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FINANCIAL ACCOUNTING FRAUD DETECTION USING BUSINESS INTELLIGENCE

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ABSTRACT

The paper investigates the inherent problems of financial fraud detection and proposes a forensic accounting framework using business intelligence as a plausible means of addressing them. The paper adopts an empirical case study approach to present how business intelligence could be used effectively in the detection of financial accounting fraud. The proposed forensic accounting framework using business intelligence (BI) provides a three-phase model via novel knowledge discovery technique to perform the financial analysis such as ratio analysis for a business case scenario. The implementation of the framework practically demonstrates by using their accounting data how the technologies and the investigative methods of trend analysis could be adopted in order to investigate fraudulent financial reporting unlike traditional methods of vertical and horizontal analysis for the business case study. Finally, the results justify the effectiveness of the proposed BI model in proactively identifying, classifying and evaluating financial fraud in the organisation. This research further leads to practical follow-up steps that would serve as guidelines for the forensic accounting auditors and management to focus on the prime areas of financial fraud present in the case study. Overall, the proposed model caters to detecting various types of accounting fraud as well as aids in continuous improvement of an organisation's accounting, audit, systems and policies through the feedback loop.

Keywords: Financial accounting fraud, Forensic accounting, Fraud detection framework, Business intelligence, Data analysis, Trend analysis.

Contribution/ Originality

This study originates new forensic accounting framework using business intelligence (BI) that provides a three-phase model via a novel knowledge discovery technique to perform the financial trend analysis for fraudulent financial reporting in a business case setting.

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1. INTRODUCTION

Recently, financial accounting fraud detection has come into limelight due to the upsurge in financial frauds and white-collar crimes witnessed in the competitive economic scenario. In the last decade, high profile financial frauds committed by large companies in both developed and developing countries were discovered and reported, such as Enron, Lucent, WorldCom, Parmalat, YGX, SK Global, Satyam, Harris Scarfe and HIH (Lalit and Virender, 2012). With a huge increase in accounting fraud witnessed, the need for efficient financial accounting fraud detection has gained considerable thrust from the investors, academic researchers, media, the financial community and regulators.

Over the past few years, it has become the responsibility of accountants to take a critical assessment of the traditional practices adopted in financial statements while meeting the requirements of Generally Accepted Accounting Practices (GAAP) recommended by professional bodies (Persons, 1995). There has been a tendency for companies to enhance their financial statements to project an attractive picture for potential financial investors (Spathis, 2002; Chai *et al.*, 2006; Lalit and Virender, 2012). Though the need for forensic accountants and true interpretation of accounting data have been emphasized by professional and regulatory bodies, financial accounting fraud detection is still in its infancy. Forensic accountants are considered to be the best-equipped professionals who possess an integration of accounting, auditing and investigative skills. Recent studies have compared the financial ratios between fraudulent and non-fraudulent firms for arriving at any statistical significance and obtained mixed results (Dalnial *et al.*, 2014; Nia, 2015). However, the existing fraud detection model's accuracies are not generally high (Li, 2015). Hence, present forensic accountants are predominantly only dealing with case by case inquiry of the financial statements that are entrusted to them rather than engaging in a proactive auditing exercise for an early detection of fraud. The main reasons for a slow adoption of such a proactive approach are insufficient time given to forensic accountants, non-availability of efficient fraud detection tools, ineffective use of computer technology for fraud discovery, and lack of technical knowledge, fraud scheme and investigative techniques (Zhou and Kapoor, 2011; Yadav and Yadav, 2013).

Traditional auditing uses random-based selection techniques (Jubb, 2013) such as, random sampling, stratified random sampling or systematic sampling of populations of accounting data to discover errors. However, computer technology could be effectively used to search full populations of data to unearth anomalies, trend and fraud more accurately. Traditional approach is more suitable for discovering anomalies due to unintentional errors found regularly in data that are usually caused by weaknesses in accounting procedures and controls. In contrast to this, computer-based approaches could detect even intentional errors introduced purposely or fraud perpetrated by an employee in selected financial transactions. One such example is the WorldCom fraud discovery, where computer technology was effectively used to search all the populations of accounting data for finding intentionally manipulated data (Lalit and Virender, 2012; Lee *et al.*, 2014). In such cases, a sample of the population may not be representative as the manipulated data could be prevalent to only certain transactions and missing from the chosen samples, thereby escaping from traditional fraud discovery approaches. On the other hand, fraud detection methods that search the entire voluminous populations of financial data could be time consuming and may not be possible without resorting to computer-based data mining techniques. Computer-based fraud detection could involve different tools, software that may require certain domain knowledge of data mining techniques, data formats, database queries and scripting, security principles and encryption, etc. There could be integration issues pertaining to the software tool and the external information sources, and financial data, and requires a collaborative and robust research among various fields including legal, accounting, information systems, and mathematics. Most of the auditors have only limited experience with databases and spread sheet software and may deal with only specific analysis routines (Bell and Carcello, 2000; Yadav and Yadav, 2013). Computer-based fraud detection, a new and exciting field, could be explored to support a variety of data mining techniques with the capability of automatically finding appropriate databases to perform analysis and compare data against standard models so as to determine the exact financial accounting fraud occurring in the business (Yue *et al.*, 2007; Ngai *et al.*, 2010; Wang, 2010; Ravisankar *et al.*, 2011). We use the term "Business Intelligence" to refer to methods and technologies that transform voluminous data into meaningful information for business by making use of various data mining techniques and procedures to provide dashboards and wizards for auditors to perform analysis quickly. Typically, a business intelligence approach should provide necessary automation for scripting and dynamic querying of different data formats and database schemas in order to conduct walk-throughs based on accounting principles and methodologies for investigation without auditors having to possess the domain IT knowledge.

It should be adaptable for different uses, multiple fraud schemes and symptoms so as to assist the auditor to perform follow-up steps by automatically highlighting potential symptoms that match more appropriately with the schemes. Hence, by adopting such a business intelligence approach, we could achieve high levels of accuracy in accounting fraud detection with minimal time and expertise required from the auditors or forensic accountants. In this paper, we formulate a framework for financial accounting forensics using business intelligence and illustrate the effective implementation of the framework within a business scenario by adopting ratio analysis as an empirical case study. The rest of the paper is organised as follows.

Section 2 provides a summary of the popular data mining methods available for detecting financial fraud in businesses and the gap in literature. Section 3 describes our research approach adopted in this study. In section 4, we present our proposed forensic accounting framework using business intelligence modelling. The implementation of the framework for a business case study is illustrated in section 5 and the findings are described. Finally, section 6 provides the conclusion and future directions of this research.

2. REVIEW OF EMPIRICAL STUDIES

There are different data mining techniques used in various industry applications to detect fraud, especially in information security (Alazab and Venkatraman, 2013). In accounting, data mining technique was successfully adopted to identify fraud committed internally by employees in misappropriating companies' assets (Albrecht, 1992). In another popular study, Nigrini (2000) identified Benford's Law as one of those techniques which was about business transactions involving small sums being more than those involving large sums. Transactions with large amounts deserve closer scrutiny. The advantage of the technique is that it is simple to use and the disadvantage of it is the inability to detect abnormal patterns in business. Because of this limitation, another technique on detecting outlier, i.e. abnormal values, is recommended (Yamanishi *et al.*, 2004). Calculating z-score is one method of outlier detection. Advanced methods such as regression models are also commonly used.

