Ramanujan International Journal of Business and Research, 2023, 8(2), 50-58

doi: https://doi.org/10.51245/rijbr.v8i2.2023.1301
P-ISSN: 2455-5959
E-ISSN: 2583-0171

ARTICLE

Predicting the Likelihood of Financial Statement Fraud Through Financial Distress in India

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Abstract

The objective of the paper is to illuminates the intricate relationship between financial distress and the probability of financial statement fraud. The profound implication of the financial distress on the probability of the financial statement fraud within emerging economies like India is presented through this study. The research employs a dataset consisting of 3198 firms listed on NSE and BSE, comprising 36,947 firm-year observations spanning from 2006 to 2022. Panel regression analysis is applied to evaluate the study's findings, with data sourced from the CMIE Prowess database. The Beneish M-score serves as a robust tool for quantifying instances of financial statement fraud, while the Altman Z-score stands as a stalwart metric utilized to assess the levels of financial distress, providing valuable insights into the solvency and stability of a company's financial health. The study reveals a substantial positive relation among financial distress and the probability of financial statement fraud. In credit markets featuring financially distressed firms, this connection highlights an underlying agency problem. Consequently, when a firm experiences financial distress, the probability of financial statement fraud escalates, as it creates pressure to resort to such measures. The study is helpful to policymakers, academic researchers, and regulators with the predictive probabilities of financial statement fraud and financial distress. Policy makers and regulators can restructure the financial distressed firms to reduce the chances of financial statement fraud.

Keywords: Financial Distress, Financial Statement Fraud, Altman Z score, M score, Prediction.

1 Introduction

Predicting the probability of financial statement fraud has been a dynamic and captivating area of focus within the field of finance, business and banking due to the collapse of enormous companies across the continent that not only trembled the business environment of economies but also shackled the stakeholders' confidence. It is important to make accurate predictions because financial statement fraud adversely impact the investment decisions and extinct millions of dollars of hard-earned money of investors. Financial statement fraud has a severe effect on individual stockholders as well as the global economy's stability (Zhou & Kapoor, 2011; Pramanik & Sen, 2020). It had a significant negative influence on the company's goodwill and on its market value. As a result, the rise of financial statement fraud is a major source of concern for all parties involved. Asymmetry of information is also a major cause for financial statement manipulations (Dye, 1988; Trueman & Titman, 1988).

Asset misappropriation, corruption, and financial statement fraud are the three primary forms of fraud, according to the ACFE report 2022. Theft or misuse of organizational property is referred to as asset misappropriation. Among various types of fraud, financial statement fraud stands out as the least prevalent yet most financially burdensome. It involves significant misrepresentation or errors in a company's financial records. Corruption, exemplified by bribery, extortion, and conflicts of interest, represents another form of fraudulent activity. Notably, financial statement fraud ranks as the most financially detrimental form of fraud compared to other types (ACFE report, 2022). This study focuses on analyzing financial statement fraud due to its substantial financial impact.

The Association of Certified Fraud Examiners defines financial statement fraud as "the intentional, deliberate, misstatement or omission of material facts, or accounting data which is misleading and, when considered with all the information made available, would cause the reader to change or alter his or her judgment or decision." Various models have been developed utilizing financial ratios to identify the potential occurrence of financial statement fraud, including the Beneish M-score, Jones modified model, Altman z-score, and Dechow F-score. While the Altman Z-score model primarily aims to predict company bankruptcy, the Beneish M-score is specifically designed to assess the probability of financial statement fraud (MacCarthy, 2017).

Financial distress is one of the factors that strongly supports the manipulations in financial statements. Financial distress is an incentive for the organization to execute fraud (Huang et al. 2012). It acts as pressure on the top executives to mislead the financial statements to present a good image in the minds of the stakeholders. Companies experiencing financial difficulties are more engaged in the management of profits of the firms to meet the internal-external needs of the parties associated with the firm. In developed countries, many studies tried to find out the association between chances of financial statement fraud and financial distress (Beasley, 1996; Rezaee, 2005; Grove & Basilico, 2008; Dechow et al., 2011; Bisogno M. and De Luca R., 2015; Waznah et al., 2015; Dichev et al., 2016; Tassadaq & Malik, 2015; Ibadin and Ehigie, 2019; Handoko et al., 2020; Pratiwi et al., 2022). The current study addresses the research gap by predicting both financial statement fraud and financial distress within emerging economies like India. As of 2023, India rank the fifth position in the global GDP rankings as per the Forbes Report. Understanding the financial stability of listed companies in India is crucial for making informed investment decisions. Previous research in the Indian context has focused on predicting financial statement fraud and financial distress separately, this study offers a holistic examination of the relationship between the two through Beneish M Score and Altman Z score. Thus, the primary objective of this study is to ascertain the impact of financial distress on the probability of financial statement fraud, posing the question: Does financial distress precipitate financial statement fraud?

