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AN EFFECTIVE FRAUD DETECTION MODEL FOR THE AUDITORS AS AN ANALYTICAL TOOL: APPLICATION ON PAKISTAN FIRMS

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Abstract

This study aims to establish a rigorous and effective fraud detection model to assist auditors in mitigating and combating financial fraud. This fraud prediction model provides auditors with an analytical tool for fraud detection. The study uses the stepwise logistic regression technique, individually adding variables to the model. The variable that results in discrimination between the groups of fraud firms and non-fraud firms will then be retained, and others will not be included. There are twenty-one (21) different proxies, which are indirect measures that stand in for other variables that are difficult to measure directly, of which fourteen (14) financial ratios and seven (7) corporate governance parameters are used as metric variables to detect the non-metric variable, i.e., fraud detection, having a value of 1 for fraud firms and 0 otherwise. The study developed a fraud detection model based on financial ratios and corporate governance parameters to predict how firms manipulate financial statements and protect investors' interests. The model uses 21 financial ratios and stepwise logistic regression to identify factors influencing firm management in fraud perpetration. The model found that ownership, receivables, and total accruals to total assets significantly positively impacted fraud perpetration. The model was developed using a pool of 21 financial ratios and showed a decrease in the value of -2 log of likelihood (-2LL) at the third step of the regression, indicating a significant improvement in the model's predictive power. Auditors are the primary source of trust for the firm's stakeholders, helping them reduce the expectation gap. The essential factors contributing to auditors' fraud prevention include financial integrity, independence, competence, adherence to ethical standards, transparency, and regulatory oversight. Based on these fundamental principles, the proposed model will strengthen auditors' role in detecting fraud risk. This model has vast practical implications. Auditors can incorporate this comprehensive model into their analytical procedures, whether they opted substantive testing or a systematic-based approach. This will enable them to assess fraud risk effectively and enhance firms' financial integrity.

Key Words: Cressey's Fraud Triangle, Fraud Detection Model, Stepwise Logistic Regression, Auditors, Analytical Procedure

1. Introduction

The International Ethics Standards Board for Accountants (IESBA), as outlined in the "International Code of Ethics for Professional Accountants (revised 2024)", set out the fundamental principles of ethics for accountants. This ensures the financial integrity, objectivity, professional competence, due care, confidentiality, and professional behaviour of the accountants while performing their external or internal auditors' responsibilities. According to the Report to the Nation (RTTN) published by the Association of Fraud Examiners (ACFE) in 2024, 1,921 fraud cases were reported, causing a total loss of over $3.1 billion. Financial statement fraud is the costliest, with a median loss of $766,000 (ACFE, 2024). Although the auditing regulatory bodies highlight and emphasise the importance of financial integrity as one of the fundamental principles, the fraudulent manipulation of financial statements still exists at the firm level. This fraudulent financial activity may misleadingly portray a positive financial picture, which may cause problems for stakeholders like creditors, stockholders, and investors (Aprilia & Agustina, 2017). This also can lead to job loss, delayed returns, and a decline in public trust in the legal system.

Three institutional pillars, i.e., regulatory bodies, auditors, and management, are responsible for a firm's legitimacy. There are guidelines and standards developed by the authorities in charge of legitimacy to prevent or minimize market malpractices that could undermine investor trust, financial integrity, and a firm's legitimacy. However, the enforcement seems particularly weak with the outburst of a few financial scandals globally. Thus, the auditors put extreme efforts into creating a sound appearance with impartiality and transparency that goes beyond what is required by the drives of these forces on the ground (Rashid et al., 2023). The International Standards on Auditing set ISA520: Analytical Procedures for the auditors to evaluate the financial information by measuring the ratios, comparing with expected ratios and previous ratios. These key ratios are related to profitability, working capital efficiency ratios, liquidity ratios, and others, but no such ratios or models help the auditors determine or mitigate the fraud risk. Auditors should focus on mitigating and combating financial fraud as it may affect the public and interested parties (Omar et al., 2017). Thus, this study develops a financial prediction model based on Cressey's Fraud Triangle approach to determine the fraud risk and increase the financial integrity of the auditors. This method seems beneficial as one of the tools of the analytical procedure.

The study is structured as follows: the subsequent section provides an overview of the empirical and theoretical perspectives derived from previous research regarding fraud detection, followed by a discussion on logistic regression and data sources in the research methodology section. The following section presents the empirical findings, and the concluding section summarises the critical implications and offers recommendations for future research. This study addresses a research gap and enhances our understanding of issues and relevant tools to facilitate fraud detection by addressing these aspects.

2. Literature Review

2.1 Fraud Theory

The early 20th century saw a surge in scams, with the establishment of corporations generating new opportunities for fraud. Among pioneer fraud scandals that changed the landscape of financial practices and auditing are the South Sea Bubble in France, the Mississippi Company scandal in 1711, savings and loan scandals in the 1980s, and the boom of several fraud scandals that caused the loss of investor confidence, market repercussions, reputation damages, legal and financial consequences in the 1990s to 2000s. There was a rise in fraudulent activities across multiple industries, including waste management, pharmacy, manufacturing, energy, and telecommunications. However, Enron and WorldCom were prominent examples of corporate fraud (Izzalqurny *et al.,* 2019) and became the reason for the Sarbanes-Oxley Act (SOX) legislation. The fraud environment is a pendulum that rapidly changes from one extreme to another; therefore, ACFE identified three categories of fraud: financial statement fraud, asset theft, and corruption (ACFE, 2024).

