Detecting Fraudulent Financial Reporting with Financial Ratios: Case Study on Indonesia Stock Exchange

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ABSTRACT

This study aimed to examine the significant differences in the financial ratios of FFR and non-FFR companies listed on the Indonesia Stock Exchange (IDX) in 2018-2019. It used the difference test of two population means and the Mann-Whitney U test to determine the financial ratios useful in distinguishing the companies. Furthermore, multiple logistic regression was employed to determine significant financial ratios as predictors against Fraudulent Financial Reporting (FFR). The M-Score formula was applied to classify the sample into 19 non-FFR and 59 FFR public companies. The results showed that seven financial ratios effectively differentiate FFR and non-FFR companies. Moreover, one significant financial ratio predicts FFR in public companies listed on the Indonesia Stock Exchange.

Keywords: Financial Ratios, Fraudulent Financial Reporting, Indonesia Stock Exchange, Predictors.

I. INTRODUCTION

The Association of Certified Fraud Examiners (ACFE) (2022) divided fraud into corruption, asset misappropriation, and Fraudulent Financial Reporting (FFR). In 2022, ACFE reported 2,110 fraud cases in 133 countries, with a loss of more than $3.6 billion. The average loss per case is $1,783,000, while the loss of $1,000,000 and above is 21%. Furthermore, the Association of Certified Fraud Examiners Indonesia Chapter 111 (ACFEIC) (2020) reported 239 fraud cases in 2019. The resulting loss was IDR 873,430,000,000, with an average loss per case of IDR 7,248,879,668. Additionally, 38.5% of cases resulted in a loss of IDR 1,000,000,000 and above. The biggest loss is in FFR, with an average loss per case of IDR 11,011,818,181.

This study only examined FFR but did not discuss corruption and asset misappropriation. Several studies focused on factors causing FFR, such as the fraud triangle theory (Lou & Wang, 2009; Albrecht et al., 2010; Dellaportas, 2013) and the diamond fraud theory (Wolfe & Hermanson, 2004; Shelton, 2014; Syahria, 2019; Omar & Din, 2010). In this study, FFR was examined through financial report analysis using financial ratios, as conducted by Kirkos et al. (2007), Dalnial et al. (2014a), Dalnial et al. (2014b), Ravisankar et al. (2011), and Kanapickienė and Grundienė (2015).

Fridson and Alvarez (2022) stated that financial report analysis is an important decision-making skill for investment managers, lenders, or individuals. According to Robinson (2020), analysis is needed in evaluating investments in several securities with equity and debt characteristics. It is also necessary to evaluate the performance, financial position, and value of the company issuing the securities before making investment decisions or other recommendations. Therefore, an analyst should have a solid understanding of the information in financial reports, including records (Robinson, 2020).

Mohamed Yusof (2016) stated that financial reports manifest the responsibility and efficiency in managing company resources. In line with this, Fridson & Alvarez (2022) stated that financial reporting disseminates company profitability and financial condition statements. The reports are also important in making decisions by most investors, creditors, and others needing accounting information (Chen, 2016). Moreover, Dalnial et al. (2014a) stated that FFR could be analyzed using analytical procedures that refer to financial ratio analysis. Fraud investigators suggested and recommended financial ratios to detect FFR (Dalnial et al., 2014a; Dalnial et al., 2014b; Bai et al., 2008; Spathis, 2002; Persons, 1995).

