Financial Statement Fraud Detection Using Ratio and Digital Analysis

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Financial statement fraud has had the most significant monetary impact on companies compared to the other categories of fraud. Over half of the financial statement frauds were committed through improper revenue recognition. According to a survey of 652 companies, revenue provides the greatest risk and impact to financial statements. The revenue recognition rules published by IFRS will not alleviate this concern. The purpose of this study is to analyze whether two analytical procedures described in fraud examination textbooks correctly identify known earnings manipulators.

FINANCIAL STATEMENT FRAUD

According to the Association of Certified Fraud Examiner's "Report to the Nation 2010" less than five percent of the total fraud reported by its respondents was categorized as financial statement fraud with a median loss of $4,000,000. In contrast, asset misappropriation is 90% of total fraud reported with a median loss of $135,000. A third of the total fraud reported is categorized as corruption with a median loss of $250,000. Several fraud cases included schemes in more than one category.

A major motivation for financial statement fraud is earnings management. When companies intentionally violate generally accepted accounting principles (GAAP) through earnings manipulation it is considered fraudulent financial reporting. Arthur Levitt, former Chairman of the SEC, believes that both earnings management within and outside of GAAP has a similar effect. The SEC's investigations and enforcement actions that require the restatements of these financial statements is considered fraud (Giroux 2004). Earnings management and its detection are areas that are of most interest to accounting professionals. Akers, Giacomino and Bellovary (2007, p. 65), defined earnings management as follows:

> Earnings management is recognized as attempts by management to influence or manipulate reported earnings by using specific accounting methods (or changing methods), recognizing one-time non-recurring items, deferring or accelerating expense or revenue transactions, or using other methods designed to influence short-term earnings.

According to Giroux (2004) there are three main reasons why management manipulates earnings: debt obligations, executive bonuses, and meeting stock analysts' expectations. The detection of earnings manipulation is important because earnings management adversely affects the economic decisions of external users of the financial statements: investors and creditors. In contrast to other categories of fraud, financial statement fraud does not necessarily involved the removal of cash. This does not necessarily mean that this type of fraud is any less harmful as illustrated by the high profile frauds of Enron, WorldCom, etc.

The SEC has given guidance to auditors through *Staff Accounting Bulletin No. 99 – Materiality* (SAB No. 99) (1999) [http://www.sec.gov/interps/account/sab99.htm] on the evaluation of the materiality of financial statement reporting and earnings manipulation. A major highlight of *SAB No. 99* includes the SEC directive that even though management may consider misstatements as immaterial, if the misstatements are intentional they are unacceptable. The SEC (1999, 7) states: "In certain circumstances, intentional immaterial misstatements are unlawful." The SEC (1999, 6) also cautions auditors not to accept material overstatements of revenue that are offset against material understatements of expenses. The intentional manipulation of earnings or its components is unacceptable.

This research study concentrates on revenue recognition. The Committee of Sponsoring Organization (COSO) sponsored research on fraudulent financial reporting from 1987 to 1997 (1999). They found that over half of the methods used to perpetuate financial statement frauds were in revenue recognition – recording revenue fictitiously or prematurely. The General Accounting Office's (GAO) in 2002 found that 38% of financial restatements from 1997-2002 involved revenue recognition. Cost or expense related issues constituted 16% of the cases.

REVENUE RECOGNITION IN IFRS AND GAAP

In an interview Kenneth Bement, assistant project manager at FASB, stated: that revenue recognition is one of the largest and most complex convergence projects of the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) (Johnson, 2007). Both Boards' revenue recognition rules are consistent in principle. IASB's revenue recognition standard is based on single standard applied to different types of transactions. FASB's revenue recognition standard comes from the conceptual framework and many pronouncements that make recognition more prescriptive. Different pronouncements give more specific guidance for particular industries (software and real estate) and based on different types of contracts.

The SEC is allowing international companies to report their financial statements using the international standards. The international standards allow for companies to recognize revenue to be more flexible in recognizing revenue. Where GAAP requires the amortization of revenue recognition, international standards will allow for revenue recognition up front. This has given international companies filing in the U.S. an advantage.

RevenueRecognition.com (2008) conducted a survey of 652 businesses (141 from outside the US). Companies do not believe that IFRS will simplify accounting for revenue nor do they believe that IFRS would reduce the risks of error or inaccuracies. Although they believe, expense reporting to have the highest risk for fraud, they also believe that fraud or errors in revenue reporting will have the greatest material impact to the financial statements. The switch to IFRS may result in greater earnings management by management through manipulation of revenue recognition.

OBJECT OF STUDY

The purpose for this research is to compare the effectiveness of two analytical procedures in detecting earnings management through revenue manipulation. Auditors could use these analytical procedures to determine earnings manipulation by current and future clients. The effectiveness of the analytical procedures as indicators of earning manipulation will be evaluated using the financial statements of companies that were identified by the SEC as having revenue recognition problems.