In the modern technology era, fraud has become more complex and challenging to detect, mainly when it involves collusion and is committed by high-level management (Alleyne & Howard, 2005; Skousen et al.*,* 2009). Antifraud stakeholders must understand the fraudsters' motivations and methods of preventing the fraud risk (Loebbecke et al., 1989). Pioneer work by Cressey (1953) identified the three components shared by fraudsters, including i) pressure (sometimes called a "non-shareable need" and typically referred to as motivation), ii) rationalization (of personal ethics), and iii) opportunity (chance to execute the crime) (Ozcan, 2016), which is famously recognized as Fraud Triangle.

The fraud triangle comprises pressure stemming from personal needs, social and political survival, and egotistical motivations (Diansari & Wijaya, 2019). Expectations, lifestyle choices, and financial demands can pressure individuals significantly. Pressure is the most significant trigger factor for fraud, motivating the management of a firm to engage in unethical acts (Demetriades & Agyei, 2022; Huang et al.*,* 2017). The manipulation of earnings by management may be triggered by financial stability, pressure from third parties, and intimidation of personal financial status. Similarly, Skousen *et al.* (2009) emphasize that financial stability, external pressure, personal financial needs, and financial targets measure the pressure component.

Another element in the fraud triangle is the opportunity. Fraudsters often have the means and knowledge to perpetrate their crimes due to their familiarity with internal control flaws and long-term tenure in staff and management positions (Bach *et al.,* 2018). According to Haqq and Budiwitjaksono (2019), the weakness of internal controls is the primary factor contributing to opportunity. Moreover, the nature of a firm's activities can also provide opportunities for management to engage in fraudulent activities (Sukmadilaga *et al.,* 2022). The negligent role or override of the control of management leads to a lack of emphasis on internal controls, increasing fraud chances (Dimitrijevic *et al.*, 2015). Insufficient monitoring systems can also exacerbate financial statement fraud risk (Rezaee, 2005). Yendrawati *et al.* (2019) pointed out that the likelihood of fraud increases when opportunities result from weak internal controls. Effective internal control can prevent fraud and preserve financial statement accuracy (Fraihat *et al.*, 2024). Therefore, the three proxies that measure the opportunity component are industry nature, ineffective monitoring, and organizational structure (Skousen et al.*,* 2009).

Rationalization is the third crucial component of the fraud triangle theory, where management (or individuals) justify their fraudulent actions (Holton, 2009). Indarto and Ghozali

(2016) stated that it is a mindset that allows specific individuals to steal money, believing their wrongdoings are neither morally repugnant nor criminal (Omar *et al.,* 2017). White-collar offenders often adhere to personal and moral codes of ethics; some may even seek fair treatment (Gottschalk & Hamerton, 2024). Rationalization is based on management's integrity and belief in their ability to steal and break employee confidence (Fitri *et al.,* 2019). It allows perpetrators to feel comfortable with their actions and continue to commit fraud without experiencing guilt (Situngkir & Triyanto, 2020). This component of the fraud triangle serves as a psychological trigger, prompting management to rationalize their unethical practices and seek justifications for their fraudulent behaviors (Nakitende *et al.*, 2024). Therefore, the rationalization component is measured by auditor opinion and total accrual to total assets (Skousen *et al.,* 2009).

2.2 Fraud Models and Practical Implication of Fraud Theory

A long list of past studies has been conducted to determine the significant level of all three components of the fraud triangle theory: pressure, opportunity, and rationalization. Mix findings have been found, ranging from all three highly significant to non-significant. Lin *et al. (2015) found that all three components of the* fraud triangle theory significantly influenced fraudulent financial reporting in Taiwanese firms. Nakashima (2017) found the same result, where these three components positively influenced the probability of fraudulent financial statements in the case of Japanese firms.

Another cohort of studies has found that either pressure and opportunity or pressure and rationalization significantly influence detecting fraudulent activity. Skousen *et al.* (2009) investigated the effectiveness of Cressy's fraud risk theory in detecting financial statement fraud, using 86 fraud firms from 1992 to 2001 and developing a wide range of variables as proxies for fraud detection. Results indicated that pressure and opportunity have a significant effect on the occurrence of fraud, while rationalization has a statistically insignificant effect. Apriliana and Agustina (2017) explored the prediction of fraudulent financial reporting in 46 manufacturing firms listed on the Indonesia Stock Exchange (IDX) from 2013 to 2015 by employing logistic regression analysis found that pressure and opportunity had a positive significant impact on detecting fraudulent financial reporting within the manufacturing industry. According to Supri *et al.* (2018), pressure and rationalization had a significant positive impact on detecting fraudulent financial reporting in the case of manufacturing firms using the logistic regression technique. Koharudin and Januarti (2021) also found that pressure and rationalization played a statistically significant positive role in detecting fraudulent financial reporting, while opportunity had a statistically insignificant effect in the case of all manufacturing firms listed on the stock exchange.

Another group of studies only found single components of the fraud detection model that could detect fraudulent activity. Within Indonesia's context, Manurung and Hadian (2013) found that only pressure significantly impacted fraudulent financial reporting. Achmad and Pamungkas (2018) found that pressure positively impacted the detection of fraudulent financial reporting in the banking industry using regression analysis. Sharing the same finding, Haqq and Budiwitjaksono (2019), Rahmatika et al. (2019), Christian et al. (2021), and Achmad et al. (2022) found that only pressure had a statistically significant effect on the fraudulent statement, while opportunity and rationalization were statistically insignificant. These studies used statistical

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methods, such as multiple regression and purposive sampling, to analyze data. Focusing on the opportunity, only Rohmatin et al. (2021), while exploring the role of fraud theory in detecting fraudulent financial reporting using data from banking companies from 2016-2019, found a statistically significant positive effect on detecting fraudulent financial reporting. This study uses logistic regression. Sabatian and Hutabarat (2020) and Aripin et al. (2022) show significant results for rationalization. Studies by Aripin *et al.* (2022) examined the influence of pressure, opportunity, and rationalization utilizing firms listed on the Malaysian Stock Exchange from 2016 to 2020.