Based on the description, this study aimed to examine the FFR of public companies listed on the Indonesia Stock Exchange (IDX) in 2018-2019. The analysis used a financial ratios approach obtained from published financial report data. This study followed the same financial ratios used by Persons (1995), Spathis (2002), Dalnial et al. (2014a), and Dalnial et al. (2014b). Therefore, it aimed to analyze significant differences in the financial ratios of FFR and non-FFR companies. The purpose was to establish whether these differences could be determined using published financial data. Additionally, the study investigated the financial ratios that significantly predict FFR in public companies listed on the IDX in 2018-2019.
II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

A. Agency Theory

Agency theory regulates the implicit and explicit relationship between principals and agents in information asymmetry situations. This relationship is a rational choice and interdependent, though they have different goals (Verstegen, 2001). According to agency theory, humans have interests that cause conflicts among themselves. This theory has become an influential perspective in studies on company governance and policymaking (Yusuf et al., 2018). It is also rich in theoretical frameworks for principals and agents to understand processes within the company (Boučková, 2015). Furthermore, the theory has been used to study the improvement of company performance by reducing information asymmetry between agents and principals (Dossi & Patelli, 2010; Maestrini et al., 2018).

Jensen and Meckling (2019) stated that an agency relationship is a contract to work on behalf of principals with agents needing a job. The study also found that in the contract, the agents receive a delegation of authority from the principals, including decision-making. The contract’s objective may be to maximize utility for principals and agents. In this case, the agents maximize their interests and disregard the principals. Based on Jensen and Meckling (2019), there is a possibility that agents would practice FFR.

B. Fraudulent Financial Reporting

The many cases of FFR in public companies increase concern among investors, auditors, creditors, and other stakeholders (Razali & Arshad, 2014). The company's motivation to exercise FFR is caused by poor financial performance, the desire to achieve analyst estimates, and fulfill external funding needs (Zhang et al., 2022). In line with this, external funding needs have also been associated with the occurrence of FFR (Erickson et al., 2000; Burns & Kedia, 2006). Beneish et al. (2012) defined FFR as intentional misstatement by omitting a certain amount of money or information that should have been disclosed in the financial reports. It is a violation and material negligence against generally accepted accounting standards (Dalnial et al., 2014b; Hajek & Henriques, 2017). According to Huang et al. (2014), FFR is the intentional issuing of misleading financial reports to avoid negative opinions about the company's finances and business stability.

C. Financial Report Analysis

Financial reports reflect the financial status and help shareholders and banks make decisions regarding investing their shares and providing loans to companies (Ravisankar et al., 2011). The reports are concrete statements of business performance, financial condition, and social responsibility (Chen, 2016). Fridson and Alvarez (2022) stated that the main purpose of financial reporting is to disseminate statements about the companies’ profitability and financial condition. However, FFR may also be carried out by fraudulent companies. This means that financial report users should analyze before making a decision. Robinson (2020) stated that financial report analysis is important in evaluating investments in several securities with equity and debt characteristics. It is also necessary to evaluate the performance, financial position, and value of the company issuing the securities before making investment decisions or other recommendations. Therefore, investment managers, lenders, or individuals need strong skills and understanding of the information in financial reports, including financial records (Robinson, 2020; Fridson & Alvarez, 2022).

D. Hypothesis Development

This study aimed to determine the significant differences between the financial ratios of FFR and non-FFR companies. It also investigated the financial ratios that significantly predict FFR in public companies listed on the IDX. Therefore, two hypotheses were developed to answer the study objectives.

Persons (1995), Spathis (2002), Dalnial et al. (2014a), and Dalnial et al. (2014b) showed that several financial ratios have been used to detect FFR. These ratios include Financial Leverage proxied by Total Debt to Total Assets (TD/TA), Total Debt to Total Equity (TD/TE), and Profitability proxied by Net Profit to Total Assets (NP/TA). Other ratios are Asset Composition proxied by Current Assets to Total Assets (CA/TA), Inventory to Total Assets (INV/TA), Receivables to Total Assets (REC/TA), Liquidity proxied by Working Capital to Total Assets (WC/TA), and Capital Turnover proxied by Revenue to Total Assets (REV/TA). These financial ratios were used in the hypothesis test. The first hypothesis to test the differences in the financial ratios of FFR and non-FFR companies was proposed as follows:

H1: The average financial ratios significantly differ between FFR and non-FFR companies.

