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Financial Ratios and Fraudulent Financial Statements Detection: Evidence from Egypt

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Abstract : *This paper aims to identify which financial ratio is significant to detect fraudulent reporting. Moreover, the logistic regression model of fraud detection in financial statements has been developed. The empirical analysis covers the period from 2009 to 2015. Using a sample of 66 companies in Egypt, this study tests twenty five financial ratios based on studies that examined financial ratios indicative capabilities. Only three ratios were included in Logistic regression model. The model correctly classifies fraud and non- fraud financial statements approximately 66.4%. This concludes that financial ratios have the ability the occurrence of Fraudulent Financial Statements. The research is unique for being the first empirical study of its type in Egypt.*

Keywords: Fraudulent Financial Statements, Financial Ratios, Logistic Regression.

1. Introduction:

Fraud is a broad concept with two basic types of fraud seen in practice. The first is the misappropriation of assets and the second is fraudulent financial statements.

Fraudulent financial statements usually occur in the form of falsification of financial statements in order to obtain some forms of benefit. Others believe that fraud involves an intentional distortion of financial statements (Dalnial et al., 2014).

Fraud detection is one of the specific tasks assigned to auditors as stated in ISA 240. With the appearance of an increasing number of companies that resort to these unfair practices, auditors have become overburdened with the task of detection of fraud (Ujal et al., 2012). Auditors commonly use tools known as analytical procedures to assist them in detecting fraud (Albrecht et al., 2009).

Analytical procedures refer to the analysis of significant ratios and trends as well as the resulting investigation of fluctuations and relationships that are inconsistent with other relevant information or which deviate from predicted values. Many researchers and fraud investigators recommend financial ratios as an effective tool to detect fraud

(Subramanyam and Wild, 2009; Bai, Yen and Yang, 2008; Spathis, 2002; Persons, 1995).

The objectives of this paper are firstly; to investigate which financial ratios are significant to fraudulent financial statements. Secondly, this paper proposes appropriate detecting model for fraudulent financial statements of listed companies in Egypt.

2. Similar Studies:

Recent studies have attempted to build models that will predict the presence of fraud in financial statements. Based on stepwise logistic regression, Persons (1995) found that financial leverage, capital turnover, asset composition and firm size are significant factors associated with fraudulent financial statements.

Summers and Sweeney (1998) investigated the relationship between insider trading and fraud. They found that in the presence of fraud, insiders reduce their holdings of company stock through high levels of selling activity.

Spathis (2002) examined published data to develop a model for detecting factors associated with false financial statements. A sample of a total 76 firms includes 38 with false financial statements and 30 non false financial statements. Ten financial variables are selected for examination as potential predictors of false financial statements. Logistic regression is used to develop a model to identify factors associated with false financial statements. The model was accurate in classifying the total sample correctly with accuracy rate exceeding 84%.

Dalnial et al. (2014) investigated whether there are any significant differences between the means of financial ratios of fraudulent and non- fraudulent firms and which financial ratio is significant to detect fraudulent reporting. The sample comprised of 65 fraudulent firms and 65 samples of non-fraudulent firms of Malaysian Public Listed Firms, available between the year of 2000 and 2011. The study found that there are significant mean differences between the fraud and non-fraud firms in ratios such as total debt to total equity, account receivables to sales. In addition, Z- score which measures the bankruptcy probability is significant to detect fraudulent financial statements.

3. Hypotheses Development:

For this study, one hypothesis was developed for further testing as well as to support the research objectives. Evidence suggests that accounting data are useful to assist investors in making investment decisions as well as to enable auditors to assess the likelihood of fraudulent financial statements (Persons, 1995). This suggests that there is an association between financial statements analyses and fraudulent financial statements. Analyzing financial statements information can be used to identify fraudulent and non-fraudulent firms via financial data (Dalnial et al., 2014). Based on those foundations, the hypothesis was developed:

H_1: Financial Ratios are significant predictors to fraudulent financial statements.