While the above study found that either all components, two components, or single components are significant as fraud-detecting approaches, few studies found insignificant results for all components. Exploring the issue in Indonesia's banking sector, Manurung and Hardika (2015) found that pressure, opportunity, and rationalization have statistically insignificant effects on detecting fraudulent financial reporting. Differences in results obtained between this study and those obtained by Manurung and Hardika (2013) and Apriliana and Agustina (2017) might be due to the choice of industry. Sukmadilaga et al. (2022) also found a similar insignificant finding while investigating the role of fraud theory in fraudulent financial reporting, using pressure, opportunity, and rationalization in logistic regression.

3. Methodology

According to Lou and Wang (2009), Indarto and Ghozali (2016), and Omar *et al.* (2017), the logistic regression (LR) provided higher accuracy for fraud detection in comparison to other techniques. LR is a non-linear method in which the dependent variable is dichotomous, containing values one (1) and zero (0), also known as a nonmetric variable. The value is one (1) for the fraudulent firm and zero (0) for the non-fraudulent firm. The probability (P) for the fraudulent firm with the multiple regressors variables (X) is determined by:

$$P = \frac{e^{f(x)}}{1 + e^{f(x)}} \qquad \text{eq. (3.1)}$$

The probability (P) for the non-fraudulent firm with the multiple regressors variables (X) is determined by:

$$1 - P = \frac{1}{1 + e^{f(x)}} \qquad \text{eq. (3.2)}$$

Dividing equation (3.1) by (3.2), the value of the "odds ratio" is estimated for each firm as:

$$Odds = \frac{P}{1 - P} = e^{f(x)} \qquad \text{eq. (3.3)}$$

The value of the odd ratio is used to determine the probability of each firm being fraudulent or non-fraudulent based on the value greater than or less than one (1). If the value of the odd ratio is more significant than one (1), it means the firm is a fraudulent firm and vice versa. The logit value is estimated by taking the natural log of the odd ratio and is reported as:

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$$logit(P) = log_e\left[\frac{P}{1-P}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots.. + \beta_k X_k \qquad \text{eq. (3.4)}$$

The interpretation of logistic coefficients of eq. (3.4) is like the regression equation. It explains the effect of variation on each metric variable's value and for estimating each firm's logit value. If the value of the logistic coefficient is more significant, it is more likely to be a suitably identified variable in identifying the cheating and non-cheating firms. Logistic regression (LR) is a valuable technique for its ease of interpretation. It uses nonmetric variables with values between 0 and 1, which can deviate from the normal distribution assumed in classical regression. The logistic curve, which describes the relationship between nonmetric and metric variables, has a slope that never hits zero (0), even as the metric variable's extent decreases and the probability value approaches zero (0). The LR model's probability value is restricted between 0 and 1, and the slope of the curve never comprehensively approaches one. This range represents the linear component asymptotically bound to upper and lower bounds. However, using a nonmetric variable can lead to heteroscedasticity, where variance and covariance vary throughout the variable's levels, contradicting the conventional regression's homoscedasticity assumption.

Unlike multivariate statistical techniques, logistic regression does not depend on fixed assumptions such as homoscedasticity, multicollinearity, normal distribution of metric variables, or linearity. It can also lead to heteroscedasticity or unequal covariances, but the estimation of logistic regression remains unaffected by this violation. In conclusion, logistic regression offers a valuable and flexible approach to analyze fraud risk. It allows for estimating non-linear, polynomial, and exponential relationships and can be improved by adjusting the sample size and metric variables.

Inductive classification, using stepwise logistic regression, to improve understanding of fraud and its association with financial indicators using Cressey's Fraud Risk theory, which suggests fraud is a function of pressure, opportunity, and rationalization. The financial ratios reported in empirical studies are used as proxies for this theory. The research focuses on detecting fraud using Beneish's M-score. It has been argued for its effectiveness in detecting non-manipulated financial statements and its role in revealing financial statement manipulation. Beneish's M-score (1997) model is used as the proxy for fraud detection due to its reliability, high efficacy, and accuracy and provided results with an accuracy of over 70% for fraudulent financial reporting, with a 77.1% accuracy for fraudulent financial statements compared to 80% for non-fraudulent statements and the Beneish’s M-score eight (8) factors model is:

$$\begin{aligned} M - score = & -4.84 + 0.92\, DSRI + 0.528\, GMI + 0.404\, AQI + 0.892\, SGI + 0.115\, DEPI \\ & - 0.172\, SGAI + 4.679\, TATA - 0.327\, LVGI \end{aligned}$$

Eight (8) different financial predictors are used to estimate the M-Score, shown in Table 4.1. Beneish’s M-score model threshold is -1.78 for the coefficients (Beneish, 1999; Beneish et al., 2013). If the value lies below -1.78, the firm is less likely to be a fraudulent firm; otherwise, it is categorized as a fraud firm. The dependent variable is the firm’s likelihood of fraud detection; it is a binary variable containing two values, i.e., one (1) for the fraudulent firm and zero (0) for the non-fraudulent, as shown in Table 1.

<Insert Table 1 Here>

The independent variables are the three components of Cressey's Fraud Risk Theory, i.e., pressure, opportunity, and rationalization. The twenty-one (21) different proxies are used to measure fraud components of Cressey's Fraud Triangle. The different proxies are used for the pressure leg, i.e., a) financial stability, b) external pressure, c) personal financial need, and d) financial targets (Manurung & Hadian, 2013). To measure financial stability, the six (6) different ratios, for external pressure, three (3) different ratios; for personal financial needs, one (1) ratio; and for financial targets, one (1) ratio is used in literature, as shown in Table 2.