Financial leverage is a significant factor related to FFR (Persons, 1995). Alkhatib and Marji (2012) stated that the financial leverage ratio measures a company's ability to pay its obligations at maturity. A high debt structure makes managers manipulate financial reports and transfer risk from equity holders and managers to debtors (Kirkos et al., 2007). The financial leverage ratio of FFR companies is higher than non-FFR ones (Kirkos et al., 2007; Dalnial et al., 2014a). This implies a difference in financial leverage between FFR and non-FFR companies (Kanapickienė & Grundienė, 2015), supporting Spathis (2002) and Persons (1995). Therefore, the sub-hypotheses for financial leverage proxied by total debt to total assets and total equity were proposed as follows:

H1.1: The total debt to total assets ratio is significantly higher in FFR than in non-FFR companies.

H1.2: The total debt-to-equity ratio is significantly higher in FFR than in non-FFR companies.

Profitability is a financial ratio used to measure companies' ability to generate profit (Alkhatib & Marji, 2012). Small profit makes the management commit fraud by overstating income or understating costs (Dalnial et al., 2014a). According to Spathis (2002), a very low profitability ratio means the companies are facing difficulties and manipulating financial reports by increasing income or reducing expenses. FFR companies have lower profitability ratios than non-FFR ones (Spathis, 2002; Persons, 1995), as reported by Kirkos et al. (2007). Therefore, the sub-hypothesis for profitability proxied by net profit to total assets was proposed as follows:

H1.3: The average net profit to total assets ratio is significantly lower in FFR than in non-FFR companies.

The most common technique companies use to perform FFR is asset overstatement (Zager et al., 2016). The largest
proportion of companies' current assets involved in FFR comprises receivables and inventories (Dalnial et al., 2014a; Persons, 1995). These accounts are subjective and commonly manipulated, where the reported value depends on estimates of bad debts and obsolete inventory. Therefore, the higher number of these accounts indicates an overstatement that leads to an FFR (Dalnial et al., 2014a). This means that the asset composition ratios of current assets, inventory, and receivables to total assets in FFR companies exceed non-FFR ones (Persons, 1995). Kanapickiené and Grundienë (2015) also stated that the ratio of current and inventory to total assets differs between FFR and non-FFR companies. Therefore, the sub-hypotheses for asset composition proxied by current assets, inventory, and receivables to total assets were proposed as follows:

**H1:** The average current to total assets ratio is significantly higher in FFR than in non-FFR companies.

**H2:** The average inventory to total assets ratio is significantly higher in FFR than in non-FFR companies.

**H3:** The average receivables to total assets ratio is significantly higher in FFR than in non-FFR companies.

Low liquidity promotes management to conduct FFR (Dalnial et al., 2014a). The study reported that companies with a low ratio of working capital to total assets could not fulfil their obligations. This means that the lower liquidity promotes the management to conduct FFR (Dalnial et al., 2014a). The explanation indicates that the liquidity ratio is lower for FFR than for non-FFR companies (Spahis, 2002; Persons, 1995), supporting Kirkos et al. (2007). Therefore, the sub-hypothesis for liquidity proxied by working capital to total assets was proposed as follows:

**H4:** The average working capital to total assets ratio is significantly lower in FFR than in non-FFR companies.

Companies less competitive in using assets to generate sales experience difficulties in situations of intense competition. This inability to compete promotes management to carry out FFR (Dalnial et al., 2014a). Persons (1995) stated that the ratio of revenue to total assets is higher in FFR than in non-FFR companies, supporting Kirkos et al. (2007). Therefore, the sub-hypothesis for the capital turnover ratio proxied by revenue to total assets was proposed as follows:

**H5:** The average revenue to total assets ratio is significantly smaller in FFR than in non-FFR companies.

Financial report analysis reduces dependence on intuition, assumptions, and perceptions that cause uncertainty but provides a systematic basis for analysis (Dalnial et al., 2014a). Studies have conducted analyses to determine the financial ratios most sensitive to the companies’ motives for committing fraud (Kanapickiené & Grundienë, 2015). The results showed that the financial leverage ratio proxied by total debt to total assets predicts FFR (Persons, 1995; Spahis, 2002; Kanapickiené & Grundienë, 2015). Dalnial et al. (2014a) and Dalnial et al. (2014b) reported the proxy of total debt to total equity. Furthermore, the profitability ratio as a predictor of FFR proxied by net profit to total assets was shown by Spahis (2002). Persons (1995) and Kanapickiené and Grundienë (2015) analyzed the asset composition ratio as a predictor of FFR proxied by current assets to total assets. Dalnial et al. (2014b) reported the proxy of inventory to total assets. Moreover, Spahis (2002) examined the liquidity ratio with a proxy of working capital to total assets. Persons (1995) and Dalnial et al. (2014b) investigated the capital turnover ratio with a proxy of revenue to total assets. The studies show a relationship between financial ratios and FFR, supporting Bai et al. (2008). Therefore, the second hypothesis was proposed as follows:

**H6:** Financial ratios predict FFR in public companies on the Indonesia Stock Exchange.

### III. METHODS

**A. Operationalization and Variable Measurement**

This study used FFR as the Dependent Variable (DV). According to Herawati (2015), the Beneish Model, termed the M-Score, could classify FFR public companies. Based on Aghghaleh et al. (2016), the M-Score formula is given in (1).

\[
M - Score = -4.84 + 0.92 \times DSRI + 0.528 \times GMI + 0.404 \times AQI + 0.892 \times SGI + 0.115 \times DEPI - 0.172 \times SGAI + 4.679 \times TATA - 0.327 \times LVGI
\]

(1)

where,

- **DSRI** = Days’ 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
- **TATA** = Total Accruals to Total Assets Index
- **LVGI** = Leverage Index

The M-Score is calculated using financial reports issued in two consecutive years. Companies are classified as non-FFR in the accounting period when the M-Score < -2.22. Conversely, companies are FFR in the accounting period when the M-Score > -2.22.

### TABLE I: OPERATIONALIZATION AND MEASUREMENT OF VARIABLES

<table>
<thead>
<tr>
<th>Variable</th>
<th>Proxy Variable</th>
<th>Equation</th>
<th>Measurement</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFR (DV)</td>
<td>M-Score</td>
<td>(1)</td>
<td>Dummy variable = 1 if the M-Score of public companies &gt; -2.22, otherwise = 0</td>
<td>Nominal</td>
</tr>
<tr>
<td>Financial Leverage (IV)</td>
<td>Total Debt to Total Assets</td>
<td>TD / TA</td>
<td>-</td>
<td>Ratio</td>
</tr>
<tr>
<td>Profitability (IV)</td>
<td>Total Debt to Total Equity</td>
<td>TD / TE</td>
<td>-</td>
<td>Ratio</td>
</tr>
<tr>
<td>Asset Composition (IV)</td>
<td>Net Profit to Total Assets</td>
<td>NP / TA</td>
<td>-</td>
<td>Ratio</td>
</tr>
<tr>
<td>Liquidity (IV)</td>
<td>Current Assets to Total Assets</td>
<td>CA / TA</td>
<td>-</td>
<td>Ratio</td>
</tr>
<tr>
<td>Capital Turnover (IV)</td>
<td>Inventory to Total Assets</td>
<td>INV / TA</td>
<td>-</td>
<td>Ratio</td>
</tr>
<tr>
<td></td>
<td>Receivables to Total Assets</td>
<td>REC / TA</td>
<td>-</td>
<td>Ratio</td>
</tr>
<tr>
<td></td>
<td>Working Capital to Total Assets</td>
<td>WC / TA</td>
<td>-</td>
<td>Ratio</td>
</tr>
<tr>
<td></td>
<td>Revenue to Total Assets</td>
<td>REV / TA</td>
<td>-</td>
<td>Ratio</td>
</tr>
</tbody>
</table>

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The financial ratios with their proxies were used as the Independent Variable (IV). The operationalization and measurement of variables are shown in Table I.