In the subsequent sections, the research progresses as follow-Section 2 presents the theoretical underpinning and hypothesis development. It discusses the literature review on financial statement fraud and financial distress while identifying the research gaps. Next section elucidates the research methodology employed in the paper. Section 4 explores the results and analysis, in the last section, conclusion, future avenues and limitations of the study are discussed.

2 Theoretical Underpinning and Hypothesis Development

Since the 1980s, the relationship between the possibility of financial statement fraud and financial distress has been a hot topic of theoretical debate. But there are inconsistencies in the findings on the impact of financial distress on the likelihood of financial statement fraud.

2.1 Theoretical Underpinning

Different theories in the literature describe the drivers, factors, and motivators of the propensity to commit fraud. Some of them are discussed below:

Fraud triangle Model

Cressey (1950) coined the term "fraud triangle"to characterize a type of white-collar crime. The three key drivers of fraudulent behavior were identified by Cressey (1950; 1953) on the basis of interviews with white collar offenders. Pressure/incentives, opportunity, and rationalizations are the three key drivers of the fraud triangle theory. The perceived threat of a non-shareable problem provided a motive or incentive to execute fraud. An incentive to fulfil financial needs, adhere to debt covenants, meet analyst expectations, meet internal targets, decrease taxation, insider trading, reduce the possibility of a takeover, and buyback of shares to boost stock market value. Financial distress can also be an incentive for a company to indulge in fraudulent practices (Zhou and Kapoor 2011; Huang et al. 2012). The circumstances or situation that would permit an individual to conduct fraud is known as perceived opportunity. It's linked to the organization's governance system's structural flaws and inefficient controls. (Fama & Jensen, 1983). Rationalization refers to a person's ability to justify a fraudulent behaviour as per their personal code of ethics. It is the defense of unethical behaviour as ethical. After doing an act that breaches ethical, legal, or societal norms, rationalization involves lowering cognitive dissonance. The combination of these three factors constitutes the fraud triangle theory.

Fraud Scale Model

Based on the perspectives of internal auditors who were associated with fraudulent organizations, Albrecht et al. (1984) developed the fraud scale theory. It was an analysis of 212 fraud cases. The authors revealed that it is very difficult to measure the likelihood of fraud. But it can be evaluated by estimating the relative forces of pressure, opportunities, and personal integrity. The fraud scale model is an extension to the fraud triangle theory where rationalization is substituted with personal integrity. Personal Integrity can be measured by looking at a person's decisions and how they make them.

Fraud Diamond Model

Wolfe and Hermanson (2004) explored the fraud diamond model, by incorporating (a fourth factor) Capability in Cressey's model. Individual capability is described as personal traits and abilities that influence the possibility of fraud. Internal weakness of the organization. One must have the capability to exploit the internal weaknesses within the organization. These different theories explain the factors, motivators, or drivers of propensity to execute fraud. The fraud triangle is the most popular model among these models.

Failure, insolvency, bankruptcy, and default are four basic generic terms for corporate financial distress. When the realized rate of return is less than the return on comparable investments, or when revenue is insufficient to pay costs, it is referred to as failure. If a company incapable of fulfilling its present obligations, it is considered insolvent. Bankruptcy is defined as when a court declares that a company is in financial trouble (Tyagi, 2023). Default is described as technical and legal default. Legal default refers to a company's inability to return a loan and interest on a regular basis, whereas technical default refers to a company's failure to meet a contractual term. The legal and technical defaults both signal a decline in corporate performance and financial distress (Habib et al., 2018; Altman and Hotchkiss, 2006). Although financial distress does not always mean that a company will collapse, a significant and enduring decline in a company's financial performance can lead to bankruptcy, resulting in substantial financial losses for stakeholders. (Habib et al., 2018). "When a firm's business deteriorates to the point where it cannot meet its financial obligations, the firm is said to have entered a state of financial distress," according to Baldwin and Scott (1983, p. 505). In the 1960s, research into the origins and ramifications of financial distress, along with the creation of reliable and resilient financial distress prediction models, was initiated. Beaver's (1966) study marked the inception of this field, identifying 30 financial ratios across six components of financial distress prediction through univariate data analysis. Altman (1968) further advanced this research by employing Multiple Discriminant Analysis (MDA) to develop the Z-score model, which pinpointed a set of ratios for forecasting financial distress. Many academics have employed the Z- Score model since then, including Taffler (2007); Adi et al., (2018). Ohlson proposed a new model based on logit analysis and nine financial ratios to overcome the constraints of MDA. Furthermore, Zmijewski (1984) investigated another prediction model based on Probit analysis using three variables. Several other markets based and artificial intelligence-based methods were developed to predict the financial distress but accounting based method like Altman Z score method is widely used in previous studies to predict financial distress (Yousaf et al., 2022).