The second component of Cressey's Fraud Risk Theory is opportunity. The different proxies are used for the opportunity leg, i.e., a) nature of the industry, b) ineffective monitoring, and c) organizational structure. To measure the nature of the industry, two (2) ratios, five (5) ratios for ineffective monitoring, and one (1) ratio for organizational structure, as shown in Table 2, are used in the literature. The third component of Cressey's Fraud Risk Theory is rationalization. The two (2) different proxies are used for the opportunity leg, i.e., a) auditor opinion and b) total accrual to total assets, i.e., Skousen et al. (2009) and Rahmatika et al. (2019).

<Insert Table 2 Here>

The Pakistan Stock Exchange (PSX) listed 537 firms in 37 sectors. 72% of these firms are non-financial, with 382 from these sectors. Financial predictor data will be gathered from the firms' annual reports from 2009 to 2023, as agreed upon by the SECP and ICAP to ensure full compliance with IFRS for the financial statements of listed companies, except banks and financial institutions, from the 2009 financial year (Deloitte, 2008). The total sample consists of 2,818 firms' year observations, out of which the 2,244 firms' years observations (79.63% of the total sample) belong to firms with 0 value for Beneish score (indicating non-fraud firms) since 2009. The rest of the sample, 574 firms' years of observation (20.37% of the total sample), belongs to firms with 0 value for Beneish score (indicating fraud firms) since 2009.

4. Analysis and Results

Logistic regression has been proven to rank second in prediction accuracy among thirty-two (32) techniques for predicting firms' financial health (Lim et al., 2000). Table 3 shows the means, standard deviation, skewness, and kurtosis of twenty-one (21) variables. Seven variables show a high standard deviation from the mean value, all variables are highly skewed, and the maximum variables are leptokurtic.

<Insert Table 3 Here>

The metric variables are identified as having a significant difference in the two group means by using the value of the f-test, as shown in Table 4. Out of twenty-one (21) financial ratios

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and corporate governance parameters, two (2) pressure variables (i.e., finance and ownership), six (6) opportunity variables (i.e., receivables, inventory, audit committee, audit committee size, expert and CEO and chairperson are identical) and one (1) rationalization variable, i.e., total accruals to total assets) have a significant f-value, meaning these categorical and matric variables are only considered for stepwise logistic regression.

<Insert Table 4 Here>

By adding the discriminatory metric variables of financial ratios and corporate governance parameters in the stepwise logistic regression, only three (3) variables (one (1) from pressure, one (1) from opportunity, and one (1) from rationalization are identified, as shown in Table 5.

<Insert Table 5 Here>

$$logit(P) = log_e\left[\frac{P}{1-P}\right] = log_e\left[\frac{\dfrac{e^{f(-1.4470^{*}+0.004^{*}\ OSHIP_{it}+0.022^{*}\ REC_{it}+0.168^{*}TACC_{it}+\varepsilon_{it})}}{1+\ e^{f(-1.4470^{*}+0.004^{*}\ OSHIP_{it}+0.022^{*}\ REC_{it}+0.168^{*}TACC_{it}+\varepsilon_{it})}}}{1-\dfrac{e^{f(-1.4470^{*}+0.004^{*}\ OSHIP_{it}+0.022^{*}\ REC_{it}+0.168^{*}TACC_{it}+\varepsilon_{it})}}{1+\ e^{f(-1.4470^{*}+0.004^{*}\ OSHIP_{it}+0.022^{*}\ REC_{it}+0.168^{*}TACC_{it}+\varepsilon_{it})}}}\right]$$

Table 5 shows the estimated coefficients of the proposed fraud detection model. The metric variables, ownership, total accruals to total assets, and receivables, have significant coefficients of 0.004, 0.022, and 0.168, respectively. These results indicate that *pressure*, *opportunity,* and *rationalization* are critical factors that influence the management of a firm in fraud perpetration. The odd values explain that as the value of ownership increases by one unit, the probability of fraud increases by 0.996 times. So, the likelihood of being a member of a fraud group rises by 99.6. Similarly, the chance of fraud increases by 0.845 times when the value of receivables increases by one unit. The likelihood of being a member of a fraud group thus rises by 84.5 times. In the same way, the likelihood of fraud increases by 0.979 times when the value of total accruals to total assets increases by one unit. The probability of belonging to a fraudulent firm thus rises by 97.9 times. The model was developed using a pool of financial ratios and showed a decrease in the value of -2 log of likelihood (*-2LL*) at the third step of the regression, indicating a significant improvement in the model's predictive power.

The classification matrix for the identification of correctly classified and misclassified firms' year observation is shown in Table 6. The 1,922 firms' year observations are correctly specified, which is related to the non-fraud firm group, i.e., 85.65%, and the 372 firms' year observations are correctly specified, which is related to the fraud firm group, i.e., 64.81%. The hit ratio of the proposed model is 81.41%, which is higher than the overall classification of the Skousen et al. (2009) model and the Dechow et al. (2011) model.

<Insert Table 6 Here>

Beasley et al. (1999). Skousen and Wright (2006) and Skousen et al. (2009) identified *"ownership"* as a discriminatory variable for determining firm manipulation and as a proxy for pressure leg, as increasing the percentage of shares owned by insiders decreases the chances of fraud perpetration. Loebbecke *et al. (1989) and Robinson (2002) identified "receivables" as a discriminatory variable and as* a proxy of opportunity leg. A high value of receivables indicates a company's financial instability, while a lower value indicates a low chance of fraud. Francis and Krishnan (1999), Cicilia and Sergius (2015), and Noble (2019) suggested that accruals overuse must be cited in audit reports, *"total accruals to total assets"* can be used to detect fraud in financial statements and is a proxy of rationalization leg. A high revenue percentage in the accrual value can lead to the disclosure of financial reporting fraud, as shown in Table 7.