B. Population and Sample

The study sample comprised 78 public companies selected through purposive sampling. The population consisted of 176 public companies in the consumer cyclical and non-cyclical sectors listed on the Indonesia Stock Exchange. The considerations used in this purposive sampling method are 1) annual financial reports from 2018-2019, 2) financial reports presented in rupiah, and 3) the annual financial reports have complete data to calculate the M-Score. Furthermore, 78 public companies were classified as FFR and non-FFR using the M-Score formula. The classification resulted in 19 non-FFR and 59 FFR companies.

C. Data and Their Source

The study used secondary data comprising the annual financial reports of public companies from 2018-2019. The data were taken to calculate financial ratios in the M-Score formula and independent variables. The data source was the Indonesia Stock Exchange, located at Jalan Sudirman Kav 52-53 South Jakarta 12190, Indonesia.

D. Data Analysis

A data normality test using the w/s test quoted from (Kanji, 2006) was applied to the sub-hypotheses in the first hypothesis. The results showed that all financial ratio data for the independent variables are not normally distributed except the CA/TA ratio data (sub-hypothesis 1.4). Furthermore, the data not normally distributed were transformed into a base 10 logarithm and retested. The results showed that the log data of independent variables' financial ratios were normally distributed, except for the REC/TA ratio (sub-hypothesis 1.6) and the WC/TA ratio (sub-hypothesis 1.7).

A second difference test was performed for normally distributed financial ratios. The findings indicated that the average population variance was the same, except for the CA/TA ratio. The dissimilar variance was determined through the variance similarity test. Meanwhile, the Mann-Whitney U test was used for the ratios of REC/TA and WC/TA, which were not normally distributed. Multiple logistic regression was used to test the second hypothesis. Field (2009) and Hair Jr Joseph et al. (2009) stated that multiple logistic regression is the most appropriate analytical tool when the categorical variable/non-numeric/binary with two categories is the dependent variable while the numeric/metric variables are independent. Therefore, multiple logistic regression was used to estimate the relationship between the numeric, categorical and predictor variables (Hair Jr Joseph et al., 2009).

The multiple logistic regression formula is written as (2).

\[ FFR = \alpha_0 + \beta_1 TDTA_i + \beta_2 TDE_i + \beta_3 NPTA_i + \beta_4 CAT_i + \beta_5 INVTA_i + \beta_6 RECTA_i + \beta_7 WCTA_i + \beta_8 REVTA_i \]

Hair Jr. Joseph et al. (2009) stated that the goodness-of-Fit of the estimated model in multiple logistic regression is determined by calculating the prediction accuracy and classification using the pseudo-R² value. Both methods were used in this study. Classification prediction accuracy is calculated using the probability formula from Agresti (2018). According to Field (2009), the three pseudo R² values are Cox and Snell's ($R_{CS}^2$), Hosmer and Lemeshow's ($R_{HL}^2$), and Nagelkerke's coefficient ($R_{N}^2$). In this study, Nagelkerke's coefficient ($R_{N}^2$) was used to determine the pseudo-R² because it reaches one value (Field, 2009). The Nagelkerke coefficient is interpreted similarly as the value of R² in multiple linear regression (Field, 2009; Hair Jr Joseph et al., 2009). The Wald test with the formula quoted from Field (2009) was used to determine the significant effect of each independent variable on the dependent variable. It was applied to compare the calculated sig value with the chosen level. The significant level used for hypothesis testing is 95%, and data processing used SPSS version 20.

