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THE EFFECT OF FRAUD DETECTION USING M-SCORE ON EXPECTED RETURNS IN PUBLICLY LISTED INDONESIAN MANUFACTURING COMPANIES

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ABSTRACT

Fraudulent financial statements cause economies to suffer significant income loss. As the Indonesian economy grows, so too has financial statement fraud such that it has become a priority concern among accountants and auditors. Messod D. Beneish developed a mathematical ratio called m-score to detect earning manipulation in financial statements. Companies with a higher m-score are more likely to be flagged with a red flag for manipulating their financial statements. Firms that commit financial fraud will also earn lower future returns. A higher m-score results in lower returns. This research examines the relationship between m-score and expected returns (CAR) of green and red flagged publicly listed Indonesian manufacturing companies.

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INTRODUCTION

In 1990, Dr. Joseph T. Wells, CFE, CPA, founder of the Association of Certified Fraud Examiner (ACFE) and his team designed surveys about fraud schemes and how fraud was committed and detected. They determined the costs and duration of fraudulent schemes, fraudulent profiles, and the demographics about victim organisations among other pertinent information. After some years composing the research, ACFE issued its first report to the Nation on Occupational Fraud and Abuse in 1996. In their report, occupational fraud can be classified into three primary categories: asset misappropriation, corruption and financial statement fraud. Occurring in more than 83% of cases, asset misappropriation was by far the most common fraud, but financial statement fraud caused the most significant financial loss (Report to the Nations, 2016).

The past decade has witnessed many cases of financial statement fraud. One of the most notorious accounting scandals was perpetrated by America's seventh largest company which suffered a dramatic collapse after the United States Securities and Exchange Commission detected fraud. The company had inflated its income by around $586 million since 1997 and had huge debts off the balance sheet. This case represents the tip of the iceberg regarding financial statement fraud.

Indonesia has not been free from financial statements fraud. As its economy grows, the risk of financial statement fraud has increased across industries. One publicly listed manufacturing company was discovered overstating its net profit by IDR 32.7 Billion. Also, a major operator of public railways in Indonesia submitted fraudulent financial statements in 2002 by inflating its income by IDR 6.9 Billion whereas it recorded a loss of IDR 63 Million in that period. In another case, a major bank in Indonesia, upon investigation by Bapepam (the regulatory authority), had suffered losses of IDR 22.8 Trillion despite having submitted a positive annual financial statement to the Indonesian Stock Exchange.

According to the Report to the Nations (ACFE, 2016), the manufacturing sector records the second highest frequency of fraud with 192 cases, and manufacturers experienced the third highest median loss among all industry groups. The nature of this industry makes it susceptible to noncash fraud including the stealing of goods and materials by employees, as well as intellectual property such as trade secrets or technology. Billing fraud is popular because of the various products used in assembly. Additionally, expense reimbursement fraud is common among the sales forces employed by manufacturing companies. According to the Lindstrom (Fraud Prevention and Detection in Manufacturing Environment, 2006), fraudulent financial statements in the manufacturing industry include asset overstatement and revenue overstatement which could be predicted by the potential red flags.

Indonesia's manufacturing industry enjoys a dominating role in the Indonesian economy. Its manufacturing sector ranks 10th globally according to United Nations Industrial Development Organisations. There are three sectors in manufacturing industries which consist of several subsectors. The nature of industry differs within each sector which means the risk also differs. As manufacturing is prone to financial statements fraud, then it is tangible that the financial statement fraud will differ for each sector.

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Auditors have long sought to find a method to detect financial statements fraud to prevent its significant adverse impacts. Beneish (1999) in his *The Detection of Earnings Manipulation* had formulated eight mathematical ratios (M-score) to identify the likelihood of manipulations by a company. Each ratio represents the characteristics of a typical earnings manipulator. The m-score gained popularity by successfully detecting financial scandals before the public discovered them. Daud (2015) stated that the most significant divergence on several issues was the respective views of the auditor's responsibilities to detect fraud.

Firms that had committed a fraudulent financial statement in the past will have lower future returns. Beneish (2014) found in his observations of 252 red and green-flagged firms that there is a higher probability of manipulation (m-score) in earning lower returns based on size, book-to-market, momentum, accruals, and short-interest. Fraudulent financial statements have caused a significant loss for financial markets. It is a barrier to investor confidence in companies.

Indonesia's manufacturing sector has developed significantly in the past nine years, yet according to ACFE (The Report to the Nations on Occupational Fraud and Abuse, 2016), manufacturing is among the top three industries most likely to be hit by fraudulent financial statements. Therefore, the demand for a method to detect fraud is gaining momentum.

Given that publicly listed companies aim to attract investors, if the company committed financial statements fraud, then it will fail to meet that objective. The need for a method to detect fraudulent financial statements is not only to protect the investor's rights but also to predict the significant effect on stock returns.