<Insert Table 7 Here>

5. Conclusions

The legitimacy of firms depends on three key pillars, i.e., regulatory bodies, management, and auditors. Several factors, such as financial and human resource constraints, regulatory capture on legal disclosure requirements, inadequate whistle-blower protection system, and delayed enforcement action, have impaired the effectiveness of the regulatory bodies in preventing fraud risk for firms. The role of management of a firm is always questioned in the light of convicted fraud scandals. Enron (2001), WorldCom (2002), Parmalt (2003), and Lehman Brothers (2008) doubted the management's ability to mitigate the fraud risk effectively.

Auditors should include a comprehensive model in their analytical procedure, either opting for substantive testing or a systematic-based approach to assess the fraud risk effectively and enhance their financial integrity. This model has included the proxies representing the three legs of Cressey's Fraud Triangle approach, providing a more robust framework for accessing and preventing fraud risk within the firm.

The study suggests that enhancing employee awareness programs, integrating a real-time internal control system, and employing multi-layered security measures to strengthen the fraud detection process is crucial. Policymakers should strive to understand these detection models comprehensively to improve the integrity of financial reporting and avoid future financial scandals, thereby improving the firm's absolute performance. Additionally, the study recommends adopting sustainable business practices, as they offer opportunities for high returns and firm stability. To achieve this, future studies may investigate industry-specific variables.

References:

ACFE (2024), "Report to the Nation on Occupational Fraud & Abuse'. In Global Fraud Study.

Achmad, T., & Pamungkas, I. D. (2018). *Fraudulent financial reporting based of fraud diamond theory: A study of the banking sector in Indonesia.* Jurnal Ilmiah Akuntansi Fakultas Ekonomi, 4(2), 135-150.

Achmad, T., Ghozali, I., & Pamungkas, I. D. (2022). *Hexagon fraud: Detection of fraudulent financial reporting in state-owned enterprises Indonesia.* Economies, 10(1), 13.

Alleyne, P., & Howard, M. (2005). *An exploratory study of auditors' responsibility for fraud detection in Barbados.* Managerial Auditing Journal, 20(3), 284-303.

Apriliana, S., & Agustina, L. (2017). *The analysis of fraudulent financial reporting determinant through fraud pentagon approach.* Jurnal Dinamika Akuntansi, 9(2), 154-165.

Aripin, R. M., Mahmud, R., Sabli, N., & Tapsir, R. (2022). *Fraudulent financial reporting in Malaysia: from fraud triangle theory perspective.* Advanced International Journal of Banking, Accounting, and Finance, 4(11), 30-48.

Bach, M. P., Dumičić, K., Žmuk, B., Ćurlin, T., & Zoroja, J. (2018). *Internal fraud in a project-based organization: CHAID decision tree analysis.* Procedia computer science, 138, 680-687.

Beasley, M. S., Carcello, J. V., & Hermanson, D. R. (1999). *COSO's new fraud study: What it means for CPAs.* Journal of Accountancy, 187(5), 12.

Beneish, M. D. (1997). *Detecting GAAP violation: Implications for assessing earnings management among firms with extreme financial performance.* Journal of accounting and public policy, 16(3), 271-309.

Beneish, M. D. (1999). *The detection of earnings manipulation.* Financial Analysts Journal, 55(5), 24-36.

Beneish, M. D., Lee, C. M., & Nichols, D. C. (2013). *Earnings manipulation and expected returns.* Financial Analysts Journal, 69(2), 57-82.

Christian, N., Kho, J., Kho, K., Cahya, C., & Agustina, M. (2021). *Is fraud pentagon effective in detecting fraudulent financial statement in Cambodia?* Jurnal Ilmiah Mea (Manajemen, Ekonomi, & Akuntansi), 5(2), 1163-1182.

Cicilia, O., & Sergius, R. P. (2015). *The effectiveness of fraud triangle on detecting fraudulent financial statement: using beneish model and the case of special companies*. Jurnal Riset Akuntansi dan Keuangan Vol, 3(3).

Cressey, D. R. (1953). *Other people's money: a study in the social psychology of embezzlement* Glencoe, IL: The Free Press.

Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (2011). *Predicting material accounting misstatements.* Contemporary accounting research, 28(1), 17-82.

Deloitte. (2008). Pakistan moving toward IFRS in 2009. Retrieved from https://www.iasplus.com/en/news/2008/November/news4381

Demetriades, P., & Owusu-Agyei, S. (2022). *Fraudulent financial reporting: an application of fraud diamond to Toshiba's accounting scandal.* Journal of Financial Crime, 29(2), 729-763.

Diansari, R. E., & Wijaya, A. T. (2019). *Diamond fraud analysis in detecting financial statement fraud.* Journal of Business and Information System (e-ISSN: 2685-2543), 1(2), 63-76.

Dimitrijevic, D., Milovanovic, V., & Stancic, V. (2015). *The role of a company's internal control system in fraud prevention.* Financial Internet Quarterly, 11(3), 34-44.

Fitri, F. A., Syukur, M., & Justisa, G. (2019). *Do the fraud triangle components motivate fraud in Indonesia?.* Australasian Accounting, Business and Finance Journal, 13(4), 63-72.

Fraihat, H.A., Fraihat, Y.M.A., & Qudah, G.M.A.A. (2024). *Financial Internal Control Optimization Of Accounting Firms Based On Information Management Technology In Jordan.* Educational Administration: Theory and Practice, 30(5), 4932-4941.

Francis, J. R., & Krishnan, J. (1999). *Accounting accruals and auditor reporting conservatism.* Contemporary accounting research, 16(1), 135-165.

Gottschalk, P., & Hamerton, C. (2024). *Characteristics of Crime Convenience: The Case of Corporate Offenders.* Deviant Behavior, 1-11.