IV. RESULT

A. Descriptive Analysis and Testing the Average Difference in Financial Ratios

Table II presents the average financial ratios of FFR and non-FFR companies, statistical t-test, and sig values for differences in financial ratios (sub-hypothesis 1.1, 1.2, 1.3, 1.4, 1.5, and 1.8) in both groups of companies. The t-test and sig value show differences in financial ratios between FFR and non-FFR companies, which help detect FFR. Similarly, Table III presents the average rank ratios of FFR and non-FFR companies, Z-count, and probability values for significant differences in financial ratios (sub-hypotheses 1.6 and 1.7) using the Mann-Whitney U test.

1) Financial Leverage

The average TD/TA log ratio of FFR companies is 1.5843, higher than non-FFR at 1.3943. The difference in the TD/TA ratio in the two groups of companies is significant, as indicated by the sig value <0.05 in Table II. This TD/TA ratio effectively distinguishes public FFR and non-FFR companies in Indonesia.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variance</th>
<th>Mean</th>
<th>FFR</th>
<th>Non-FFR</th>
<th>T-TEST</th>
<th>Sig</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log TD/TA</td>
<td>Equal</td>
<td>1.5843</td>
<td>1.3943</td>
<td>2.209</td>
<td>0.030</td>
<td>Significant</td>
<td></td>
</tr>
<tr>
<td>Log TD/TE</td>
<td>Equal</td>
<td>1.8511</td>
<td>1.6962</td>
<td>1.161</td>
<td>0.249</td>
<td>Not Significant</td>
<td></td>
</tr>
<tr>
<td>Log NP/TA</td>
<td>Equal</td>
<td>0.5069</td>
<td>0.1791</td>
<td>2.131</td>
<td>0.036</td>
<td>Significant</td>
<td></td>
</tr>
<tr>
<td>CA/TA (%)</td>
<td>Not Equal</td>
<td>50.79</td>
<td>23.19</td>
<td>7.585</td>
<td>0.000</td>
<td>Significant</td>
<td></td>
</tr>
<tr>
<td>Log INV/TA</td>
<td>Equal</td>
<td>1.2089</td>
<td>0.3882</td>
<td>5.913</td>
<td>0.000</td>
<td>Significant</td>
<td></td>
</tr>
<tr>
<td>Log REV/TA</td>
<td>Equal</td>
<td>2.0625</td>
<td>1.2816</td>
<td>10.795</td>
<td>0.000</td>
<td>Significant</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Rank Mean</th>
<th>Z-count</th>
<th>Probability</th>
<th>level</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>RECTA</td>
<td>44.23</td>
<td>28.24</td>
<td>-3.248</td>
<td>0.0006</td>
<td>0.05</td>
</tr>
<tr>
<td>WCTA</td>
<td>42.98</td>
<td>28.68</td>
<td>-2.392</td>
<td>0.0085</td>
<td>0.05</td>
</tr>
</tbody>
</table>
The results indicate that FFR companies have a high debt structure that encourages this practice, supporting Kanapickienė and Grundienė (2015), Dalnial et al. (2014a), Kirkos et al. (2007), Spathis (2002), and Persons (1995). Similarly, the average log ratio of TD/TE for FFR companies is 1.8511, higher than non-FFR at 1.6962. The difference in the ratio was insignificant, as indicated by a sig value >0.05 in Table II. Therefore, it is not used effectively to distinguish between FFR and non-FFR companies, supporting Dalnial et al. (2014a).

2) Profitability

These results show that FFR companies have an average log ratio of NP/TA of 0.5069, higher than non-FFR at 0.1791. The difference in the average ratio is significant, as indicated by the sig value <0.05 in Table II. Therefore, the NP/TA ratio effectively distinguishes FFR and non-FFR public companies in Indonesia. The results showed that the NP/TA ratio is higher in FFR companies than in non-FFR companies. This means that public FFR companies may have manipulated financial reports by increasing revenue or understating expenses. Meanwhile, previous studies reported a significant difference in the NP/TA ratio between fraudulent and non-fraudulent companies. However, the NP/TA ratio was lower for fraudulent than non-fraudulent companies (Kirkos et al., 2007; Spathis, 2002; Persons, 1995).