Recently, data mining techniques that could predict accounting fraud has gained importance. Looking at trends by comparing amounts over time can help to discover symptoms of fraud. Regression models and cluster analysis are advanced methods in trend analysis in analyzing more sophisticated frauds.

Fraud in presenting the financial statements can be detected using techniques such as vertical and horizontal analysis, ratio analysis. Vertical analysis expresses the relationship of the items in the financial statements to the base amounts in the statements. Horizontal analysis reveals the dollar and percentage change of amounts in the financial statements. Ratio analysis concerns expressing one number over another to discover the relationship between them.

3. RESEARCH METHODOLOGY

This research adopts a case study approach. The prime aim of the study is to investigate how business intelligence within a systemic framework could be adopted for achieving proactive fraud detection in the financial reporting of a business case scenario. In order to achieve this objective, we develop and propose a framework for forensic financial accounting using business intelligence and use the accounting data from the case scenario to illustrate the practical implementation of the framework and analyse the results obtained. The framework proposed in this paper follows the general philosophy of Total Quality Management (TQM) framework for incorporating continuous improvement in a company's venture for financial fraud detection and control.

Traditional financial fraud detection methods assume that the auditor or fraud investigator is intelligent and possesses the required experience to apply reasoning and common sense to accounting transactions. When financial investigators conduct routine audits, they look for anomalies and conduct further investigations if the reasoning behind the accounting transactions does not make sense. While such an inductive approach could help in reactive fraud detection, with increase in high profile frauds being discovered recently, studies have reported the importance of adopting data mining techniques using outlier analysis and Benford's Law analysis, which includes sophisticated methods derived from statistics and artificial intelligence such as neural networks and regression analysis, to improve fraud detection rate (Durtschi *et al.*, 2004).

Data mining routines are being incorporated in specialised fraud detection components for software such as SAS, SPSS and even traditional audit programs such as ACL and IDEA. More recently, research studies suggest the use of new models, for example Zipf's law has significant potential for fraud detection as a supplement to other analysis techniques. Dedicated fraud detection programs in Picalo and other software packages such as EnCase and Forensic Toolkit (FTK) provide single purpose utilities for accounting fraud forensics. With such software, there is much emphasis given to: on one hand, the issues of flexibility such as dealing with different data formats, searching for graphics, and keyword search, etc., and on the other hand, the concerns regarding data security and privacy. Hence, studies related to such data mining tools are increasingly growing to embrace the various complexities of accounting fraud detection. However, more research is needed as an increasing number of researchers are finding that 'poor' corporate governance and business practices are resulting in manipulated financial reports. Little academic research has been done on the business analysis and investigative analysis that are required to analyse and correct any existing defects in the financial reporting system of a company. This would involve knowledge expertise of the business as well as investigative processes of the company, which predominantly deals with unstructured data. Business intelligence could handle such unstructured data and processes and could be adopted within a forensic investigation framework to help identify, interpret and rectify financial reporting defects and fraudulent business practices. Hence, there is a great need for a framework that provides a systemic guidance to forensic accountants in utilising their accounting, auditing, legal, and investigative skills and business intelligence proactively.

As the purpose of this paper is to formulate forensic accounting framework using business intelligence, underlying constructs and issues relating to financial accounting fraud, detection and analysis from literature were collected to incorporate these within the framework with a three-phase mechanism for continuous improvement feedback loop. To illustrate the implementation of the proposed forensic accounting framework using business intelligence, an interpretative case study approach is adopted.

4. PROPOSED FORENSIC ACCOUNTING FRAMEWORK USING BUSINESS INTELLIGENCE

At present, there are barriers existing for effective use of computer-based financial fraud detection approach. They do not conform to industry standards and they lack both integration with existing systems as well as alignment with individual business strategy or scope. As a first step to overcome these barriers, in this paper, we propose a forensic accounting framework using business intelligence (Figure 1) with three main data analytics phases for forensic accounting: 1. Business Analysis 2. Technology and Data Analysis and 3. Investigative Analysis.

