatic process that uses statistical techniques, mathematics, artificial intelligence, and machine learning to extract and identify potential knowledge and useful information stored in a large database. Data mining technique used in this research is Logit Regression. Data mining begins with testing the Principle Component Analysis (PCA) to variable of Beneish M-Score model. PCA is used to determine what variables of M-Score Beneish model that is predictive of financial fraud. The Logit Regression model of this study are:

$$FRAUD = \beta_0 + \beta_1 DSRI + \beta_2 GMI + \beta_3 AQI + \beta_4 SIGI + \beta_5 DEPI + \beta_6 SGAI + \beta_7 TATA + \beta_8 LVGI + \varepsilon_i$$

Where:

FRAUD= Dummy Variable (1 for fraud-committed companies and 0 for non-fraud-committed companies)

DSRI = Sales Index

GMI = Gross Margin Index

AQI = Asset Quality Index

SIGI = Sales Growth Index

DEPI = Depreciation Index

SGAI = Sales and General Administration Expenses Index

TATA = Total Accrual

LVGI = Leverage Index

ε_i = Residual

4. Research Result

This research data was company's fraud financial statements issued by the Capital Market Supervisory Agency or Services Authority Finance (FSA) in the period of 2001-2014. After tabulation, we obtained 35 companies that committed fraud. For comparison, 35 companies that did not commit fraud were selected based on the equality of assets and same category of industry. Table 1 below is descriptive statistics of the Beneish M-Score.

Tabel 1. Descriptive Statistics

Variable	Minimum		Maximum		Mean		Std. Deviation	
	Fraud	Non Fraud	Fraud	Non Fraud	Fraud	Non Fraud	Fraud	Non Fraud
DSRI	.000	.103	15.845	3.036	1.367	1.111	2.576	.470
GMI	-81.180	-18.928	48.335	26.811	.601	.902	16.349	6.517
AQI	.057	.027	14.432	4.478	1.533	1.035	2.445	.819
SGI	.320	.515	4.286	11.431	1.249	1.379	.722	1.771
DEPI	-728.537	.002	1.732	1.434	-21.281	.923	123.117	.232
SGAI	.158	.079	5.570	1.595	1.071	1.070	.834	.287
LVGI	.317	.100	12.737	1242.494	1.376	36.453	2.004	209.854
TATA	-4.363	-.975	.544	.568	-.365	.003	1.018	.270
TOTAL	0.008	-21.360	270.288	465.848	10.660	12.313	45.871	79.066

Table 1 shows that DSRI value for companies committing fraud had the lowest value of 0.000, the highest of 15.845, and the average value of 1.367, and a standard deviation of 2.576. While the non-fraud companies had a lowest value of 0.103, the highest of 3.036, the average value of 1.111 with a standard deviation of 0.470.

Table 1 also shows that GMI value for companies committing fraud had the lowest value of -81.180, the highest of 48.335, the average value of 0.601, and a standard deviation of 16.349. While the non-fraud companies had the lowest value of -18.928, the highest of 26.811, the average of 0.902 with a standard deviation of 6.517.

The test results also showed that DEPI for companies committing fraud had the lowest value of -728.537, the highest of 1.732, the average of -21.281, and a standard deviation of 123.117. While the non-fraud companies had a lowest value low of 0.002, the highest of 1.434, the average value of 0.923, and a standard deviation of 0.232.

The next step was to test the Principle Component Analysis (PCA) to variables of Beneish M-Score model. Based on the Principle Component Analysis (attachment 1), the SGI component was not used for explanatory factor because it had a negative value, so the variables on Beneish M-Score Model used to detect fraud were DSRI (Sales Index), GMI (Gross Margin Index), AQI (Asset Quality Index), DEPI (Depreciation Index), SGAI (Sales and General Administration Expenses Index), TATA (Total Accrual), and LVGI (Leverage Index).

In assessing the suitability of this research model, we used the statistic value of Chi-Square Homer and Lemeshow Goodness of Fit. Based on logistic regression test, as in Table 3, the value of Chi-Square Hosmer and Lemeshow Goodness of Fit was 5.459 with a significance value of 0.708 ($\text{sig} > 0.05$), this means that the model developed fit the data used in this study. Therefore, it can be said that the binary models in this study is acceptable and feasible to be used on further analysis.

Test on the overall model (overall model fit) is determined based on the value of -2 Log Likelihood. Based on tests carried out, the initial value of -2 Log Likelihood (Block Number: 0) was 97.041, while the final value of -2 Log Likelihood (Block Number: 1) was 60.193. These tests showed a decrease in the value of Log Likelihood as much as to 36.848, therefore it can be stated that these figures illustrate the suitability of the model used in this study. Nagelkerke R Square value was 0.546. It shows that the variability of the fraud data can be explained by the independent variable by 54.6%, while the rest was explained by other variables not used in this study.