3) Asset Composition

The average CA/TA ratio of FFR companies is 50.79% higher than non-FFR at 23.19%. Also, the average log INV/TA ratio of FFR companies is 1.2089 higher than non-FFR at 0.3882. The difference between these two ratios is significant, as seen from the sig value <0.05 in Table II. Furthermore, the average rank of the REC/TA ratio is higher in FFR than in non-FFR companies. The difference is significant, as seen from the probability value <0.05 shown in Table III. Therefore, these three asset composition ratios effectively distinguish between FFR and non-FFR public companies in Indonesia. This confirms that the current assets are higher for FFR than non-FFR companies, especially in inventories and accounts receivable, which are the easiest to manipulate. The results support Persons (1995), Dalnial et al. (2014a), and Kanapickienė and Grundienė (2015).

4) Liquidity

The average rank of the WC/TA ratio is higher for FFR than for non-FFR companies. The difference is statistically significant, as shown by the probability value <0.05 in Table III. Therefore, this ratio could distinguish FFR and non-FFR public companies in Indonesia. Previous studies found that the WC/TA ratio was lower for FFR than for non-FFR companies (Kirkos et al., 2007; Spathis, 2002; Persons, 1995). On the contrary, the WC/TA ratio of FFR companies was higher in this study. This means the companies may have manipulated current assets, especially in inventory and accounts receivables. It is reflected in the CA/TA, INV/TA, and REC/TA ratios, which are higher than the non-FFR companies.

5) Capital turnover

The average log REV/TA ratio of FFR companies is 2.0625, greater than non-FFR at 1.2816. There is a significant difference between the two groups of companies, as seen from the sig value <0.05 in Table II. Therefore, the ratio effectively distinguishes FFR and non-FFR public companies in Indonesia. This study found that the REV/TA ratio is greater for FFR than for non-FFR companies. The results indicate that the possibility of income manipulation by reporting is greater in FFR companies. This strengthens the finding that the NP/TA ratio of FFR companies is greater. However, the results contradict previous reports that the REV/TA ratio is smaller for FFR than for non-FFR companies (Persons, 1995; Kirkos et al., 2007).

B. Logistic Regression Result

Table IV presents the logistic regression results, indicating the coefficient, Wald and sig values of financial ratios that possibly predict FFR in public companies in Indonesia (Hypothesis 2).

Table IV shows the financial leverage ratio proxied by TD/TA and TD/TE, as well as profitability ratio proxied by NP/TA. There is also asset composition ratio with the proxy of CA/TA, INV/TA, and REC/TA, and liquidity ratio proxied by WC/TA. The ratios have a logistic regression coefficient insignificant in predicting FFR in public companies in Indonesia, as indicated by Sig. > 0.05. This result contradicts previous studies that the TD/TA ratio could predict FFR (Persons, 1995; Spahis, 2002; Kanapickienė & Grundienė, 2015). Furthermore, the ratios of TD/TE (Dalnial et al., 2014a; Dalnial et al., 2014b), NP/TA (Spahis, 2002), CA/TA (Persons, 1995; Kanapickienė & Grundienė, 2015), INV/TA (Dalnial et al., 2014b), and WC/TA (Spahis, 2002) predict FFR.