3.1. Research Design:

This study examined 66 firms (399 Observations consisting of 180 observations for fraudulent financial statements and 219 observations for non fraudulent financial statements from the Egyptian Public Listed Firms available between the year of 2009 and 2015. Financial statements classification as fraudulent and non fraudulent are obtained using Beneish M- Score model, 1999. This study utilizes the secondary data obtained from published audited financial statements as the main source of information from the corporate annual reports of the public listed firms in Egypt.

3.2. Independent Variables and Dependent Variables:

3.2.1. Independent Variables:

For the purpose of this study, five aspects of firm's financial ratios were identified. These variables are profitability, liquidity, activity, financial leverage, and asset composition. The independent variables are comprised of:

a. Profitability:

Profitability is measured by Net Profit to Net Sales (NP/ NS), Net Profit to Total Assets (NP/TA), and also Net Profit to Owner's Equity (NP/ OE).

b. Liquidity:

Liquidity is measured by Current Asset to Current Liabilities (CA/ CL), Working Capital to Total Assets (WC/ TA), Cash to Current Liabilities (Cash/ CL), and Quick Liquidity Ratio.

c. Activity:

Activity Ratios is measured by Net Sales to Working Capital (NS/ WC), Cost of Sales to Inventory (CS/ INV), Net Sales to Current Assets (NS/ CS), Net Sales to Long Term Assets (NS/ LA), Net Sales to Total Assets (NS/ TA), Net Sales to Accounts Receivable (NS/ REC) and Operating Profit to Net Sales (OP/ NS).

d. Financial Leverage:

Financial Leverage is measured by Total Liabilities to Total Assets (TL/ TA), Total Liabilities to Owner's Equity (TL/ OE), Current Liabilities to Owner's Equity (CL/OE), Debt/ Total Assets (D/TA), Debt to Owner's Equity (D/ OE), Lone Term Liabilities to Total Assets (LL/TA), Owner's Equity to Total Assets (OE/ TA), and Equity Turnover (ET).

e. Assets Composition:

Assets Composition is measured by Current Assets to Total Assets (CA/ TA), Inventory to Total Assets (INV/TA), Accounts Receivable/ Total Assets (AR/ TA)

3.2.2. Dependent Variables:

The dependent variable comprises fraud firms (F) and non-fraud firms (N). Using (Beneish, 1999) (M- Score Model), we can identify Egyptian firms that committed fraud on their financial statements. The formula of Beneish M- Score is as follows:

M = -4.840+0.920DSRI+0.528GMI+0.0404AQI +0.892SGI+0.115DEPI-0.172SGAI+4.679TATA-0.327LVGI

If the M-score>-2.22, it shows indications of financial fraud within companies, otherwise the firm become non-fraud firm. If the firm is associated with fraud activities take the value (1), if not take tha value (0).

3.2.3. Logistic Regression Model:

Stepwise logistic regression was performed on each variable individually to identify the most effective ratios.

Logistic regression is non- linear method for modeling dichotomous dependent variables. That is, the classifying variable can only have two values, which is, in our research, defined as fraud/ non- fraud. The relationship between model probability (*P*) and a vector of influencing factors (X) is modeled as:

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

Where in this context is the probability that a given institution is operating lawfully. If relation (1) is valid, then the probability that an institution is operating unlawfully is:

$$1 - P = \frac{1}{1 + e^{f(x)}} \qquad (2)$$

Combining equations (1) and (2) yields the "odds Ratio" for the institution:

$$Odds = \frac{P}{1-P} = e^{f(x)} \quad (3)$$

An Odds ratio (determined by X) greater than one indicates a probability greater than 0.5 that the firm is honest (that it belongs to the "true" or "success" group). The natural logarithm of the odds ratio is a linear function of X:

$$\text{logit}(P) = log_e\left[\frac{P}{P-1}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$$

The logistic regression function has the advantage of being easily interpreted: each coefficient β_k gives the effect of a one- unit change in its corresponding variable on the logarithm of the predication odds ratio. Thus, variables with a larger coefficient are more useful in detecting fraudulent cases. A maximum likelihood method is usually used to find the model that best distinguishes the two groups. A claim is associated with the value "0" if regular and "1" if irregular (Liou, 2008).