Based on the above problems, this research seeks to detect red flags for financial statement fraud using the m-score model which contains several ratios and to examine its effect on expected returns.

LITERATURE REVIEW

Isa (2011) concluded that financial statement fraud involves misrepresentations of financial or non-financial details to mislead individuals who rely on the statements to make economic decisions. Falsifying financial statements consists of manipulating elements by overstating assets, sales and profit, or understating liabilities, expenses or losses. Wells (2007) found that fictitious revenue, timing differences, improper asset valuations, concealed liabilities and expenses and improper disclosure are major categories of financial statements fraud. Perols (2011) found a positive relationship between earning management and financial statements fraud.

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Firms that in the prior years have managed earnings will most likely commit financial statements fraud in the following year. The longer fraud schemes are concealed, the more people are involved. The median loss caused by financial statement fraud is the highest among two others occupational frauds category (ACFE, 2016). Financial statements fraud does harm not only the many parties involved but also the nation. For this reason, academicians and experts in accounting have formulated techniques to detect fraud and assess the extent of the deception. The techniques used to detect fraud will depend on the magnitude and nature of fraud (Linville, 2011).

Beneish developed the m-score model using forensic accounting principles. Proceeding from the Altman Z-Score, Messod D. Beneish—an associate professor at the Kelly School of Business, Indiana University—researched the quantitative differences between public companies that had committed financial statement manipulations and those that had not. He formulated the m-score as a mathematical model that uses eight financial ratios. In many ways, it is similar to the Altman Z-score but optimised to detect earnings manipulation rather than bankruptcy. He developed a statistical model to discriminate manipulators from non-manipulators. The variables are constructed from the company's financial statements, and a score is derived from the model to describe the degree to which the earnings have been manipulated (Nwoye, Okoye, & Oraka, 2013). Furthermore, this model is used to detect companies that are most likely to manipulate their financial statements. Beneish theorised there might be up to five useful predictors of earnings manipulation, which he defined as "an instance in which a company's managers violate generally accepted accounting principles (GAAP) to favourably represent a company's financial performance" (Beneish, 2001).

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Days Sales in Receivables Index (DSRI) is measured as the change in receivables in the first year that the manipulation is discovered (year t) by comparing them with the same measure in year t-1 according to sales. A large increase in days' sales in receivables could be the result of a change in credit policy to spur sales in the face of increased competition, but disproportionate increases in receivables relative to sales could also suggest revenue inflation.

Gross Margin Index (GMI) is measured as a ratio of total sales revenue minus the cost of goods sold divided by sales in year t-1 to the corresponding measurement in year t. A GMI above 1 indicates a decline in gross margins, which in turn is related to poorer business prospects and a higher probability of manipulation. Küçükkocaoğlu and Dikmen (2010) suggested that GMI and the probability of earnings manipulation are positively correlated. Finding a high GMI means auditors and CFEs should look deeper into reporting of sales and cost of goods sold (Harrington, 2005)

Asset Quality Index (AQI) measures the percentage of total assets that are intangible assets this year divided by the same percentage calculation for the last year. An increase in this measure is predicted to increase the probability of manipulation. An AQI greater than 1.0 indicates that the company has potentially increased its cost deferral or increased its intangible assets, and committed earnings manipulation (Warshavsky, 2012). Asset quality index and financial information manipulation are suggested to be positively correlated.

Sales Growth Index (SGI) is the measure of growth in revenue in one year over the revenue of a prior year. An index greater than 1 represents a positive growth while less than 1.0 represents a negative growth in the year under review. According to prior studies such as Küçükkocaoğlub & Dikmen (2010), companies that take sales growth into account are more likely to have earning manipulation compared to other companies.

Total Accruals to Total Assets Index (TATA) is used to measure the extent to which sales are made on a cash basis. The total accruals metric is computed as change in working capital (except cash) less depreciation for the year under review adjusted for changes in income tax payable and current portion of long-term debt. An increasing degree of accruals as part of total assets would indicate a higher chance of manipulation (Prevoo, 2007).

Harrington (2005) argued that Beneish's eight independent variables can be divided into a manipulation group and a motivation group, and were structured so that an increase in the variable means a higher probability of manipulation: Manipulation signals are: days sales in receivables index (DSRI) for revenue inflation; asset quality index (AQI) for expenditure capitalisation; total accruals to total assets (TATA) for accounting not supported by cash, gross margin index (GMI) and sales growth index (SGI).

Motivation signals are: for deteriorating margins; for sustainability concerns; selling, general, and administrative index (SGAI) for decreasing efficiency; and leverage index (LEVI) for tighter debt constraints.