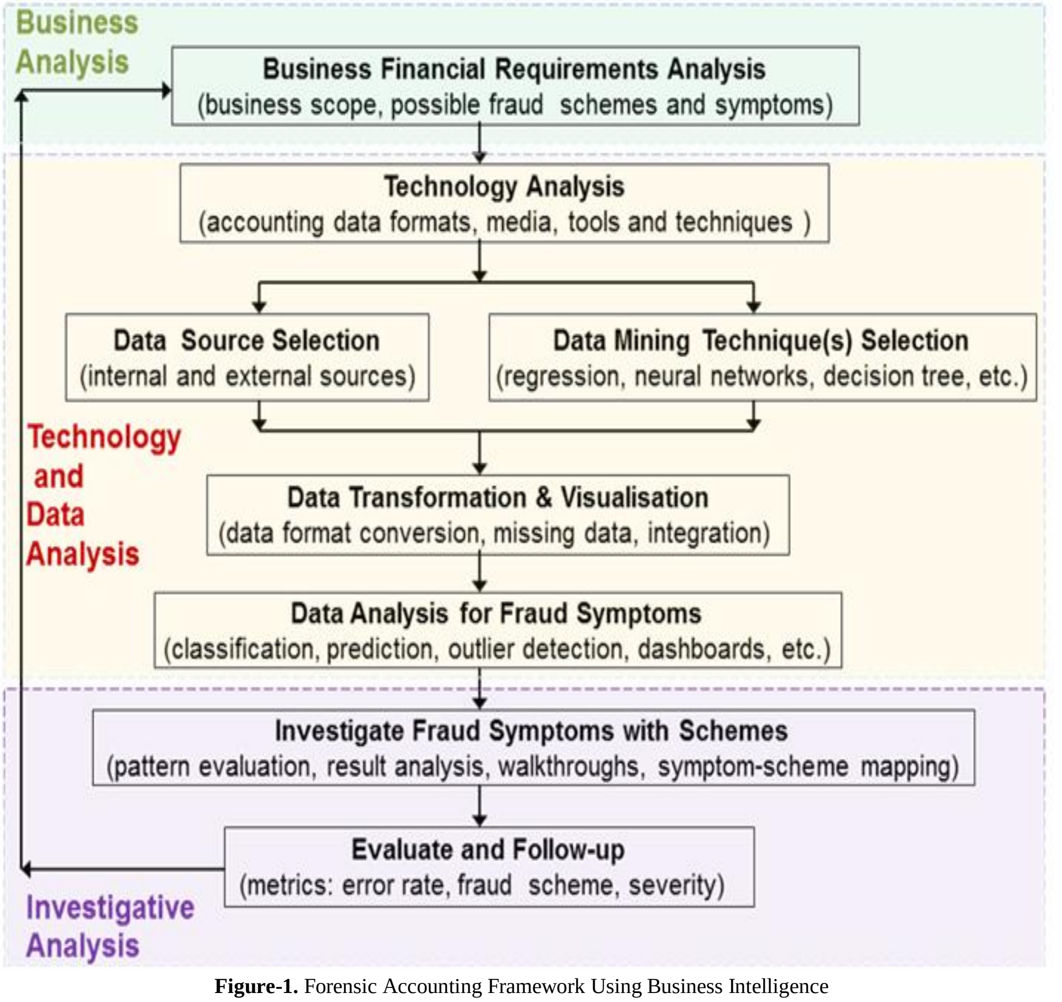

Figure-1. Forensic Accounting Framework Using Business Intelligence

Source: Our own

Phase 1: Business Analysis

This first phase involves understanding the specific business, its scope, operations and industry experiences in financial fraud. Apart from studying corporate policies and procedures, it also involves the various financial statements and possible fraud symptoms and schemes within the industry context. Financial frauds are committed in many ways predominantly through misrepresentations affecting a companies' financial statement for the purpose of deceiving the public, investors or regulatory bodies (Odueke and Weir, 2012). Some of the common ways of misrepresentation of a financial statement are:

- Asset Overstatement: Organisations could adopt different methods of providing a generalised picture by means of asset-based business valuation, which could be overstated in terms of their capabilities and strengths.
- Sales Revenue Overstatement: Businesses could overstate the sales figures in their profit and loss account to create an enhanced public image.

- Expenditure Understatement: Organisations could understate their costs and expenses so as to portray higher profit for attracting potential investors.
- Liabilities Understatement: Businesses could create an illusion through devaluation of their liabilities to project an increased equity or net worth.
- Accounts Misclassification: Businesses could misclassify their accounts to camouflage their true position in the market.

Fraud detection should focus on the controls, symptoms and schemes that are commonly adopted in the industry context as well based on historical practices of the specific business, and such information should be collected from a variety of sources, including internal and external auditors, management, and employees, and from published financial data (Fanning and Cogger, 1998; Spathis *et al.*, 2002). With each fraud scheme there could be a handful of symptoms associated and information technologies should be effectively used to store these data for analysis and inference drawn from the business data. By using this approach, it is ensured that the database queries for discovering fraud symptoms are linked together to higher-level business functionalities, goals and strategies. The business analysis of this phase would result in identifying the weaknesses present in their audit control mechanisms and the business knowledge gathered would serve as an input to the second phase of our business intelligence framework. Such business analysis when combined with the technology and data analysis of the second phase described below would provide the necessary avenue for a proactive fraud prediction and prevention.

Phase 2: Technology and Data Analysis

Typically, accounting data are in different formats, media and protocols required based on the processing platforms and tools adopted. Even within specific industry, there could be differences in techniques, business processes, databases, data types and relationships with other information systems (Grove and Basilico, 2008; Zhou and Kapoor, 2011). This second phase involves consideration of various technology differences to analyse and identify database relationships and schema to be made compatible for matching the accounting data sources with the data mining techniques for performing fraud detection as well as prediction that would aid in decision making (Bell and Carcello, 2000; Kotsiantis *et al.*, 2006). Data sources could involve internal and external, such as financial statements, audit reports, internal control, and account ledgers. These data may require to be converted into suitable formats, cleaned and sanitised for missing data and integrated with existing information systems. Industry knowledge gained from both fraud and non-fraud firms would assist the data mining technique in the form of training and testing data set. The data mining techniques such as regression, neural networks, decision tree, Bayesian belief network, Naïve Bayes, support vector machine, nearest neighbour, fuzzy logic, and genetic algorithm could be applied for the entire population of data leading to accuracy of results (Liou, 2008). Data mining techniques can be selectively applied to all the traditional mechanisms such as ratio analysis that are adopted for the detection of financial statement fraud, combined with the business analysis knowledge on the fraud symptoms and schemes of the specific industry. The data analysis for identifying fraud symptoms may adopt different data mining techniques depending on the requirements of classification or clustering of the fraud schemes or prediction and outlier detection (Yamanishi *et al.*, 2004; Perols, 2011). Our proposed business intelligence framework supports appropriate visualisation methods such as dashboards and wizards for auditors and management to easily simulate situations and make what-if queries quickly. The results of such a proactive technology and data analysis would serve as inputs to the third and last phase of the business intelligence framework, where fraud investigative analysis is performed.

Phase 3: Investigative Analysis

Based on the information and analysis gained from Phase 1 and Phase 2, this investigative analysis phase involves pattern evaluation, performing validations of the results, fraud symptoms and scheme mapping as well as use of industry metrics and error rates as benchmarks for identifying the fraud schemes and their severity. The auditors and the management should be able to perform automated visual walkthroughs to locate and correct anomalies. The results obtained in this phase would serve as meaningful feedback for the organisation to make improvements in their business practices, procedure, policies and control mechanisms. While traditional approaches are also aimed at achieving this, such approaches are constrained by time, technical knowledge and investigative experience of forensic accountants, requiring adoption of artificial intelligence techniques such as neural networks (Spathis *et al.*, 2002; Lin *et al.*, 2003; Kapardis *et al.*, 2010). In addition to automation and accuracy that results in timely fraud detection and improved decision making, our business intelligence framework adopts a feedback loop as shown in Figure 1 to follow through the three phases of analysis as part of continuous improvement in arriving at the industry specific best accounting practices.

The data from a company's financial reports are analysed within the three phases of the framework, namely Business Analysis, Technology and Data Analysis, and Investigative Analysis in order to step through the implementation process.

Financial ratio analysis is commonly used in identifying liquidity, solvency and profitability problems of an organisation. In this paper, we adopt ratio analysis to illustrate the application of our forensic accounting framework towards effective detection of errors and fraud and the ratios used for this purpose are listed below (Kimmel, 2005):

Current ratio indicates the short-term ability to pay debts and is defined as:

$$\textit{Current ratio} = \frac{\textit{Current assets}}{\textit{Current liabilities}}$$

Quick ratio is a measure of immediate short-term liquidity and excludes inventory and prepaid assets as follows:

$$\textit{Quick ratio} = \frac{\textit{Current assets - inventory}}{\textit{Current liabilities}}$$

Gross profit rate indicates the ability to maintain adequate selling price above its costs and is defines as:

$$\textit{Gross profit rate} = \frac{\textit{Gross profit}}{\textit{Sales}}$$

Inventory turnover reflects the effectiveness of inventory management and is calculated as:

$$\textit{Inventory turnover} = \frac{\textit{Cost of goods sold}}{\textit{Average inventory}}$$

Receivable turnover indicates the effectiveness of credit collection policies using a measure as follows:

$$\textit{Receivable turnover} = \frac{\textit{Net credit sales}}{\textit{Average net trade receivables}}$$

The current and quick asset ratios provide information on potential liquidity problems. The turnover and gross margin ratios are often helpful in identifying fraudulent activity or items recorded more than once, such as fictitious sales or inventory (Jubb, 2013). In addition to the above ratios, other segments of data were considered in understanding the effect on profit margin rates using ratios such as Income before taxes/Sales and Net income/Sales

5. FRAMEWORK IMPLEMENTATION AND RESULTS

1.2. Case Study

A company from the telecommunication industry that has been in existence for ten years has been chosen as the case study to illustrate the implementation of our framework for forensic accounting detection. The company has generally been successful in maintaining a competitive advantage in the industry, but a significant challenge it has been always facing is intense competition. In addition, it has always had unqualified audit opinions all these years, which makes it a good case to analyse its financial performance from its audited and unaudited financial statements. The financial statements containing actual and projected figures are considered (Jubb, 2013).