Haqq, A. P. N. A., & Budiwitjaksono, G. S. (2019). *Fraud pentagon for detecting financial statement fraud.* Journal of Economics, Business, and Accountancy Ventura, 22(3), 319-332.

Holton, C. (2009). *Identifying disgruntled employee systems fraud risk through text mining: A simple solution for a multi-billion dollar problem.* Decision Support Systems, 46(4), 853-864.

Huang, S. Y., Lin, C. C., Chiu, A. A., & Yen, D. C. (2017). *Fraud detection using fraud triangle risk factors.* Information Systems Frontiers, 19, 1343-1356.

Indarto, S. L., & Ghozali, I. (2016). *Fraud diamond: Detection analysis on the fraudulent financial reporting.* Risk governance & control: financial markets & institutions, 6(4), 116-123.

Izzalqurny, T. R., Subroto, B., & Ghofar, A. (2019). *Relationship between financial ratio and financial statement fraud risk moderated by auditor quality.* International Journal of Research in Business and Social Science (2147-4478), 8(4), 34-43.

Koharudin, A., & Januarti, I. (2021). *Lack of financial reporting using Crowe's fraud pentagon theory.* Jurnal Dinamika Akuntansi, 13(2), 148-157.

Lim, T. S., Loh, W. Y., & Shih, Y. S. (2000). *A comparison of prediction accuracy, complexity, and training time of thirty-three old and new classification algorithms.* Machine learning, 40, 203-228.

Lin, C. C., Chiu, A. A., Huang, S. Y., & Yen, D. C. (2015). *Detecting the financial statement fraud: The analysis of the differences between data mining techniques and experts' judgments.* Knowledge-Based Systems, 89, 459-470.

Lou, Y. I., & Wang, M. L. (2009). *Fraud risk factor of the fraud triangle assessing the likelihood of fraudulent financial reporting.* Journal of Business & Economics Research (JBER), 7(2).

Manurung, D. T., & Hadian, N. (2013). *Detection fraud of financial statement with fraud triangle.* 23rd International Business Research Conference, World Business Institute.

Manurung, Daniel T. H. and Hardika, Andhika Ligar (2015) *Analysis of factors that influence financial statement fraud in the perspective fraud diamond: Empirical study on banking companies listed on the Indonesia stock exchange year 2012 to 2014.* In: International Conference on Accounting Studies (ICAS) 2015, Aug 17-20, 2015, Thistle Johor Bahru Hotel, Johor, MALAYSIA.

Nakashima, M. (2017). *Can The Fraud Triangle predict accounting fraud?: Evidence from Japan. In Proceedings: The 8th International Conference of the Japanese Accounting Review. Japan: Rokkodai Campus of Kobe University.* Retrieved from http://www. rieb. kobe-u. ac. jp/tjar/conference/8th/CC2_MasumiNAKASHIMA. pdf.

Nakitende, M. G., Rafay, A., & Waseem, M. (2024). *Frauds in business organizations: A comprehensive overview.* Research Anthology on Business Law, Policy, and Social Responsibility, 848-865.

Noble, M. R. (2019). *Fraud diamond analysis in detecting financial statement fraud.* The Indonesian Accounting Review, 9(2), 121-132.

Omar, N., Johari, Z. A., & Smith, M. (2017). *Predicting fraudulent financial reporting using artificial neural network.* Journal of Financial Crime, 24(2), 362-387.

Ozcan, A. (2016). *Firm characteristics and accounting fraud: A multivariate approach.* Journal of Accounting, Finance and Auditing Studies, 2(2), 128-144.

Persons, O. S. (1995*). Using financial statement data to identify factors associated with fraudulent financial reporting.* Journal of Applied Business Research, 11(3), 38-46.

Rahmatika, D. N., Kartikasari, M. D., Indriasih, D., Sari, I. A., & Mulia, A. (2019). *Detection of fraudulent financial statement: can perspective of fraud diamond theory be applied to property, real estate, and building construction companies in Indonesia?* European Journal of Business and Management Research, 4(6).

Rashid, M., Khan, N. U., Riaz, U., & Burton, B. (2023). *Auditors' perspectives on financial fraud in Pakistan–audacity and the need for legitimacy.* Journal of Accounting in Emerging Economies, 13(1), 167-194.

Rezaee, Z. (2005). *Causes, consequences, and deterence of financial statement fraud.* Critical Perspectives on Accounting, 16(3), 277-298.

Robinson, D. (2002). *Audit Committee Composition and Financial Reporting Problems. (Doctoral dissertation).* Stillwater, Oklahoma: Oklahoma State University.

Rohmatin, B. L., Apriyanto, G., & Zuhroh, D. (2021). *The Role of Good Corporate Governance to Fraud Prevention: An analysis based on the Fraud Pentagon.* Jurnal Keuangan dan Perbankan, 25(2), 280-294.

Sabatian, Z., & Hutabarat, F. M. (2020*). The effect of fraud triangle in detecting financial statement fraud.* Jurnal Akuntansi, 10(3), 231-244.

Situngkir, N. C., & Triyanto, D. N. (2020). *Detecting fraudulent financial reporting using fraud score model and fraud pentagon theory: Empirical study of companies listed in the LQ 45 Index.* The Indonesian Journal of Accounting Research, 23(3), 373-410.

Skousen, C. J., Smith, K. R., & Wright, C. J. (2009). *Detecting and predicting financial statement fraud: The effectiveness of the fraud triangle and SAS No. 99. In Corporate governance and firm performance* (pp. 53-81). Emerald Group Publishing Limited.

Sukmadilaga, C., Winarningsih, S., Handayani, T., Herianti, E., & Ghani, E. K. (2022). *Fraudulent financial reporting in ministerial and governmental institutions in Indonesia: an analysis using hexagon theory.* Economies, 10(4), 86.