<table>
<thead>
<tr>
<th>TABLE IV: LOGISTIC REGRESSION RESULT</th>
<th>Variable</th>
<th>Proxy</th>
<th>Coefficient</th>
<th>Wald</th>
<th>Sig</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financial Leverage</td>
<td>TD/TA</td>
<td>0.087</td>
<td>1.426</td>
<td>0.232</td>
<td>Not Significant</td>
<td></td>
</tr>
<tr>
<td>Profitability</td>
<td>TD/TE</td>
<td>-0.009</td>
<td>1.094</td>
<td>0.296</td>
<td>Not Significant</td>
<td></td>
</tr>
<tr>
<td></td>
<td>NP/TA</td>
<td>-0.081</td>
<td>1.760</td>
<td>0.185</td>
<td>Not Significant</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CA/TA</td>
<td>-0.106</td>
<td>0.665</td>
<td>0.415</td>
<td>Not Significant</td>
<td></td>
</tr>
<tr>
<td>Asset Composition</td>
<td>INV/TA</td>
<td>0.221</td>
<td>1.601</td>
<td>0.206</td>
<td>Not Significant</td>
<td></td>
</tr>
<tr>
<td></td>
<td>REC/TA</td>
<td>0.110</td>
<td>1.074</td>
<td>0.300</td>
<td>Not Significant</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WC/TA</td>
<td>0.050</td>
<td>0.349</td>
<td>0.555</td>
<td>Not Significant</td>
<td></td>
</tr>
<tr>
<td>Liquidity</td>
<td>REV/TA</td>
<td>0.142</td>
<td>6.529</td>
<td>0.011</td>
<td>Significant</td>
<td></td>
</tr>
<tr>
<td>Capital Turnover</td>
<td>Constant</td>
<td>-9.609</td>
<td>5.878</td>
<td>0.015</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Nagelkerke R Square = 0.902
Predicted with correct classification
Non-FFR = 89.5%
FFR = 96.6%
Overall = 94.9%
However, this study found that the capital turnover ratio with the REV/TA proxy could significantly predict FFR in public companies. This is indicated by the positive logistic regression coefficient of 0.142 and Sig. <0.05 in Table IV. The result means that greater REV/TA ratio increases the tendency of public companies to practice FFR, supporting Persons (1995) and Dalnial et al. (2014b).

V. CONCLUSION

Investors, regulators, and capital market players are primarily concerned with the quality of financial report issued by public companies. However, the weak legal and institutional environment makes FFR common (Zhang et al., 2022). This study aimed to establish the published financial data to determine the significant differences in the financial ratios of FFR and non-FFR companies. It also sought to investigate the financial ratios that significantly predict FFR in public companies in Indonesia. Therefore, the study is intended to be useful for investors and capital market participants. These results showed the financial leverage, profitability, asset composition, liquidity, and capital turnover ratios proxied by TD/TA, NP/TA, CA/TA, INV/TA and REC/TA, WC/TA, and REV/TA effectively distinguish between FFR and non-FFR public companies. The REV/TA and NP/TA ratios are interconnected, strengthened, and higher in FFR than in non-FFR companies. Similarly, the WC/TA ratio is higher in FFR than in non-FFR companies. It is associated with higher CA/TA, INV/TA, and REC/TA ratios than non-FFR companies.

The REV/TA ratio has a significant logistic regression coefficient as a predictor of FFR in public companies in Indonesia. Other financial ratios were found not to predict FFR significantly. This logistic regression model is supported by the goodness-of-fit of the estimated model. The model indicated an accurate classification for FFR and non-FFR companies of 96.6% and 89.5%, respectively, and a classification for the entire sample of 94.9%, as shown in Table 4. The accurate classification exceeded 73%, as reported by Dalnial et al. (2014a) and Dalnial et al. (2014b). Furthermore, the accuracy was even more than 84%, as reported by Spathis (2002). The fit of the multiple logistic regression model is 90.2%, as indicated by the Nagelkerke $R^2$ value of 0.902.

The limitation of this study is that is used only 8 of the many financial ratios available (Kirkos et al., 2007; Ravisanekar et al., 2011; Kanapickienè & Gründienè, 2015) to distinguish between FFR and non-FFR companies and to predict FFR. The sample was also only taken from the consumer sector on the IDX. Therefore, future studies could increase the financial ratios and broaden the sample coverage from other sectors. When using the M-score to classify FFR and non-FFR companies, the studies should include sectors where the Gross Margin Index (GMI) is calculated in the annual financial reports.

REFERENCES


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