With the financial data collected from the case study, the three phases of our framework for forensic accounting fraud detection are followed through in order to identify symptoms of fraud. We perform various comparisons of the actual financial situation with the projected performance in all these phases and these are described next.

Phase 1 Implementation: Business Analysis

The phase 1 of the framework is implemented by applying the business knowledge analysis of business intelligence to understand the industry trends of the company, its business scope and operations to detect any patterns and anomalies of financial items over the past three years. Knowledge discovery techniques are useful for the extraction of fraudulent account behaviour in static data sets (Edge and Sampaio, 2009). From figure 2, we find the sales of the company decreases then increases.

The financial information of the company is given in Table 1.

Table-1. Financial Information of the Case Study

Statement of financial position (in thousands of dollars)				
	Projected 30/6/13	**Un-audited 30/6/13**	**Actual 30/6/12**	**Actual 30/6/11**
ASSETS				
Cash	1046	1146	1956	1339
Receivables	4200	4147	3053	2154
Provision for Doubtful debts	(241)	(240)	(213)	(211)
Net receivables	3959	3907	2840	1943
Stock	2787	3065	2592	2657
Other currents assets	656	635	826	801
Total current Assets	8448	8753	8214	6740
Property, Plant & Equipment	27116	26869	25877	23850
Other assets	2400	2413	2690	2556
Total assets	37964	38035	36781	33146
OWNERS' EQUITY				
Share capital	1624	1624	1624	1624
Retained Earnings	12943	12881	12417	11905
Total owners'	14567	14505	14041	13529
Equity Liabilities				
Accounts Payable	3710	3750	4093	2882
Current portion of long-term liabilities	1637	1624	1534	1355
Income taxes	277	383	296	300
Total current Liabilities	5624	5757	5923	4537
Long-term liabilities	17773	17773	16817	15080
Total Liabilities	23397	23530	22740	19617
Total owners'	37964	38035	36781	33146
Equity & liabilities				
Profit & Loss Statement (in thousands of dollars)				
	Projected	Un-audited	Actual	Actual
	30/6/13	30/6/13	30/6/12	30/6/11
Net sales	9643	9644	9630	9649
Cost of goods Sold	6875	6963	6828	6851
Gross profit	2768	2681	2802	2798
Research & Development Expenditure	212	163	150	128
Selling, general & administrative expenses	904	624	882	862
Profit from Operations	1652	1894	1770	1808
Other income	6	6	5	5
Interest expense	925	925	916	913
Other expenses	9	9	11	8
Income before Taxes	724	966	848	892
income taxes	289	386	382	384
Net income	435	580	466	508

Source: Our own

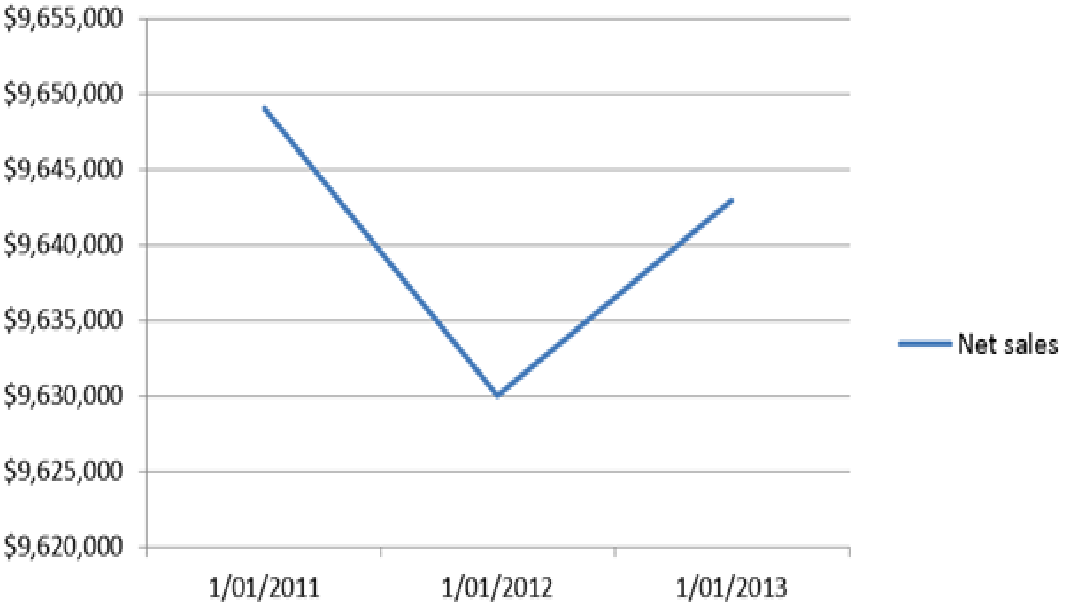

Figure-2. Net sales trend for the case study

Source: Our own

The selling, general and administrative expenses (figure 3) increases in 2011 – 2012 with sales (figure 2) decreasing in that period deserve investigation.

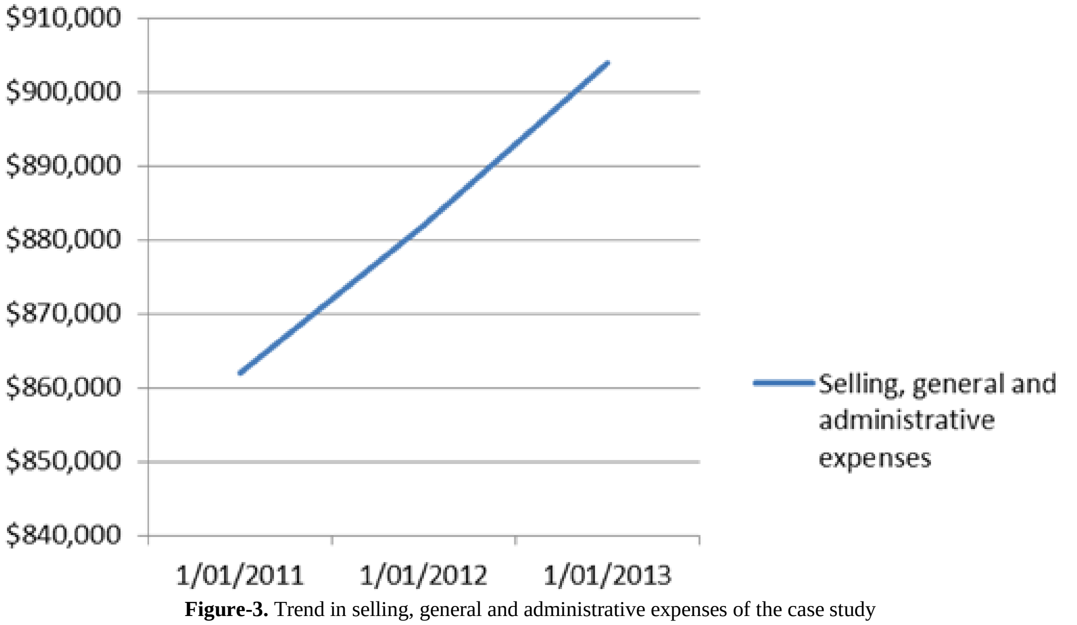

Figure-3. Trend in selling, general and administrative expenses of the case study

Source: Our own

Research and development expenditure increases (Figure 4). If the expenditure cannot bring forth revenue, it may drain away the financial resources of the organisation.