Supri, Z., Rura, Y., & Pontoh, G. T. (2018). *Detection of fraudulent financial statements with fraud diamond.* Journal of Research in Business and Management, 6(5), 39-45.

Yendrawati, R., Aulia, H., & Prabowo, H. Y. (2019). *Detecting the likelihood of fraudulent financial reporting: An analysis of fraud diamond.* Asia-Pacific Management Accounting Journal, 14(1), 43-68.

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Table 1
Proxy for Non-Metric Variable: Beneish M-Score Model Ratios

Name of Ratios	Formula of Ratios
Days' sales in receivable index (DSRI)	$\dfrac{\frac{\text{Receivables}_t}{\text{Sales}_t}}{\frac{\text{Receivables}_{t-1}}{\text{Sales}_{t-1}}}$
Gross Margin Index (GMI)	$\dfrac{\frac{\text{Gross Profits}_{t-1}}{\text{Sales}_{t-1}}}{\frac{\text{Gross Profits}_t}{\text{Sales}_t}}$
Asset Quality Index (AQI)	$\dfrac{\frac{1-(\text{Current Assets}_t+\text{PPM}_{t)}}{\text{Total Assets}_t}}{\frac{1-(\text{Current Assets}_{t-1}+\text{PPM}_{t-1})}{\text{Total Assets}_{t-1}}}$
Sales Growth Index (SGI)	$\text{Sales}_t/\text{Sales}_{t-1}$
Depreciation Index (DEPI)	$\dfrac{\frac{\text{Depreciation}_{t-1}}{(\text{Depreciation}_{t-1}+\text{PP\&E}_{t-1})}}{\frac{\text{Depreciation}_t}{(\text{Depreciation}_{t-1}+\text{PP\&E}_t)}}$
Selling, general and administrative expenses Index (SGAI)	$\dfrac{\frac{\text{Sales, General and Administrative expenses}_t}{\text{Sales}_t}}{\frac{\text{Sales, General and Administrative expenses}_{t-1}}{\text{Sales}_{t-1}}}$
Leverage Index (LVGI)	$\dfrac{\frac{\text{Total Debt}_t}{\text{Total Assets}_t}}{\frac{\text{Total Debts}_{t-1}}{\text{Total Assets}_{t-1}}}$
Total Accruals to Total Assets (TATA)	$\dfrac{\text{Total Accruals}}{\text{Total Assets}}$

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Table 2
Proxies for Metric Variables

Fraud Leg	**Proxies**	**Name of Ratios**	**Formula of Ratios**
Pressure	Financial Stability Ratios	Gross Profit Margin	Gross Profit / Net Sales
		Growth in sales	Change in sales − Industry average change in sales
		Current Assets to Total Asset	Operating Income − Cashflow from Operations/Total Assets
		Sales to Account Receivables	Sales / Account Receivables
		Sales to Total Assets	Sales / Total Assets
		Inventory to Total Sales	Inventory / Total Sales
	External Pressure Ratios	Leverage	Total Debt / Total Assets
		Finance	$\frac{Cash\ from\ Operations_t - Average\ Capital\ Exp._{t-3\ to\ t-1}}{Current\ Assets_{t-1}}$
		Free Cash flow	Net cashflow from Operating activities − Cash Dividends − Capital Expenditure
	Personal Financial Needs	Ownership	The cummulative percentage of ownership in the firm held by insiders, shares owned by management divided by the common shares outstanding
	Financial Target	Return on Assets	$Net\ Income\ before\ Extraordinary\ Items_{t-1}/\text{Total Assets}_t$

Opportunity	Nature of Industry	Receivable	$\left(\frac{\boldsymbol{Receivable_t}}{\boldsymbol{Sales_t}}\right)-\left(\frac{\boldsymbol{Receivable_{t-1}}}{\boldsymbol{Sales_{t-1}}}\right)$
		Inventory	$\left(\frac{Inventory_t}{Sales_t}\right)-\left(\frac{Inventory_{t-1}}{Sales_{t-1}}\right)$
	Ineffective Monitoring Ratios	Outside Board of Directors	Percentage of board members who are outside member
		Audit Committee	Indicator variable with the value of 1 if mention of oversight by an internal audit committee; and otherwise 0
		Audit Committee Size	The number of board members who are on the audit committee
		Independence of Audit Committee	The percentage of audit committee members who are independent of the company
		Expert	Indicator variable with the value of 1 if the audit committee does not include at least one director who is or has been a CPA; investment banker or venture capitalist; served as CFO or controller; or has a senior management position CEO; President; COO; VP; etc with financial responsibilties and 0 otherwise
	Organizational Structure	CEO and Board Chair are same person	Indicator variable with a value of 1 if the chairperson of the board holds the managerial positions of CEO or Presidents; and 0 otherwise
Rationalization		Auditor Opinion	A dummy variable for an audit where 1 is an unqualified opinion with additional language
		Total Accrual to Total Assets	Total accruals divided by total assets; where total accruals are calculated as the change in current assets; minus the change in cash, minus change in current liabilites; plus the change in short − term debt, minus depreciation and amortization expense,

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			minus deffered tax on earnings plus equity in earnings