2.2 Hypothesis Development

Prior literature proposed that financial leverage, profitability, liquidity, asset composition, and cash flow are the most common financial ratios used in models to predict financial statement fraud (Dechow et al., 2011; Kukreja et al., 2020). Agency theory or conflicts of interest emerge from the division between ownership and management, where the objectives of managers may not align with those of shareholders and this is also cause of manipulation in financial statements (Jensen & Meckling, 1976; Dye, 1988; Tassadaq & Malik, 2015; Flayyih & Khiari, 2023). In both the Anglo-Saxon model (shareholders model) and Euro-Continental model (stakeholder model), information asymmetry is observed as an origin point for manipulations in financial books (Salome et.al., 2012). A financially distressed firm will manipulate financial statements or indulge in fraudulent practices to fulfill the expectations of many internal and external stakeholders (Xie et al., 2003; Rezaee, 2005, Bisogno, M. and De Luca R., 2015, Pratiwi et al., 2022). The firm undergoing financial distress is more inclined to manipulate its financial statement to present a good-looking financial statement (Beasley, 1996). Financially distressed firms are more persuaded to apply income increasing choices than the non- distressed firms (Smith et al., 2001). Income-decreasing earning accruals are mostly used by the mangers of financially distressed firms instead of the managers of healthy companies (Habib et al., 2013). Firms in financial crisis are pressurized to perpetrate fraud than organizations in better financial position (Arshad et al., 2015). It was also determined that financial distress serves as a pressure factor, and the only solution to mitigate financial statement fraud is to emerge from the financial crisis (Aviantara, 2021). In pandemic situation like Covid 19, companies show a greater inclination towards management of earnings using accrual based than real based activities (Aljughaiman et al., 2023). Cookbooks are used by companies to boost the value of their stock (Dichev et al., 2016). Financial hardship has an inverse relationship with financial reporting fraud (Mardiana, 2015; Waznah et al., 2015). Company managers allegedly engaged in manipulation when the company was financially healthy and when its profits were high. When the firm is financially distressed, prior to the turmoil, they had used all of their resources for managing and manipulating earnings, so maybe the firm didn't see the advantages of doing so. Therefore, there are conflicting results on the relationship between fraud and financial distress, but most research show a positive relationship between the two, and financial distress acts as one of the pressures point to engage in financial statement manipulations, which lead us to form the following hypothesis:

H01: Financial distress positively associated with financial statement fraud

3 Research Methodology

3.1 Sample

The study relies on the Centre for Monitoring Indian Economy (CMIE) Prowess Database for data collection, which is a publicly accessible company-level database. The analysis focuses on companies listed on the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) from 2006 to 2022. The sample comprises 3,198 firms, totaling 36,947 observations. The chosen timeframe is influenced by amendments to Article 49[1] of the Indian Stock Exchange Listing Agreement, effective from the end of 2006. Financial institutions are excluded from the sample to maintain consistency with previous studies. All the analysis is carried out using Stata 17 statistical package.

3.2 Variable Measurement

Table 1: Description of Variables

Sr. No.	Name of the Variable	Measure/Proxy/Estimate	Description of Variable
1.	Financial Distress (Independent Variable)	Altman Z- score	Real values are considered for analysis on the basis of equation no. 1
2.	Financial Statement Fraud (Dependent Variable)	Beneish M- score	Real values are considered for analysis on the basis of equation no. 2
3.	Control Variable	Size	The log of the total assets of the firms, specifically the natural logarithm, is employed as an appropriate metric for assessing corporate size.
		Profitability (ROA)	(EBIT/TA), Earnings before interest and taxes to total assets

Source: compiled by author

Financial Distress is measured through Revised Altman Z score formulae:

$$* \text{Z score} = 3.25 + 6.56 * X1 + 3.26 * X2 + 6.72 * X3 + 1.05 * X4 \quad (1)$$

where, X1= Working Capital/Total Asset
X2= Retained Earnings/Total Asset
X3= EBIT/Total Asset
X4= Market value of Equity/Book Value of Total Liabilities

A firm is deemed Healthy if its Z score value surpasses 2.60. If the Z score falls below or equals 2.60 but remains greater than or equal to 1.10, the firm is categorized as Grey. However, if the Z score is less than 1.10, the company is identified as financially distressed, as per the criteria established by Altman in 1968 and 1982.