Table 2. Logistic Regression Test Results

Variable	Coefficients	Wald	Sig.	
DSRI	0,614	1,945	0,163	
GMI	0,984	4,141	0,042	*
AQI	0,830	2,521	0,112	
DEPI	-1,254	3,266	0,071	**
SGAI	-3,420	5,333	0,021	*
LVGI	-0,029	1,716	0,190	
TATA	-2,592	5,582	0,075	**
Constant	1,356	1,278		
Chi-Square (Hosmer and Lemeshow Test)		5,459	0,708	
-2 Likelihood (Block Number: 0)		97,041		
-2 Likelihood (Block Number: 1)		60,193		
Omnibus Test of Model Coefficients		36,848	0,000	
Nagelkerke R Square		0,546		
Overall Percentage		78,6%		

Where:

* : Significant level 5%

** : Significant level 10%

The data used in the study were 35 companies that committed fraud and 35 non-fraud companies. Based on data mining test using regression logistic, classification accuracy to detect fraud was 77.1% (27 of 35 companies that committed fraud). From the 35 non-fraud companies, as many as 28 (80%) were accurately classified as not committing fraud. However, the interesting finding in this study is that from the 35 companies categorized as non-fraud, it turned out that 7 of them were then classified as committing fraud.

Table 2 shows that GMI (Gross Margin Index), DEPI (Depreciation Index), SGAI (Sales and General Administration Expenses Index) and TATA (Total Accrual) influence the detection of financial fraud. This shows that the GMI, DEPI, SGAI, and TATA can be used to detect financial fraud. DSRI (Sales Index), AQI (Asset Quality Index), and LVGI (Leverage Index) statistically have no significant effect on the detection of financial fraud. This shows that DSRI, AQI, and LVGI are not able to detect financial fraud.

5. Conclusion

From the discussion, Beneish M-Score model can be used to detect financial fraud. The better the prospects of the company, the better it can be used to detect financial fraud. On the other hand, depreciation, cost of sales, and discretionary accrual on accounting policy may reduce the ability to detect financial fraud. Indication of recognition on increasing revenue and profit, suspension on cost of the asset, as well as the amount of debt to creditors cannot be used for detecting financial fraud.

References

- Association of Certified Fraud Examiners (ACFE), 2014, Report to The Nation, Austin, Texas.
 Akbar, F., 2013. Fraud Pengadaan Barang/Jasa, Proceeding of Conference in Business, Accounting and Management (CBAM), CBAM Vol. 1, No. 1.