Table 3
Descriptive Statistics of Variables

Variables	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**
Gross Profit Margin	(0.762)	21.147	(29.087)	928.799
Growth in Sales	0.256	1.970	21.495	556.855
Current Assets to Total Assets	0.033	1.111	28.536	1,255.931
Sales to Account Receivables	279.077	2,957.855	17.639	372.904
Sales to Total Assets	2.201	25.948	29.784	993.971
Inventory to Total Assets	2.798	91.751	37.398	1,400.450
Leverage	0.351	0.348	7.962	143.083
Finance	(1.157)	8.609	(8.094)	73.853
Free Cashflow	(10,270,210.381)	439,031,406.107	(2.390)	149.905
Ownership	22.257	28.057	1.050	(0.097)
Return on Assets	0.043	0.276	13.749	392.785
Receivables	0.024	0.882	6.452	453.732
Inventory	0.036	1.016	27.850	846.791
Outside Board of Directors	0.194	0.153	0.588	0.638
Audit Committee	0.821	0.379	(1.663)	0.786
Audit Committee Size	2.781	1.449	(0.679)	0.560
Independence of Audit Committee	0.156	0.222	1.336	1.277
Expert	0.010	0.099	9.887	95.825
CEO and Chairperson are same person	0.014	0.118	8.218	65.583
Auditor Opinion	0.718	0.450	(0.967)	(1.066)
Total Accrual to Total Assets	(1.756)	15.120	(9.119)	487.233

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Table 4
Test of Equality of Group Mean

Name of Variables	Non-Fraud Firms		Fraud Firms		F Value	Significance
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**		
Gross Profit Margin	(0.85465)	23.10175	(0.39853)	10.44616	0.829	0.363
Growth in Sales	0.22825	1.93587	0.36395	2.09780	3.855	0.050
Current Assets to Total Assets	0.03452	1.23597	0.02681	0.29582	0.808	0.369
Sales to Account Receivables	308.21852	3,192.33875	165.15100	1,761.44684	3.249	0.072
Sales to Total Assets	2.51117	29.06878	0.98989	0.66602	4.226	0.040
Inventory to Total Assets	1.89111	72.78490	6.34252	143.64061	4.194	0.041
Leverage	0.35067	0.34770	0.35174	0.34975	3.641	0.056
Finance	(1.29128)	9.09082	(0.63190)	6.36398	9.271	0.002
Free Cashflow	(7,290,303.50013)	464,632,879.21153	(21,919,881.18293)	319,925,121.10230	1.036	0.309
Ownership	21.58017	27.57921	24.90456	29.72994	9.390	0.002
Return on Assets	0.04498	0.29396	0.03629	0.19105	0.259	0.611
Receivables	(0.00088)	0.89495	0.11943	0.82528	10.511	0.001
Inventory	0.02266	0.84246	0.08640	1.51286	7.466	0.006
Outside Board of Directors	0.19113	0.15203	0.20621	0.15539	0.144	0.704
Audit Committee	0.81405	0.38476	0.85044	0.35456	17.646	0.000
Audit Committee Size	2.77325	1.47991	2.80968	1.32200	15.382	0.000
Independence of Audit Committee	0.15428	0.21795	0.16345	0.23554	5.024	0.025
Expert	0.01114	0.10498	0.00523	0.07217	6.562	0.010

CEO and Chairperson are the same	0.01604	0.12567	0.00697	0.08326	10.922	0.001
Auditor Opinion	0.71791	0.45012	0.71603	0.45132	0.032	0.858
Total Accrual to Total Assets	(2.20475)	16.91468	(0.00106)	0.16499	42.757	0.000

Table 5
Estimators of Metric Variables

Metric Variables		Coefficient	S.E.	Sig.	Expβ	Odd Ratios
X_1	Ownership (OSHIP)	0.004	0.002	0.007	1.004	0.996
X_2	Receivables (REC)	0.168	0.066	0.011	1.183	0.845
X_3	Total Accruals to Total Assets (TACC)	0.022	0.007	0.004	1.022	0.979
Intercept		(1.447)	0.062	0.000	0.235	4.252

Table 6
Classification Matrix

Proposed Fraud Detection Model	**Number of samples for analysis**	**Predictive Accuracy**					**The goodness of fit of Model**	
		Non-Fraud Firms		**Fraud Firms**		**Hit Ratio**	**Cox & Snell R^2**	**Nagelkerke R^2**
		% Accuracy	Type I Error	% Accuracy	Type II Error			
Fraud Detection Model	2,818 (100.0%)	85.65%	14.35%	64.81%	35.19%	81.4%	1.1%	1.7%

Table 7
Discriminatory Variables of the Proposed Model

Variable name	**Variable proxy**	**Description**	**Past studies utilised the same variable**
Ownership	Pressure	An increase in the percentage of shares owned (by management and directors) increases the chances of fraud perpetration (Skousen et al., 2009).	Nakashima, (2017). Pamungkas et al., 2018; Yulistyawati et al., 2019; Diansari & Wijiya, 2019; Umar et al., 2020; Anggraini & Suryani, 2020; Sabatian & Hutabarat, 2020; Khamainy et al., 2022; and Xin Xu et al., 2022.
Receivables	Opportunity	A high value of receivables means that the firm has a high tendency to fraud, showing manipulations in their receivables account (Loebbecke et al., 1989; Supri et al., 2018)	Ozcan, 2016; Supri et. al., 2018; Yulistyawati et. al., 2019; Irwandi et. al., 2019; Diansari & Wijiya, 2019; Hidaya & Saptarini, 2019; Umar et. al., 2020; Anggraini & Suryani, 2020; Saleh et. al., 2021; Christian et. al., 2021; Gepp et. al., 2021; Rimadanti et. al., 2022; and Khamainy et. al., 2022.
Total Accruals to Total Assets	Rationalization	When the overall accrual value is more than cash, there is still a chance that significant revenue manipulation may occur (Cicilia & Sergius, 2015).	Manurung & Hadiyan, 2013; Yulistyawati et. al., 2019; Irwandi et. al., 2019; Hidaya & Saptarini, 2019; Izzalqurny et. al., 2019; Umar et. al., 2020; Kukreja et. al., 2020; Anggraini & Suryani, 2020; Sabatian & Hutabarat, 2020; Situngkir & Triyanto, 2020; Nakashima, 2021; Gepp et. al., 2021; and Aripin 2022,