Beneish M Score is used as a proxy to measure Financial Statement Fraud
Professor Messod Daniel Beneish, a professional invented a method for detecting financial statement fraud through financial statement analysis.

$$M - Score = -4.84 + (0.92 * DSRI) + (0.528 * GMI) + (0.404 * AQI) + (0.892 * SGI) \\ +(0.115 * DEPI) - (0.172 * SGAI) + (4.679 * TATA) - (0.327 * LVGI) \quad (2)$$

where, DSRI = Days Sales in Receivables,

$$DSRI == Net\ Receivables\ (t)\ /\ Sales\ (t)/\ Net\ Receivables\ (t-1)\ /\ Sales\ t-1)$$

GMI= Gross Margin Index

$$GMI = [Sales\ (t-1) - COGS\ (t-1)\ ]/Sales(t-1)/[Sales(t) - COGS(t)]/Sales(t)$$

AQI= Asset Quality Index

$$AQI = 1 - [CA\ t) + PPE\ (t)\ ]/TAt)/1 - [CA(t-1) + PPE(t-1)]/TA(t-1)$$

SGI= Sales Growth Index

$$SGI = Sales\ (t)\ /Sales\ (t-1)$$

DEPI= Depreciation Index

$$DEPI = Dep(t-1)\ /\ [PPE\ (t-1) + Dep\ (t-1)]/Depr(t)/[PPE(t) + Dep(t)]$$

SGAI=Sales and General Administrative Expense

$$SGAI = [Sales\ \&\ General\ Adm\ Exp\ (t)\ /\ Sales\ (t)]/[Sales\ \&\ General\ Adm\ Exp(t-1)/Salest-1]$$

TATA= Total Accruals to Total Assets

$$TATA = [Income\ from\ pre-period\ \&\ Extraordinary\ expense\ (t)]/TA(t)$$
$$/[Incomefrompre-period\&Extraordinaryexpense(t-1)]/TA(t-1)$$

LVGI= Leverage Index

$$LVGI = [CLt\ (t) + LT\ Debt\ (t)\ ]/TA(t)[CL(t-1) + LT\ Debt(t-1)]/TA(t-1)$$

A company is deemed prone to financial statement fraud if its M-Score exceeds -2.22. Companies that are likely to commit financial statement fraud are assigned a value of 1 if their M-Score is greater than -2.22, while companies that are unlikely to commit financial statement fraud are assigned a value of 0 if their M- Score is less than -2.22 (Beneish, 1999).

3.3 Model specification

Panel regression is employed to assess the implication of financial distress on the probability of financial statement fraud, with the financial statement fraud measured by Beneish M-Score serving as the dependent variable. Financial distress is the independent variable gauzed by Altman Zscore and size of the firm and return on assets are control variables in the study.

Model: Panel Regression

$$Fraudit = \alpha + \beta 1 l.Fraud\ it + \beta 2 Zscore_W\ it + + \beta 3\ lgsizeit + \beta 4 ROAit + eit,$$

where, Fraud = Likelihood of Financial Statement Fraud
l.Fraud = Last Year Financial Statement Fraud
$Zscore_W$ = Chances of Financial Distress
Lgsize = log of Firm Size
ROA = Return on Assets
eit = Error term

4 Results and Analysis

The results and analysis section provide a thorough and objective summary of the study's findings. The methodology and data collecting sections that came before this one, as well as the discussion and conclusion sections, are connected by this section. It enables researchers to convey their findings, draw attention to significant findings, and offer a thorough analysis of the outcomes.