4. Results and Discussion:

Table I presents the results for the stepwise logistic regression. The results showed that financial ratios (NP/ TA), (Cash/ CL), (NS/ TA), (NS/ LA), (OP/ NS), (TL/ TA), (ET), (CA/ TA), (INV/TA), and (AR/ TA) have significantly different predictive abilities for detecting the likelihood of fraud financial firms.

Table (I)

Stepwise Logistic Regression Results of Non Fraud and Fraud Financial Statements

Independent Variables	Unstandardized Coefficient	S.E.	Sig.
NP/ TA	-6.240	13.140	0.000
Cash/ CL	-1.438	16.636	0.000
NS/ TA	0.498	4.008	0.45
NS/ LA	-1.350	14.529	0.000
OP/ NS	-2.102	8.620	0.003
TL/ TA	2.669	17.449	0.000
ET	-0.379	4.595	0.032
CA/ TA	-0.759	1.701	0.192
INV/ TA	1.615	2.742	0.098
AR/ TA	1.091	1.001	0.317

Table II reports the results for the stepwise logistic regression. According to the results, the overall percent if correct classification, by means of the proposed model, is 66.4%. This implies that 208 (85.6%) of non-fraudulent firms and 55 (35.9%) of fraudulent firms were classified correctly. The relationship between the dependent- Fraudulent and non-fraudulent firms- and the independent variables is statistically significant (CH^2= 36.329, p<0.001). The association strength between the dependent and independent variables R^2 Nagelkerke= 0.119.

Under this logistic regression model, the probability of fraud is calculated as:

$$Ln\left(\frac{p}{1-p}\right) = -0.209 - 1.163x_1 - 2.325x_2 + 2.683x_3$$

Where, X_1 NS/ TA (Net Sales/ Total Assets), X_2 OP/ NS (Operating Profit/ Net Sales), and X_3 TL/ TA (Total Liabilities/ Total Assets).

The results indicate that only three variables with significant coefficients entered the model. These ratios are: NS/ TA, OP/ NS, TL/ TA. NS/ TA has an increased probability of being classified with fraudulent financial statements (b=-1.163, p<0.000) and this ratio has a significant negative effect. That means that firms with high net sales to total assets have an increased probability of being classified with non-fraudulent firms. The same strong effect of being classified with the fraudulent financial statements appears to exist for the operating profit to net sales (b= -2.325, p<0.000). This ratio has a significant effect, meaning that firms with increased operating profit to net sales have an increased probability of being classified with the non-fraudulent firms. The ratio TL/TA has an increased probability of being classified as fraudulent financial statements (b= 2.683, p<0.000). This implies that firms with high total liabilities to total assets have an increased probability of being classified with fraudulent financial firms.

Table (II)

Stepwise Logistic Regression Results of Non Fraud and Fraud Financial Statements

Independent Variables	Unstandardized Coefficient	S.E.	Sig.
NS/TA	-1.163	16.776	0.000
OP/NS	-2.325	9.868	0.002
TL/TA	2.683	17.597	0.000
CHI^2	36.329		
R^2 Nagelkerke	0.119		
Correctly Predicted:			
Non Fraud	85.6%		
Fraud	35.9%		
Overall	66.4%		

5. Conclusion:

The objective of this study has been the development of reliable fraudulent financial statement detection model for Egyptian firms. In order to achieve this goal, a sample of fraudulent financial statements and non-fraudulent financial statements has been used. Also, Logistic regression technique was used to develop a model to identify factors associated with fraudulent financial statements. A total of twenty seven financial ratios are selected for examination as potential predictors of fraudulent financial statements. The variables selected by the above technique as possible indicators of fraudulent financial statements are: net sales to total assets ratio, operating profit to net sales ratio, total liabilities to total assets ratio. The model is accurate in classifying the total sample correctly with accuracy rate 66.4%. The results of this model suggest there is a potential in detecting fraudulent financial firms through analysis of publicly available financial statements. In general the indicators selected are associated with fraudulent financial statements. Companies with low net sales to total assets, low operating profit with respect to net sales, high total liabilities to total assets are more likely fraudulently financial statements according to the results of the stepwise logistic regression. The designed model can by external users of financial statement information when making decisions for investment and company evaluation.

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