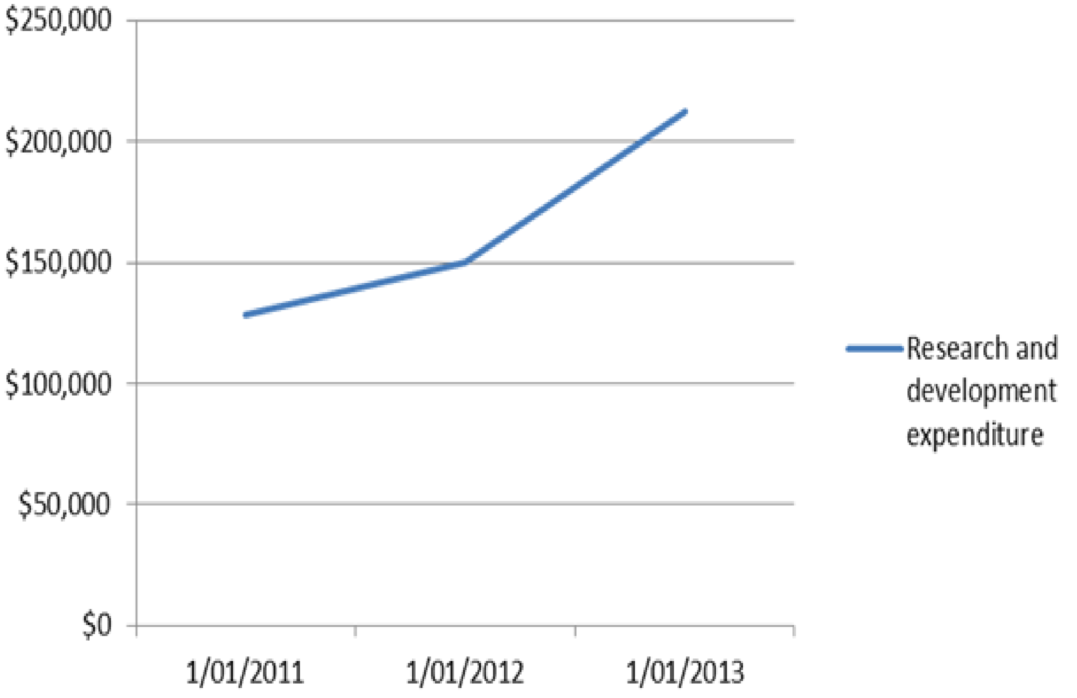

Figure-4. Research and development expenditure trend for the case study

Source: Our own

The decrease in net income (figure 5) and net income before taxes (figure 6) are due to the increase in expenses.

