Financial Fraud Prediction Models: A Review Of Research Evidence

V.K.Wadhwa, A.K.Saini, S.Sanjay Kumar

Abstract: Despite reports about significant advances in techniques for prediction of financial frauds research findings till now do not provide specific evidence or tools for predicting frauds that could be averted. Researchers have explored different methods with varied degree of success relying on financial data as well as non-financial factors for their purpose. This paper reviews reported models/evidence including adaptations/improvements in the models used during investigation. Fraud triangle theory specified by Cressey in 1953 is at the foundation applied in empirical predictive modelling postulated by a number of researchers. Prominent contributors are Beasley, M.S. (1996) , Dechow, et al. (1996), Beneish M. D. (1997), Nieschwietz et al. (2000), Skousen and Wright (2008). Convergence of fraud triangle theory to fraud diamond theory was suggested by Wolf and Hermanson in 2004. This paper additionally reviews specific computational models known as Z-Score (Altman,1968 ), M-Score (Beneish, 1999, 2012), and computer software based models from Green B.P. & Choi J.H.(1997) Zaki & Theodoulidis (2013) and Arta & Seyrek, (2009). There is a noticeable changing trend in research going towards numerous investigations now using computer supported machine learning and artificial intelligence tools for prediction of financial frauds. At the end an assessment is made about degree of success achieved in prediction of financial frauds till date. Empirical fraud prediction, Fraud Triangle/Diamond, M-Score, Z-Score, Machine Learning & Artificial Intelligence for fraud prediction.

Index Terms: Empirical fraud prediction, Fraud Triangle/Diamond, M-Score, Z-Score, Machine Learning & Artificial Intelligence for fraud prediction.

1. INTRODUCTION

This review finds out the extent and effectiveness of models used for detection/prediction of financial frauds. An attempt is made to compile available literature connected with prediction of financial frauds. It is assumed that forecast of any phenomenon is dependent on a number of inputs which also interact inter-se in a complex manner. Hence visible outcome may conceal underlying causes. The challenge is to discover well in advance the possibility of occurrence of a financial fraud. To predict occurrence of financial fraud from time to time number of factors, evident, non evident, hidden have been explored by researchers with varying degree of success. Most common and classical method relies on empirical analysis to trace the possibility of fraudulent behaviour. The following part of this paper contains individual sections separately devoted to each model found in the research. Firstly proponents of empirical prediction of financial frauds through a set of observable fraud cues are reviewed. Secondly computational models based on financial information are reviewed. These are primarily two models i.e. M-Score and Z-Score. Lastly, machine learning/artificial intelligence as a tool to predict financial frauds is reviewed.

1.1 Empirical Research on prediction of financial frauds:-

A set of predetermined standard steps/procedure cannot be applied to predict financial frauds. Auditors generally are trained to routinely follow certain standard procedure to improve effectiveness of auditing. Nieschwietz et al. (2000) reported that check lists used by auditors provide an insight into the likelihood of financial fraud. The authors further discuss that the environment in which auditors operate is assessed through the checklist and research on the predictors of fraud centres around empirical tests of validity of fraud indicators. Evidence is also presented by the authors about the detailed fraud risk assessment undertaken by the auditors at the planning stage of auditing process. Nieschwietz et al. (2000) observed in this context of auditing that the professional requirements of an auditor ensures to put in place a fraud risk management program consisting of written policies of fraud risk measurement. The scale of such measurement may include objective computation of fraud risk score or some kind of fraud risk index which is essentially in quantitative terms. The research aims to examine and get empirical evidence with respect to internal control and internal auditing. Core structure of internal auditing alongwith design of management control system plays a crucial role in measurement of likelihood of financial fraud is pointed out by the authors in the research paper. Consistent with the aforesaid finding Albrecht and Romney (1986) published their first empirical study establishing major role of red flags to predict financial frauds. Authors in their research paper entitled “Red-flagging management frauds: A validation” documented the evidentiary value of red flags for prediction of financial frauds. Surveys conducted by authors demonstrated effectiveness of red flagging to predict financial frauds. Finding of the researchers prove relevance of formation of Ex-ante warning signs of a possible financial fraud. Contribution of the authors provides attributes to red flags in predicting financial frauds. Inference of researchers support relevant professional knowledge is the key to development of mechanism of prediction of financial frauds. The study of Albrecht and Romney (1986) further argues that frauds are inherent in the organisations and skilful people can at the most reduce the likelihood of financial frauds. Financial frauds cannot be completely eliminated. Association of Certified Fraud Examiners (ACFE) is an anti-fraud organisation situated in USA providing training and education. ACFE has conducted detailed studies of fraudulent occurrences of financial statement frauds to recognize such financial statement which are manipulated. ACFE has also enlisted some of the most frequently used tactics to perpetuate frauds in financial statements. Financial statements can be manipulated in various ways. ACFE has declared one of top most cause of fraudulent manipulation is greed and secondly it is the work pressure. Causes identified by ACFE include two prime circumstantial factors which are firstly ‘when it is easy to do it’ and secondly ‘when it is unlikely that perpetrator will get caught’. ACFE enlisted five basic types of financial statement frauds as under:

Table-1: Types of financial frauds

<table>
<thead>
<tr>
<th>S.No</th>
<th>Type of fraudulent activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Fictitious sales</td>
</tr>
<tr>
<td>2</td>
<td>Improper expense recognition</td>
</tr>
</tbody>
</table>
These kinds of activities are planned in such a way that they are difficult to trace in the normal course of audit. Only comprehensive forensic audit may bring such activities to light.

ACFE enlisted the following red flags for fraud risk examiners

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Basis of Fraud Red Flag</th>
</tr>
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<tbody>
<tr>
<td>1.</td>
<td>Growth in revenues without matching rise in cash flows</td>
</tr>
<tr>
<td>2.</td>
<td>Steady sales growth although well-known competitors are facing though time.</td>
</tr>
<tr>
<td>3.</td>
<td>Baffling rise in sale along with growing inventories. Useless stock of goods may be shown as future sale.</td>
</tr>
<tr>
<td>4.</td>
<td>Rising profit margin whereas the industry is in downturn.</td>
</tr>
<tr>
<td>5.</td>
<td>Overstated life of fixed assets. Change in accounting policies without genuine reasons.</td>
</tr>
<tr>
<td>6.</td>
<td>Weak internal audit and control.</td>
</tr>
<tr>
<td>7.</td>
<td>Frequent violation of terms and conditions of loan or at the verge of default.</td>
</tr>
<tr>
<td>8.</td>
<td>Replacement of auditors without genuine reasons.</td>
</tr>
<tr>
<td>9.</td>
<td>Related party transaction not disclosed to auditors.</td>
</tr>
<tr>
<td>10.</td>
<td>Different ratios of financial statement over a period of time.</td>
</tr>
</tbody>
</table>

1.2 Fraud Triangle as predictor of financial frauds:-

Empirical research on frauds goes back to 1953 when Cressey presented with the idea of fraud triangle (Cressey, D 1953). The three aspects of fraud triangle are (i) Opportunity, (ii) Pressure and (iii) Rationalisation. Empirical research suggests that the three components of triangle can be broken down to specific measurable items and then possibility of financial frauds can be deduced from the items. These items can be called proxies of the three corners of the fraud triangle. Skousen et al. (2008) evaluated influence of fraud triangle through proxies of one part of triangle called Pressure by subdividing the concept of pressure by way of computation of (i) Gross profit margin (ii) change in sales of the company in comparison to the average change in the industry and (iii) percentage change in the assets for the two years prior to fraud. The authors say that the company face pressure to commit fraud when financial stability or profitability is under threat. The threat may be due to external factors. Albrecht (2002) suggested that sales to accounts receivable ratio along with sales to total assets ratio and inventory to total sales represent pressure. Proxies of external pressure refer to demand for financing vis-a-vis internal cash generation (Dechow et al. 1996) adjusted by cash dividend and capital expenditure. Thus it can be stated that the pressure in terms of financial performance is whether the company is in a position to meet its financial targets or not. Opportunity is the next factor of fraud triangle. Proxies of ‘Opportunity’ refer to ineffective internal control system. Variable to measure opportunity include firstly the percentage of board members who are outside member. Oversight of audit committee by an independent member of board is known to have reduced incidence of fraudulent behaviour (Beasley et al. 2000). Proxies of ‘Rationalization’ proxies include the excessive use of discretionary accruals and the resultant qualified audit reports.

Fraud diamond theory was first presented by Wolfe and Hermanson (2004) who added one more dimension to fraud triangle theory by adding capability as fourth aspect of motivation for incidence of frauds. It means that the perpetrator of financial fraud must have the necessary skill and ability to commit fraud.