4.1 Descriptive Analysis

Table 2 presents the summary statistics in the form of the mean, standard deviation, minimum, maximum, skewness, and kurtosis values for each variable under study. According to table 2, the average value of likelihood of financial statement fraud is -3.939, indicating that firms in the NSE and BSE are not manipulating their financial statements as the value is less than -2.22 according to Beneish M score. Similarly, the average chance of being financially distressed is 4.272, indicating most of the firms are healthy as the average value of financial distress is greater than 2.67 according to Altman Z score. The mean value of return on asset and firm size are -4.095 and 7.248 respectively. ROA is indicating a large variability measured by standard deviation (51.344) followed by Fraud (26.917) and Z score (14.118). Variation in the data is also presented by skewness and kurtosis.

Table 2: Summary Statistics

Variables	Observation	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Fraud	36947	-3.939	26.917	-942.246	1511.853	-1.622	496.293
Zscore_w	36947	4.272	14.118	-902.675	432.526	-21.908	1038.855
Lgsize	36942	7.248	2.174	-.916	15.675	.147	3.039
ROA	36947	-4.095	51.344	-393.37	941.667	-6.628	56.907

Source: Compiled by Author

4.2 Correlation

The correlation amongst the study variables is depicted in Table 3. The correlation between the likelihood of financial statement fraud and chances of financially distressed is positive 0.076. This suggests a positive and significant connection between financially distressed firms and financial statement fraud. The likelihood of fraud increases when a firm is in financial distress. Additionally, the return on assets and the size of the firm exhibits positive associations with financial statement fraud, indicated by correlation values of 0.109 and 0.187, respectively. Notably, the correlation values among independent variables are below 0.6, mitigating concerns of multicollinearity. Further confirmation from collinearity diagnostics, such as Variance Inflation Factor (VIF) and tolerance, supports the absence of multicollinearity concerns in the analysis, as VIF values are below 10, and tolerance values exceed 0.1.

Table 3: Correlation Matrix

Variables	Fraud	Zscore_w	Lgsize	ROA	VIF	Tolerance
Fraud	1.000				1.02	0.9777
Zscore_w	0.076***	1.000			1.05	0.9566
Lgsize	0.140***	0.187***	1.000		1.08	0.9217
ROA	0.022***	0.109***	0.187***	1.000	1.04	0.9594

* p<0.10, ** p<0.05, *** p<0.01

4.3 Panel Regression Analysis

The static panel data model requires a decision between using either its random effects or fixed effects models (Cameron & Trivedi, 2009). Within the context of this static panel model, an initial assumption is necessary to determine whether the dependent variable originates from a random sample drawn from an identical population. In the random effect model, it is assumed that the individual-specific effects are unrelated to the regressors, suggesting that these individual effects are random. In contrast, when using the fixed-effects model, there is no need for the prior assumption that individual-specific effects and the regressors are uncorrelated, as the parameter estimation inherently includes these fixed effects (Cameron & Trivedi, 2009).

Table 4 exhibits the panel regression estimates of Random effect and Fixed Effect indicating how the determinants impacts the likelihood of financial statement fraud. After checking stationarity, auto correlation and heteroskedasticity assumptions of the model, final estimates are calculated through both panel regression model. Wooldridge test for autocorrelation in panel data shows that there is problem of auto correlation (F (1, 2627) = 7.343, Prob > F = 0.0068) as p value < 0.05. The Breusch and Pagan Lagrangian multiplier test for random effects and the Modified Wald test for fixed effects are conducted to examine the presence of heteroskedasticity in the model. Both tests reveal evidence of heteroskedasticity in the models. The Hausman test yields a statistic value of 3692.59 with a p-value of .000, indicating statistical significance at a significance level of .05. Consequently, the null hypothesis is rejected, suggesting that the fixed effect is preferable due to its efficiency and consistency. To overcome autocorrelation and heteroskedasticity problem, lagged value of dependent variable and robust variance-covariance estimator are used in fixed effect. The presented R-square value of .5596 suggests that approximately 55.96% of the variation in the probability of financial statement fraud is accounted for by the Fixed Effect (FE) model. Furthermore, the reported chi-square value of 250.239, coupled with a p-value of .000 < 0.05, indicates the statistical significance of the metrics, affirming that the overall model is statistically significant and well-suited.