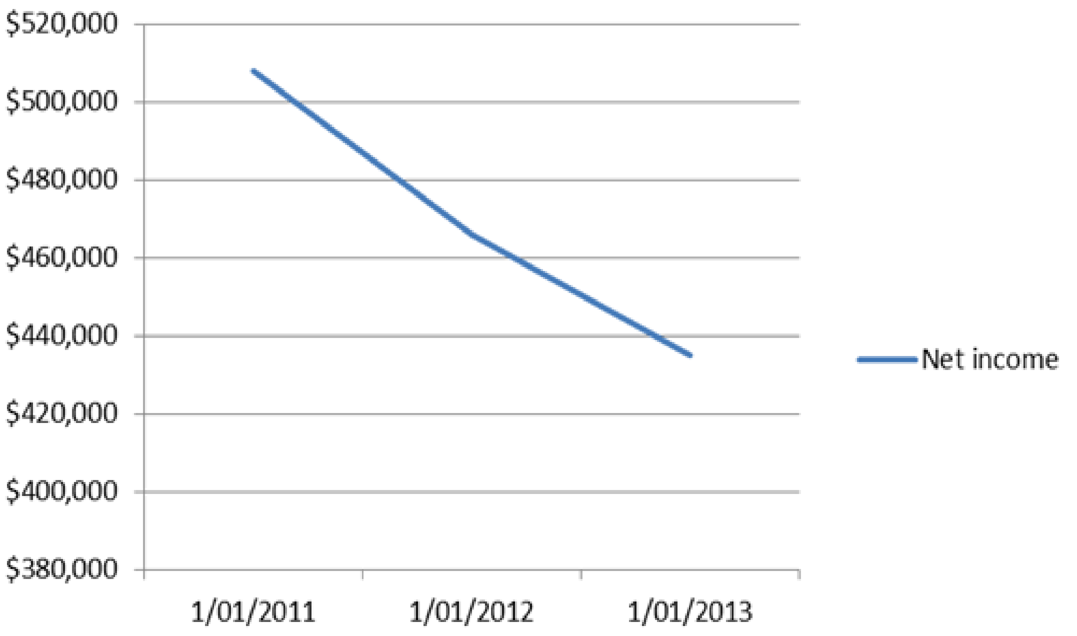

Figure-5. Net income trend for the case study

Source: Our own

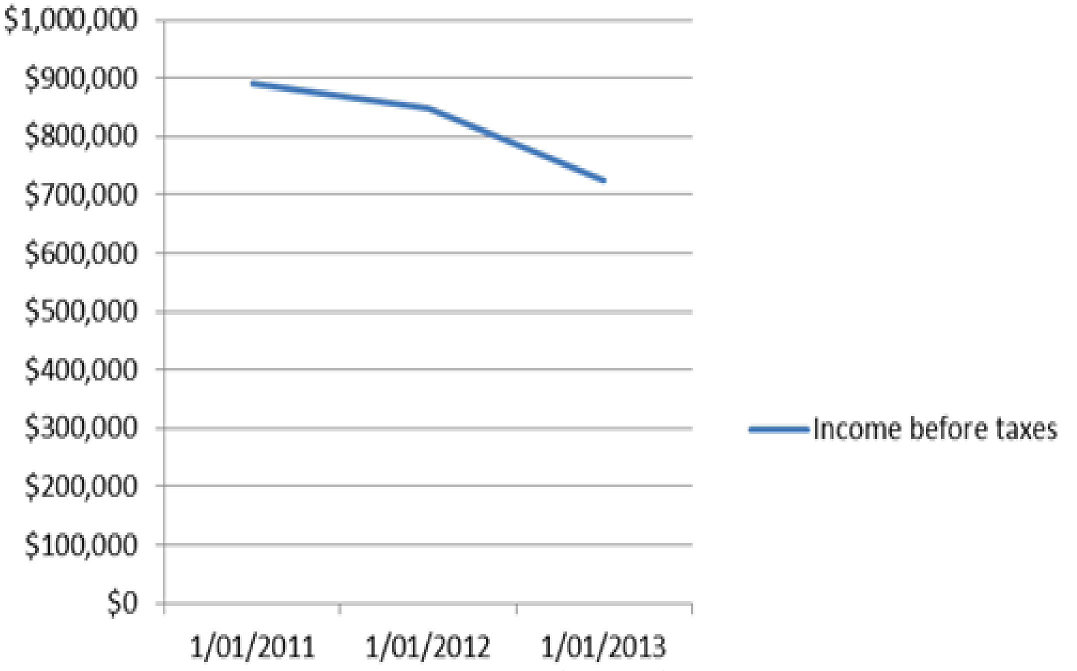

Figure-6. Trend in net income before taxes of the case study

Source: Our own

Figure 7 shows that cash decreases which has a negative impact on liquidity.

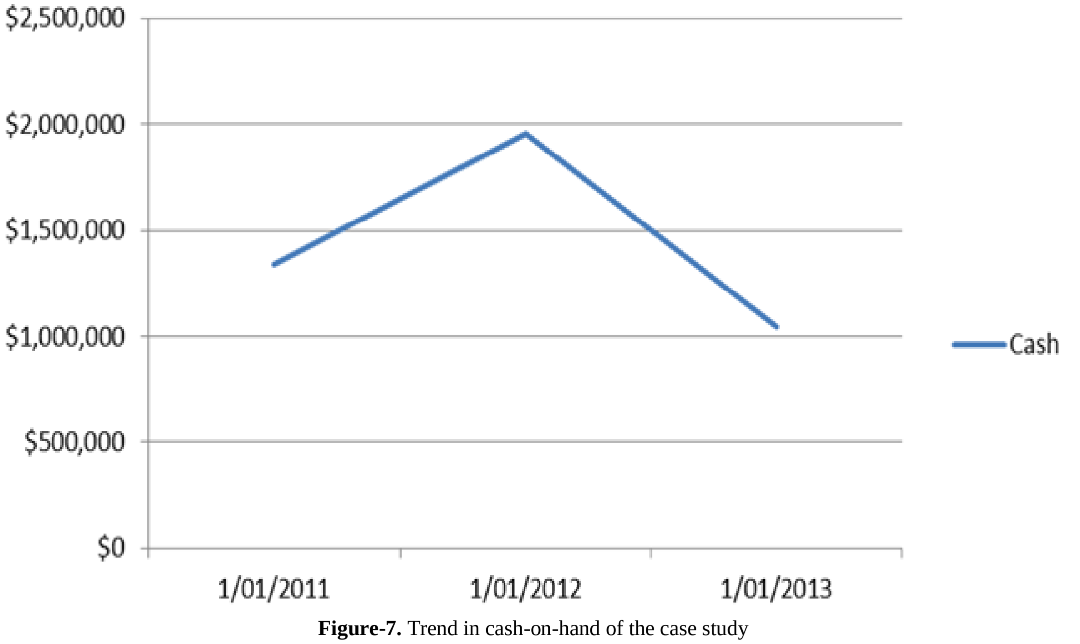

Figure-7. Trend in cash-on-hand of the case study

Source: Our own

As shown in figure 8, debt increases, which affects adversely the financial stability of the company. The company needs to borrow possibly due to the liquidity issue.

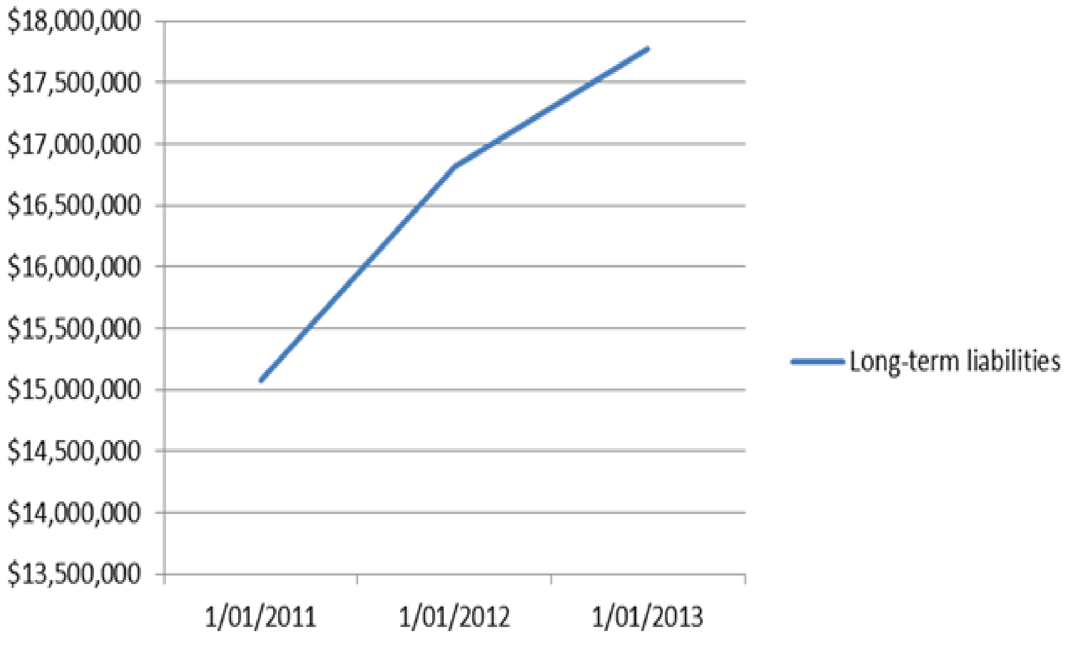

Figure-8. Long-term liabilities trend for the case study

Source: Our own

Figure 9 shows that the stock decreases and increases at a faster rate than that of the net sales (figure 2) indicates that there may be overstocking or that stock is overstated.