M-score has not only detected the red flags for certain companies but also in 1999 it successfully predicted manipulation far before it happened. This can lead to the possibility of m-score to inform of a firm's future prospects. A firm that is growing quickly (extremely high year-over-year sales), experiencing deteriorating fundamentals (as evidenced by a decline in asset quality, eroding profit margins, and increasing leverage); and adopting aggressive accounting practices (receivables growing much faster than sales; large income-inflating accruals; decreasing depreciation expense are likely practising statement fraud.

Beneish (2014) sought to prove that m-score can help predict companies' return. He compiled several studies to identify dependent variables and used the accruals method to test the m-score's ability to predict expected returns. The result is that the m-score provides additional information about the quality earnings beyond the current year's level of reported accruals. Instead, m-score has a significant ability to predict expected returns. The result is consistent with the m-score detection. Firms that are green flags earn positive CAR over four years, while the red flag firms experience average negative returns.

MATERIALS AND METHODS

This research uses secondary sources of data from listed manufacturing companies in the Indonesian Stock Exchange. The total listed companies in Indonesia Stock Exchange is 145 companies. The sample comprises 53 manufacturing companies listed on the Indonesia Stock Exchange (IDX) for the period from 2011-2015. Indonesia's manufacturing industry is divided into three sectors, and each sector has several subsectors; (1) primary industry and chemical, which has eight subsectors, (2) various industries, divided into seven subsectors and (3) consumer goods, five subsectors. Each subsector has a different growth stock rate because the Indonesian government has not maintained each of the sectors simultaneously. The nature of various industries is prone to asset misappropriation such as embezzlement. This type of fraud will most likely lead to financial statement fraud in the near future if there is no preventive action.

As independent variables, m-scores are calculated using Beneish ratios to detect red and green flags. The measurements are Days' to Sales in Receivable Index (DSRI), Gross Margin Index (GMI), Asset Quality Index (AQI), Sales Growth Index (SGI), Depreciation Index (DEPI), Sales, General and Administrative Expenses Index (SGAI), Leverage Index (LVGI) and Total Accrual to Total Assets (TATA). The sources are from the company's annual report and financial statements. Meanwhile, as the dependent variable, Cumulative Abnormal Returns (CAR) is calculated as the difference between the expected return and the actual return of a stock. The sources are Yahoo Finance and IDX Stock Summary.

The research model for m-score and cumulative abnormal return is as follow:

$AR_{it=}\ R_{it}+E(R_{it})$ = F(X) -4.84 + 0.92*DSRI + 0.528*GMI +0.404*AQI +0.892*SGI+0.115*DEPI – 0.172*SGAI + 4.679* TATA – 0.327*LVGI

Where,

AR_{it}	: The abnormal return for company *i* in period *t*
R_{it}	: The actual return for company *i* in period *t*
$E(R_{it})$	: Expected return for company *i* in period *t*
DSRI	: Days' to sales in receivable Index
GMI	: Gross Margin Index
AQI	: Asset Quality Index
SGI	: Sales Growth Index
DEPI	: Depreciation Index
SGAI	: Sales, General and Administrative Expenses Index
LVGI	: Leverage Index
TATA	: Total Accrual to Total Assets

RESULTS AND DISCUSSIONS

Primary Industries and Chemical Sector

The primary industry and chemical sector consist of six subsectors; cement, ceramics and glass, metal, chemical, packaging plastic, and paper pulp. From the m-score calculation, this industry sector has the least red flagged companies, compared with the other two sectors. This result matches with its growth in the past five years note that primary industry and chemical sector recorded growth of approximately 8%-8.6% in 2014-2016 (Kemenperin, 2016).

Typically, a company with a green flag has a positive TATA, in which TATA is the result of the calculation of operating income minus operating cash flows and divided by total assets. Moreover, this ratio is often considered as the accruals ratio. It shows that almost 80% of green flags indicated companies have positive operating cash flows and operating income.

The positive correlation between m-score and CAR, in this case, can also be explained. According to Malhotra, Thenmozhi, and Gopalaswamy (2005), factors that influence abnormal returns are intangible assets value, market capitalisation, operating activities, return on equity and leverage. As an m-score component, operating activities are calculated by TATA, which complies with the basic assumption of factors influencing the stock returns.

A correlation between red flagged companies and negative expected returns among ten companies was observed. Two companies were identified with red flags throughout the observation period (2011-2016). The two companies are from pulp and metal subsectors. They are both indicated as red flag companies, yet their expected returns remain positive. This could happen because one company started producing recyclable products made from renewable resources in 2014. Since then, its expected returns became positive. The company was red flagged because its sales growth and receivables have significant differences from 2011 until 2013. This could result from new regulations about export and import and as well as environment issues from the Ministry of Industry. This condition has had a significant impact on paper and pulp industries in Indonesia. Furthermore, from 2011 prices in the paper and pulp industry plummeted globally. This led companies to shift their focus to local markets. In late 2016, paper and pulp recorded rapid growth by increasing the pulp capacity for the 2017 batch.