2 COMPUTATIONAL MODELS:-

2.1 Altman Z-Score Model as Predictor of Financial Failure:-

Altman published Z-Score formula in 1968. It is a computational method of predicting if the firm is likely to be bankrupt within next two years. The formula given by Altman is:-

\[
Z = 1.2(T1) + 1.4(T2) + 3.3(T3) + 0.6(T4) + 0.999(T5)
\]

Where:

- \(T1 = \) Working Capital/Total Assets
- \(T2 = \) Retained Earnings/Total Assets
- \(T3 = \) Earnings Before Interest and Taxes/Total Assets
- \(T4 = \) Market Value of Equity/Total Liability
- \(T5 = \) Sales/Total Assets

If \(Z\) is greater than 2.99 it is considered safe zone and if \(Z\) is between 1.81 to 2.99 it is considered grey zone and if \(Z\) is less than 1.81 it is considered distress zone.

If the firms happens to be unlisted not having a market value than the market value gets substituted with book value of the firm. Similarly there will be small modification in the formula for non-manufacturing companies and financial sector companies. Altman Z-score would have predicted in advance fraudulent behaviour of Enron as per the published financial statements of Enron. In this it was established that financial failure could have been predicted with the publically available published financial statements.

2.2 Beneish M-Score Model for Prediction of Financial Frauds Relating to Earnings Manipulation:-

Professor M Danial Beneish from Kelley School of Business published a path breaking research paper in 1999. He found out that a set of financial ratio and eight variables can identify financial frauds relating to earning manipulation. Since all the required input is obtainable from the published financial statements of the company the whole process of prediction becomes very practical and convenient. The variables used in computation of M-score are as under:-

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Variable</th>
<th>Meaning of Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>DSRI</td>
<td>Days’ sales in receivable index</td>
</tr>
<tr>
<td>2.</td>
<td>GMI</td>
<td>Gross margin index</td>
</tr>
<tr>
<td>3.</td>
<td>AQI</td>
<td>Asset quality index</td>
</tr>
<tr>
<td>4.</td>
<td>SGI</td>
<td>Sales growth index</td>
</tr>
<tr>
<td>5.</td>
<td>DEPI</td>
<td>Depreciation index</td>
</tr>
<tr>
<td>6.</td>
<td>SGAI</td>
<td>Sales and general administration. Expenses</td>
</tr>
<tr>
<td>7.</td>
<td>LGVI</td>
<td>Leverage index</td>
</tr>
<tr>
<td>8.</td>
<td>TATA</td>
<td>Total accruals to total assets</td>
</tr>
</tbody>
</table>

If M-Score is less than -2.22 it shall mean company has not manipulated earnings and M-Score greater than 2.22 shall mean there is a good chance of manipulation of earnings. This model has been applied all over the world by a large number of other researchers confirming reasonable accuracy of the model. Results obtained in India are not much at variation.
3 COMPUTER BASED ADVANCED SOFTWARES:-

3.1 MACHINE LEARNING/ARTIFICIAL INTELLIGENCE/DATA MINING (HEREIN AFTER ML/AI/DM) FOR PREDICTION OF FINANCIAL FRAUDS:-

Sharma A and P.K.Panigrahi (2012) has observed that advancement of computer technology has brought about major change in methods of prediction of financial frauds. They have noted that ML/AI/DM have occupied a centre stage now in devising procedures for prediction of financial frauds. ML/AI/DM methods are divided into two categories of models called supervised methods and unsupervised methods. Green and Choi (1997) presented in their research article entitled “Detecting management fraud through neural network technology” a technique to find out fraudulent activity from the published financial statements. Green and Choi (1997) initially from the data of fraud firms fed input values to the machine learning software in order to train the software subsequently the trained software were applied on raw data to filter possibility of incidence of financial frauds. The process involves feeding of data to the machine for the machine to learn and subsequently apply the learnt algorithm to test the unknown situation to show generalised rules being applied for prediction of financial frauds. Consistent with Green and Choi (1997), Juszezak et al.(2008) concluded the problem of prediction of financial frauds can be considered as a problem of classification. By classifying unknown firms in two parts as fraudulent firms and non fraudulent firms we can predict that a firm is likely to engage in fraudulent activity or not. Authors pointed out that the machine learning models improve their performance with experience. In some cases the coefficient are computed at the time of feeding of data and in some other cases the processing is lazy because the updating is done while the data is being processed.

3 CONCLUSION:

Varied models examined in this paper provide inclusive evidence about the most accurate method of prediction of financial fraud. Most of the models lack generalisation potential because of over dependency on small size of data. All the models are highly data bias and therefore low in generalisation. It is a serious limitation which can be overcome only if large data size is available for dispensation. Finally it can be concluded that none of model could provide perfect solution for prediction of financial frauds and there is a lot yet to be done. However future is quite promising in view of available latest tools particularly machine learning and artificial intelligence is titivating all along.

REFERENCES


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