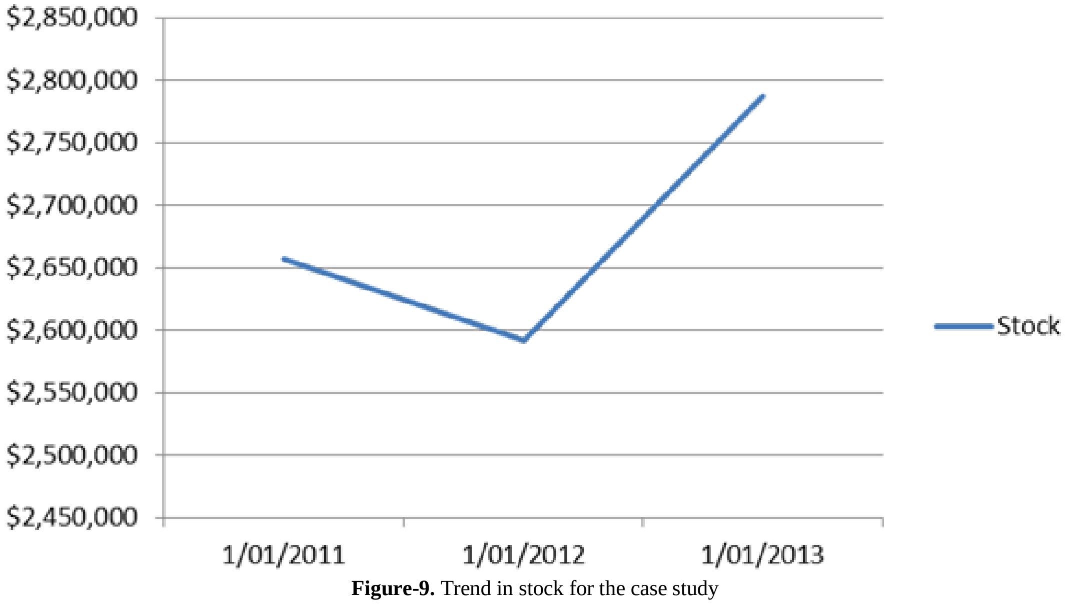

Figure-9. Trend in stock for the case study

Source: Our own

Property, plant and equipment (figure 10) increases. The asset need to be checked to see whether it brings in additional revenue to justify the increase in the investment or it may be overstated.

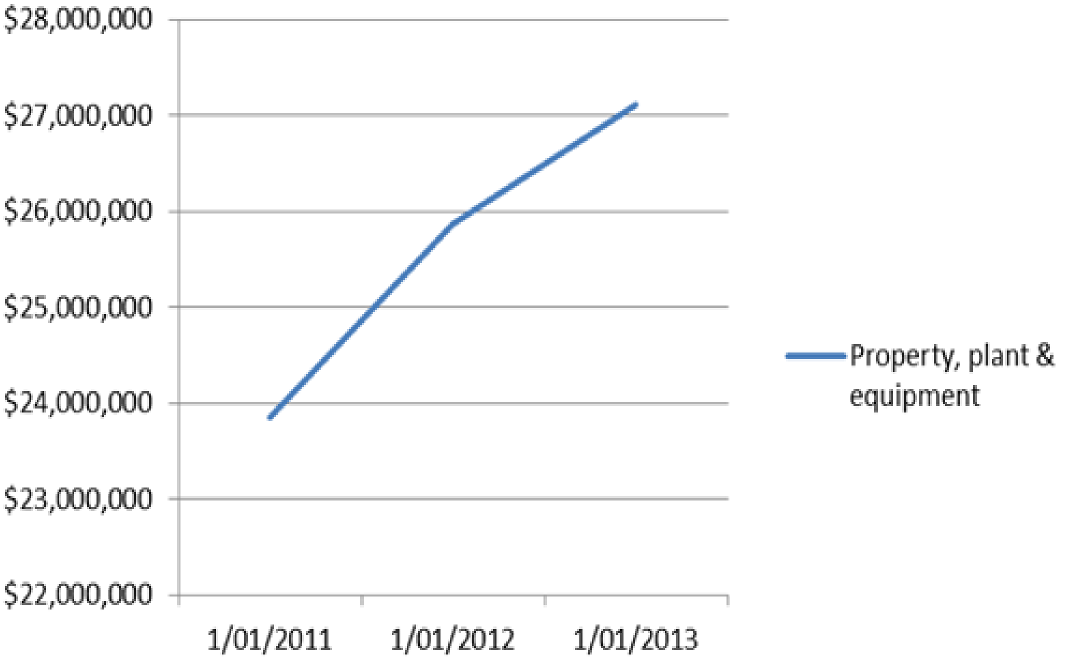

Figure-10. Trend in investment on property, plant and equipment of the case study

Source: Our own

Suspicion arises when the provision for doubtful debts (figure 11) does not increase in proportion to the increase in receivables (figure 12). The provision may be understated.