The other company was also red flagged in 2014 and 2015, yet its stock returns remain positive. The company had negative operating income and recorded a sharp fall in its total assets. This could be because the steel and metal industry has been facing stiff competition since 2013 which has resulted in sluggish growth. Although the operating income is negative, its stock returns continue to attracting investors since it has a good name in the market and in 2016 the company also involved voluntarily in government product, which will be perceived as goodwill for investors.

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Various Industrial Sectors

The various industries subsector contain seven subsectors. This research focused on three subsectors. This factor is a consideration given that some types of financial statements are missing from certain subsectors. Various industries play a significant role in the manufacturing industry. In May 2017, it strengthened IHSG, and it became top stock for two weeks

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The relationship between green flagged companies and positive expected returns showed there is two negative CAR from the textile subsector. Even though major stocks from various industries are attractive and have a good grade, the government must pay attention to this subsector because most of the companies are still using old machines to produce their products which resulted in their dependence on machines that imported from abroad. Furthermore, the raw material is still very expensive, and local materials are sub-standard. Many companies also lack professional workers, which resulted in inefficient and ineffective output. This affected their inflating operating expense, yet their operating income is usually negative or very far from the expectations. The above issues are among the reasons as to why the textile subsector is having negative expected returns, notwithstanding that it is a relatively big subsector in Indonesia. The investor considers these issues as unattractive features of the textile subsector.

Eleven red flagged companies had negative expected returns comprising five companies from the automotive subsector, three from textile and three from cable. These companies share negative operating income and cash flows as depicted in TATA ratios, and lower LEVI or leverage of debt. It indicates that the companies are having difficulty paying their debts.

The automotive industry is having difficulty due to stiff competition from international brands. Moreover, labour and overhead costs are relatively constant over all models. Nonetheless, on average, trucks contribute more profit per unit, followed by large luxury automobiles. Trucks are redesigned infrequently, so tooling investment per unit is relatively low. Historically, small cars have been less profitable than large cars, and there has been greater competition in this market segment from imports. Larger cars can command higher prices because of their size and features.

Consumer Goods Sector

Consumption goods sector contains five subsectors in which this research only took data from three subsectors because the other two sectors do not provide complete financial statements, as well as the number of companies in those subsectors, are too few to be processed.

There is a significant correlation between green flagged companies and positive expected returns. Consumer goods sector has the best future prospect among other sectors according to the Ministry of Industry. This is supported by the fact that Indonesian consumer goods companies have developed significantly which is why the consumer goods sector has been nominated as the best sector in manufacturing by the Ministry of Industry. Furthermore, this condition leads the companies to make improvements in its financing structure and compliance financial statements which attract investors.

The correlation between red flagged companies and negative expected return's result for this hypothesis is significant. This means that the investor reacts responsively towards differences in the companies' financial statements. A pharmaceutical company was convicted of fraudulent financial statements in 2012. The m-score had successfully detected this with a red flag indicator. Moreover, another pharmaceutical company had an issue regarding an injection that led to several deaths in 2013. Besides being red flagged, the actual return for this period was also negative, and the market reacted adversely to the bad news.

In conclusion, this research has applied the m-score on15 subsectors within the three sectors of Indonesian manufacturing. Most of the manufacturing sectors have green flagged firms. The red and green flags are basically based on the nature of the industry. This is consistent with the ACFE report (2016) that financial statement fraud is based on the nature of the sample.

Furthermore, a common characteristic of red-flagged companies is that they have negative operating cash flows and operating incomes. This is consistent with Beneish theory (2014). High m-score firms have higher means for variables entering the model with a positive coefficient (DSR, AQI, GMI, SGI, and DEPI), and have lower means for the variables entering the model with a negative coefficient (SGAI, LEVI, and TATA).

Additionally, some of the red-flagged firms may have experienced economical headwind and issues in the past. They have struggled to cope with this condition and apply some earnings management and end up being red-flagged due to aggressive earning management.

For the correlation between m-score and CAR, there is a positive relation between green flag companies and positive expected returns. Also, there is a positive correlation between red flag companies and negative expected returns. Both hypotheses are accepted, which means that there is a significant relationship between CAR and m-score. This is because CAR is easily affected by other factors such as firm size, intangible assets, total liability, leverage and current phenomenon (Factors influencing Stock Returns Abnormal Returns Around Bonus and Right Issue Announcement, 2005). The above factors are depicted by Beneish ratios; Intangible Asset (AQI), Total Liability and Leverage (LVGI).

The following table summarises the results per sector based on the SPSS test:

Table 1: *Result per sector based on the SPSS test*

Primary Industry and Chemical		**Various Industries**		**Consumer Goods**	
H1	H2	H1	H2	H1	H2
Significant	Not significant	Not significant	Significant	Significant	Significant

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