- Alleyne, Philmore and Howard, Michael. 2005. An Exploratory Study of Auditors' Responsibility for Fraud Detection in Barbados. *Managerial Auditing Journal* Vol. 20 No. 3, pp. 284-303.
- Ata, Ali. And Seyrek, Ibrahim, 2009. The Use of Data Mining Techniques in Detecting Fraudulent Financial Statements: An Application on Manufacturing Firms, *The Journal of Faculty of Economics and Administrative Sciences*, Vol. 14, No. 2, pp. 157-170.
- Beneish, Messod D., 1999. The Detection of Earnings Manipulation, *Financial Analysts Journal*, September/October, pp. 24-36.
- Beneish, Messod D., 2012. Fraud Detection and Expected Return, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1998387
- Beasley, Mark S., 1996. An Empirical Analysis of the Relation Between the Board of Director Composition and Financial Statement Fraud. *The Accounting Review* Vol. 71, No. 4, pp. 443-465.
- Bierstaker, James L.; Brody, Richard G.; & Pacini, Carl. 2006. Accountants' Perceptions Regarding Fraud Detection and Prevention Methods. *Managerial Auditing Journal* Vol. 21 No. 5, pp. 520-535.
- Bishop, Toby J.F., (2004). "Preventing, Deterring, and Detecting Fraud: What Works and What Doesn't ", *Journal of Investment Compliance*, Vol. 5 Iss 2 pp. 120 – 127.
- Debreceny, Roger S. & Gray, Glen L. 2010. Data Mining Journal Entries for Fraud Detection: An Exploratory Study. *International Journal of Accounting Information Systems* 11, pp. 157-181.
- Gamar, Nur; dan Djahuri, Ali. 2015. Auditor Internal Sebagai "Dokter" Fraud Di Pemerintah Daerah. *Jurnal Akuntansi Multiparadigma* Vol 6, No 1.
- Glancy, Fletcher H. & Yadav, Surya B. .2011. A Computational Model for financial Reporting Fraud Detection. *Decision Support Systems* 50, pp. 595-601.
- Gottschalk, Petter. 2011. Prevention of White-Collar Crime: The Role of Accounting. *Journal of Forensic & Investigative Accounting*, Vol. 3, Issue 1.
- Hutomo, Oki Suryo. 2012. Cara Mendeteksi Fraudulent Financial Reporting Dengan Menggunakan Rasio-Rasio Finansial. *Fakultas Ekonomika Dan Bisnis. Universitas Diponegoro. Semarang.*
- Kaminski, Kathleen A.; Wetzal, T. Sterling; & Guan, Liming. 2004. Can Financial Ratios Detect Fraudulent Financial Reporting? *Managerial Auditing Journal*, Vol. 19 No. 1, pp. 15-28.
- Kathleen Kaminski, A. 2004. Can Financial Ratios Detect Fraudulent Financial Reporting. *Journal Of Accounting Research*. Vol. 19 No. 1, Pp.15-28.
- Kirkos, E., Spathis, C., Manolopoulos, Y., 2007. Data Mining techniques for the detection of fraudulent financial statement, *Expert Systems with Applications* 32, pp. 995-1003.
- Koroy, T.R. 2008. Pendeteksian Kecurangan (fraud) Laporan Keuangan Oleh Auditor Eksternal. *Jurnal Akuntansi dan Keuangan*, Vol. 10, No.1, Mei 2008:22-33
- Kummer, Tyge-F.; Singh, Kishore; & Best, Peter, 2015. "The Effectiveness of Fraud Detection Instruments in Not-For-Profit Organizations", *Managerial Auditing Journal*, Vol. 30 Iss 4/5 pp. 435 – 455.
- Lari, Leonard Rang'Ala. 2009. The Power Of Financial Ratios In Detecting Fraudulent Financial reporting: The Case Of Savings And Credit Co-Operative Societies In Kenya. *Strathmore University.*
- Lisic, Ling Lei; Silveri, Sabatino (Dino); Song, Yanheng; & Wang, Kun. 2015. Accounting Fraud, Auditing, and The Role Of Government Sanctions in China. *Journal of Business Research* 68, pp. 1186-1195.
- Mariana, Lia, 2014. Analisis Kecurangan Laporan Keuangan: Studi kasus pada PT Bumi Resources Tbk dan PT Berau Coal Energy Tbk.
- Owusu-Ansah, Stephen; Moyes, Glen David; Oyeler, Peter Babangida; & Hay, David, 2002."An empirical analysis of the likelihood of detecting fraud in New Zealand", *Managerial Auditing Journal*, Vol. 17 Iss 4 pp. 192 – 204
- Persons, Obeua S. 1999. "Using Financial Information To Defferentiate Failed Vs Surviving Finance Companies In Thailand: An Implication For Emerging Economies", *Multinational Finance Journal*, Vol. 3 No.2, Pp. 127-145.
- Persons, Obeua S. 1999. "Using Financial Statement Data To Identify Factors Associated With Fraudulent Financial Reporting. *Journal Of Applied Business Research*. Vol. 11 (3): Pp.131-146
- Pradana, Y., Tarjo & Kompyurini, N., 2013, Detection of Fraud in Public Sector Organization : Case in Indonesia, The 5th International Conference on Financial Criminology (ICFC) 2013 "Global Trends in Financial Crime in the New Economics", 28-29 May 2013 Holiday Inn Glenmarie, Shah Alam, Malaysia.
- Rezaee, Hogan, E.Chris, Zabihollah, Richard A. Riley, Jr., & Uma K. Velury. 2008. Financial Statement Fraud: Insights From The Academic Literature. *Journal Of Auditing*. Vol. 27 No.2, Pp.231-252.
- Skousen, C. J., & C. J. Wright. 2006. Contemporaneous risk factors and the prediction of financial statement fraud. Working paper, University of Texas at Arlington.
- Skousen, Christopher J. dan Brady James Twedt. 2009. "Fraud Score Analysis in Emerging Markets". *Journal of Accounting and Economics*, Vol. 16, No. 3, h. 301-315
- Summers, S. L., Dan John T. Sweeney. 1998. Fraudulently Misstated Financial Statement And Insider Trading: An Emphirical Analysis The *Accounting Review*. (January): Pp. 131-146.
- Spathis, Charalambos T. 2002. Detecting False Financial Statements Using Published Data: Some Evidence from Greece. *Managerial Auditing Journal* 17/4, p.179-191.
- Tarjo, 2008. Effect of Institutional Ownership Concentration and Free Cash Flow to Leverage, Profit Management, Shareholder Value and Cost of Equity Capital. *Dissertation, Graduate Program, University of Airlangga, Surabaya, Unplished.*
- Tarjo, 2010, Relevance concentration of ownership and the Debt Policy Affecting Earnings Management, Shareholder Value and Cost of Equity Capital.
- Turban, Aronson, & Liang, 2005, *Decision Support Systems and Intelligent Systems*, 7th Edition, Prentice Hall, New Jersey.

Zaki, M., & Theodoulidis, Analyzing Financial Fraud Cases Using a Linguistics-Based Text Mining Approach, This paper was part of PhD research investigated at Manchester Business School, University of Manchester.