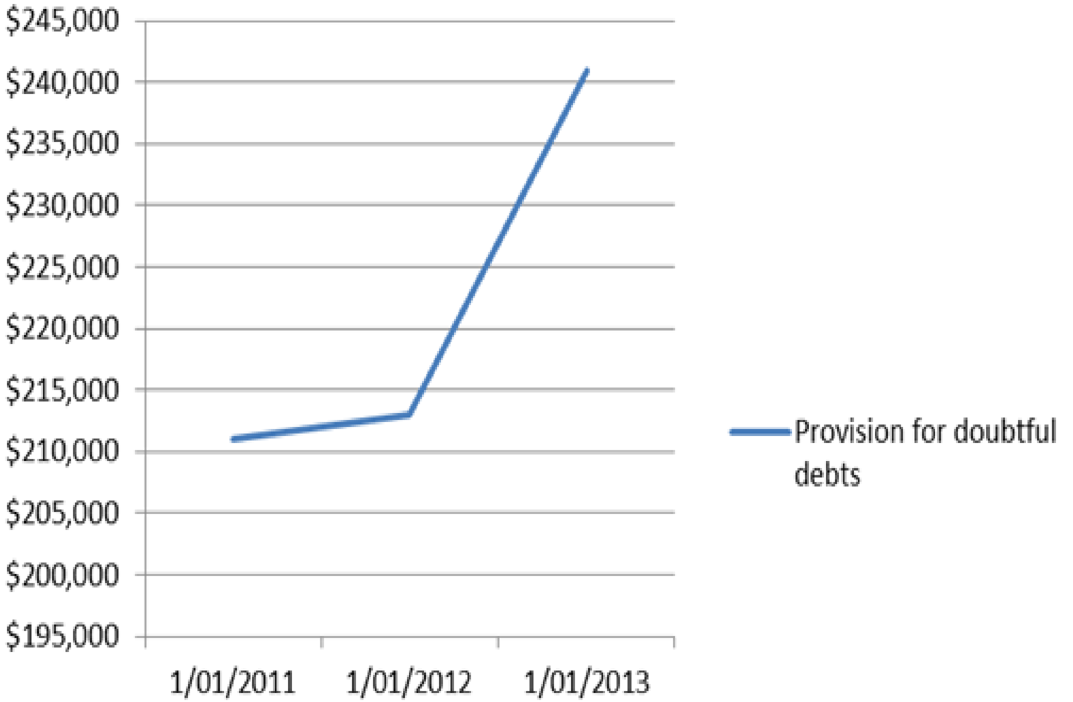

Figure-11. Trend in the provision for doubtful debts of the case study

Source: Our own

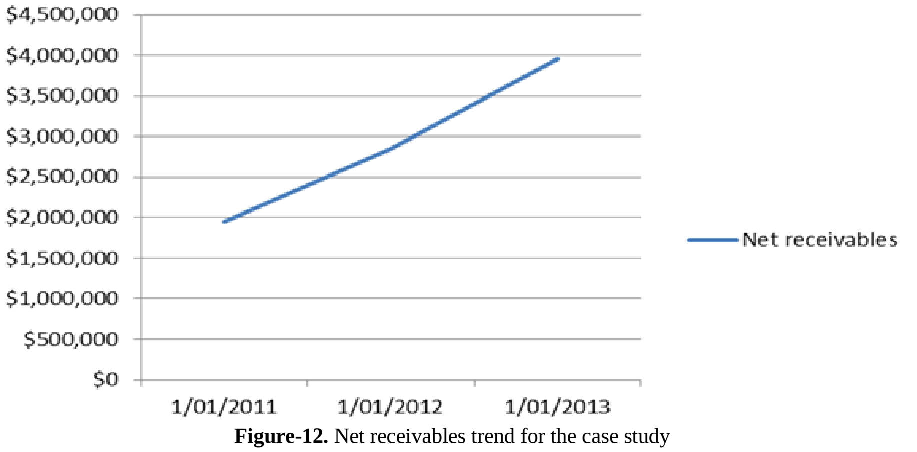

Figure-12. Net receivables trend for the case study

Source: Our own

Auditors should study the motivations for management to commit fraud. Situations such as remuneration based on performance, pressures to improve financial performance and financial position may lead to management fraud.

The scheme of understatement of expenses and overstatement of assets indicates that internal control is manipulated.

The weakness in internal control may be due to factors such as dominant management, absence of internal audit which require investigation by the auditor.

Phase 2 Implementation: Technology and Data Analysis

For the phase 2 implementation of the framework on technology and data analysis, financial ratio analysis is used to investigate fraudulent symptoms that could exist in the company. While some studies have used financial ratios with limited capabilities (Kaminski *et al.*, 2004) we have adopted key ratios that have been applied quite effectively in detecting accounting fraud (Grove and Basilico, 2008). Based on the financial statements of the case study, the financial ratios are prepared in Table 2.

Table-2. Financial Ratio Analysis

Financial Ratios	Projected 30/6/2013	Un-audited 30/6/2013	Actual 30/6/12	Actual 30/6/11
Current ratio	1.50	1.52	1.39	1.48
Quick ratio	1.01	0.99	0.95	0.90
Gross profit rate	0.287	0.278	0.291	0.290
Inventory turnover	2.47	2.27	2.63	2.58
Receivable turnover	2.44	2.47	3.39	4.96
Income before taxes/sales	0.075	0.100	0.088	0.092
Net income/sales	0.045	0.060	0.048	0.052

Source: Our own

The gross profit rate drops indicating problems with cost of goods sold and/or sales. Cost of goods sold may increase which is not matched with the corresponding increase in selling price.

The income before taxes to sales and the net income to sales decrease as gross profit rate decreases indicating the company may encounter operational difficulties.

The inventory turnover decreases leading to increase in inventory indicating the existence of overstocking.

The receivable turnover drops significantly affecting the liquidity of the company. The decrease in inventory turnover also adversely affects the liquidity of the company.

The increase in current ratio is partly due to the increase in inventory and receivables which are less liquid assets the ratio may not be a reliable indicator of improvement in liquidity.

The quick ratio rises partly because of the increase in receivables. Again, this may not truly reflect the true liquidity of the company.

Phase 3 Implementation: Investigative Analysis

Frauds such as contract rigging, duplicate bank accounts or defective shipments cannot be detected by mere business and digital data analysis and require further investigative analysis (Bierstaker *et al.*, 2006). Hence, the last phase of the framework concerns investigative analysis into trends, patterns and their evaluation. In this phase 3 implementation, operational problems and fraud issues are identified for the case study.

The increase in selling expenses with decrease in sales deserves the auditor's attention. Inefficient sales and promotion programs or overcharging of sales commission may be the explanation for such.

Research and development expenditure increases while sales decrease shows that the expense may not be productive. The auditor can look into the type of the expenditure to decide whether the right investment is made.

The auditor can look into the decreasing sales which may be due to factors such as decrease in demand or inefficient sales program.

The decrease in revenue affects the liquidity which triggers the increase in borrowing. The company is facing liquidity issues which the auditor should investigate.

Auditor should look into the decreasing receivable turnover which may be due to inefficient credit policy or collection of debts.

Inventory turnover slows requires auditor's attention. The issue may be due to decrease in sales or over stocking. Inventory may become obsolete and auditor need to check whether the stock reflect its true value.

5.2. Summary of Findings

Financial ratios are useful to compare the company's performance with that of other companies to see how the company stands in the industry and verify whether there is motivation to falsify the financial statements.

Fraud symptoms exist with the overstatement of inventory, property, plant and equipment and understatement of provision for doubtful debts. The motivation for this overstatement of assets and understatement of expenses may be due to the decreasing revenue projecting a negative image for the company. Hence, further investigation should be carried out into the investment of inventory, property, plant and equipment and provision for doubtful debts.

Concerning the provision for doubtful debts of the company, the auditor is recommended to check the ageing schedule of accounts receivables, by assessing the percentage of uncollectible amounts, comparing company's estimate with his own estimate and evaluating the subsequent collection of accounts receivables.

Further investigations into inventory should be carried out. The amount of the actual stock count should be reconciled with the stock records to identify overstatement of stock items.

When investigating into the investment of property, plant and equipment, the auditor is recommended to check whether the provision for depreciation is understated and whether property, plant and equipment have any sign of obsolescence leading to the overstatement of the value of the asset.

Projected ratios for 2013 are prepared to permit the auditors to have an objective view of the account balances based on the auditors' estimates. Where amounts in account balances are different from their estimates, explanations should be sought from management. However, the auditors need to bear in mind of the inaccuracy of the projections affecting the efficiency of audit or avoid losing scepticism if the actual figures are as projected.

Finally, the auditor should inform management of the discovery of these inefficiency, errors and fraud and advise management to investigate and take action. They should also follow up on ensuring management's measures of errors and fraud detection and prevention are effective.

6. CONCLUSION AND FUTURE DIRECTIONS

This paper has argued the need for a proactive detection of financial accounting fraud in response to the recent upsurge in high profile financial frauds committed by large companies in both developed and developing countries. To fill the gap we have proposed a forensic accounting framework using business intelligence with a three-phase analysis approach from the business, technology & data, and investigative perceptions of an organisation. A walkthrough of the proposed framework was demonstrated using a case study wherein ratio analysis was employed as a business intelligence tool in the successful detection of fraud areas identified within the organisation's financial reports. The results have shown that the technique is also useful to identify symptoms of fraud for management to take investigative follow-up actions paving way towards continuous improvement. Hence, this paper has taken a key step to bridge the gap between theory and practice of adopting traditional fraud detection such as vertical and horizontal analysis and has proposed new approach such as trend analysis using knowledge discovery techniques.

The paper has used only past three years' financial data of a company to illustrate how business intelligence is employed in the investigation of fraudulent financial reporting. As an ongoing research, we would consider investigating the effectiveness of the framework in the detection and prevention of financial accounting fraud based on larger data sets of a company collected over several years to be important for future research. In addition, the impact of such a proactive fraud detection approach in enhancing corporate awareness, influencing attitudes and changing accounting methods with regard to accurate financial reporting would be some of key future research directions.

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