Examining the results of table 4, the fixed effect model results show that lagged dependent variable (previous year value of financial statement fraud), financial distress, ROA and firm size have positive coefficients of .308, .061, .001, 2.028. It means there is positive impact of lagged value, financial distress, ROA and firm size on the probability of financial statement fraud. The p value of 0.000, 0.013, .000 of lagged financial statement fraud, financial distress (measured by $Zscore_W$) and lg size is less than 0.05 indicating that previous year value of financial statement fraud, financial distress and size of the firm are statistically significant. Whereas, the p value of ROA is not deemed statistically significant, as the value of .889 exceeds than 0.05 threshold at a 5% significance level. In particular, the lagged financial statement fraud exhibits a positive and statistically significant coefficient of .308. This implies that if a firm engaged in financial statement manipulation in the previous year, there is a corresponding increase of 0.308 points in the likelihood of manipulating financial statements in the current year. Thus, instances of manipulated financial statements in the prior year are indicative of a higher likelihood of manipulation in the subsequent year.

Likewise, financial distress is positively and significantly correlated with financial statement fraud, with a positive coefficient of .061. This suggests that a one percent increase in the likelihood of financial distress results in a corresponding increase of .061 in the likelihood of financial statement fraud. In essence, a financially distressed firm faces elevated pressure, leading to a higher probability of engaging in financial statement manipulation. The study further reveals a significant association between the likelihood of financial statement fraud and the likelihood of financial distress ($p=0.000$, $p< 0.05$). In essence, when a firm is in the state of financial distress, it is more inclined to manipulate its financial statements to fulfill the expectations of both internal and external stakeholders. These findings align with prior research studies (Zhou and Kapoor 2011; Huang et al. 2012; Pratiwi et al., 2022). Size of the firm is also positively and significantly associated with financial statement fraud as p value .000 <.05. This means larger the firm size, higher the chances of manipulations in the financial statement. Large firms can easily manipulate or cook their statements to present a desired good picture in front of the stakeholders. While the p-value for ROA is .889, exceeding the .05 threshold, it indicates that the profitability of the firm is not a statistically significant contributor to the manipulation of accounts.

Table 4: Panel Regression Analysis

Variables	Fixed Effect			Random Effect		
Fraud	Coef.	Robust St.Err.	p-value	Coef.	Robust St.Err.	p-value
L	.308	.045	.000***	.476	.055	.000***
Zscore_w	.061	.025	.013**	.066	.022	.003***
ROA	.001	.006	.889	.003	.005	.603
Lgsize	2.028	.284	.000***	.995	.116	.000***
Constant	-17.784	2.167	.000***	-9.117	1.032	.000***
No. of observation		32597			32597	
R-squared		0.5596			0.7291	
F-test		37.957	0.000			
Chi-square					250.239	0.000
Hausman test	3692.596					
P-value	.000					

*** p<.01, ** p<.05, * p<.1

Results of the study are consistent with previous literature that the firm experiencing financial distress will more likely manipulate its financial statement to present a good-looking financial statement (Beasley, 1996; Rezaee, 2005; Bisogno M. and De Luca R., 2015; Aljughaiman et al., 2023).

5 Conclusion and Implications

The research delves into the correlation between the likelihood of financial statement fraud and the chances of financial distress. Financial distress is gauged using Altman Z score, while the likelihood of financial statement fraud is assessed through Beneish M score. The empirical investigation utilized a sample of 3,198 Indian firms listed on the NSE and BSE from 2006 to 2022, comprising 36,947 company-year observations. Fixed-effect panel regression was employed to scrutinize the study's hypotheses. The findings reveal a noteworthy positive correlation between financial statement fraud and the lagged occurrence of financial statement fraud, financial distress, and firm size. In essence, if a firm manipulates its financial figures in the preceding year, there is an increased likelihood of such manipulation in subsequent years. Managers may resort to manipulative practices during periods of financial distress to fulfill both internal and external stakeholder expectations. Financial distress acts as a pressure point for managers, driving them to manage and manipulate earnings. Conversely, a larger firm size heightens the probability of financial statement fraud, given the greater resources and intricate financial structures that larger companies possess, making them susceptible to manipulation. However, profitability, as measured by ROA, does not exhibit a significant association with financial statement fraud. Therefore, it can be concluded that financial distress, firm size, previous year fraud impacts the chances of the financial statement fraud. If the firm is already classified as financially distressed, fraudulent in previous year then, there are more chances of manipulations in the financial statement in current year. The study's conclusions compelled policy makers and regulators to create rules and legislation that would guarantee the veracity and authenticity of information reported in order to safeguard stakeholders' interests. Corporate governance factors and other proxies for financial distress and financial statement fraud can be used in future studies. Dynamic panel models can also be used in future research especially GMM methods. Notwithstanding these limitations, the present study endeavors to comprehend the factors influencing financial statement fraud.

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