In recent years, there has been an increase in the number of textbooks specializing on Fraud examination and forensic accounting including numerous materials provided by the Association of Certified Fraud Examiners (ACFE) (Meier et al, 2010). Financial ratios and trend analysis are recommended by textbooks on fraud examination (Albrecht et al, 2009 and Giroux, 2004). This paper would like to examine the usefulness of detecting financial statement fraud using the analytical techniques covered in these textbooks.

Beneish's probit model incorporates the recommended ratio and trend analysis by comparing relationships of key financial statement items to indicate earnings manipulation. For example, one indicator compares the changes in number of days in receivables with the corresponding changes in sales.

Beneish's model is discussed further in another section. This method is more sophisticated than ratio analysis but still simple enough for the auditor to use.

Another method described in the fraud examination textbooks (Albecht, et al 2009) to detect fraud is digital analysis based on Benford's Law. Benford's research focused on the comparison of the actual frequency of some digits in different positions in a data set to the expected frequency. For instance, he calculated the expected frequency of the first digit position to be a "1", thirty percent of the time, a "2", seventeen % of the time, etc. He calculated the frequency of digits in the second position, third position. He contends that not all data sets follow this law. The data will not conform to his law when there are upper and lower limits where numbers are assigned or when the numbers are strongly influenced by human thought. These methods, Beneish and digital analysis, do not prove there is a fraud incurring, but indicates the need for further investigation into the company's financial information. In addition, both these methods are relatively inexpensive and easy to perform.

This research is presented as follows: description of selection of companies in this study; description of each analytical procedure and the results of the analysis; comparison and discussion of results; and the conclusion.

DATA SELECTION

In this study companies were selected that had participated in earnings management as identified in the SEC's Accounting and Auditing Enforcement Releases (AAER). AAERs from December 13, 1999 to June 17, 2008 (AAER numbers 1213 to 2839) were examined and yielded 116 firms that had revenue recognition violations. The revenue recognition violations were improper revenue recognition, fictitious sales, and bill and hold schemes. The relevant annual and quarterly financial statement data two years before the violation (t-1, t-2) and two years (t+1, t+2) after the violation were collected from Research Insight (COMPUSTAT). Prior studies mainly looked at earnings manipulation in the event year t. This focus only on the earning manipulation event year t sometimes resulted in a minor percentage of Type 1 errors wherein manipulators were classified as non-manipulators. This study attempts to look at the indicators for the year t-1 and t+1 to minimize Type 1 errors. The financial statement data for some companies were incomplete which decreased the sample size to 93 companies. Almost 30% of the companies identified as "earnings manipulators" were in the technology industry.

BENEISH'S PROBIT MODEL

Beneish (1999) developed a probit model to detect earnings manipulation. The model (1999, p. 24) captured "financial statement distortions or preconditions that might prompt companies to engage in such activity." He chose companies that had to restate their earnings to comply with GAAP (GAAP violators). He also sought a control group of companies that had large discretionary accruals and had increasing sales but were not identified as GAAP violators by the SEC. These companies were called "aggressive accruers." Since the aggressive accruers could also be GAAP violators, Beneish's probit model was considered conservative.

The variables Beneish chose to put in his model relate to financial information that would indicate whether earnings manipulation exists. His model examines relationship of changes in financial data from the year (t-1) before the earnings manipulation event is identified to the event year (t). The eight variables he included are:

1. Days sales in receivables index (DSRI). This index compares the change in receivables with the change in sales. An increase in the days in receivables could "suggest revenue manipulation." Beneish (1999)
2. Gross margin index (GMI). This index assesses the deterioration of the gross margin rate in the event year t as compared to the year t-1

3. Asset quality index (AQI). This measures whether the company has the propensity to record cost deferrals. It is calculated by comparing the change in noncurrent assets (excluding property plant and equipment) as a percentage of total assets.
4. Sales growth index (SGI). This index measures the growth in sales. According to Beneish (1999, p. 27), “growth companies are more likely than others to commit financial statement fraud, because their financial positions and capital needs put pressure on managers to achieve earnings targets.” There is an incentive for high growth companies to show increasing sales because it is expected of them. Any sign of a deceleration in sales growth usually adversely affects stock prices.
5. Depreciation index (DEPI). This index measures the change in depreciation rate from year t-1 to year t. If this is greater than 1, this means that the depreciation rate has slowed, which could mean that earnings are being manipulated upwards.
6. Sales, general, and administrative expenses index (SGAI). This index compares the percentage of sales, general, and administrative expenses to sales from year t-1 to year t. If the increase in these expenses are disproportionate, it is considered a “negative signal” (Beneish 1999) about a company’s future prospects.
7. Leverage index (LVGI). This index measures the debt to asset ratio from year t to year t-1. An increase in leverage can indicate a desire to manipulate earnings to meet debt covenants.
8. Total accruals to total assets (TATA). This ratio measures the proportion of earnings which are cash-based. The “higher positive accruals are associated with a higher a higher likelihood of earnings manipulation.” Beneish (1999)

Beneish applied his model to his holdout sample and found that the manipulators were 10 times more likely to manipulate earnings non-GAAP manipulators. He concluded that accounting information provides useful information to external users to assess the reliability of financial reporting and “potential manipulators can be identified for future investigation” (Beneish 1999, p. 34). For companies that manipulated earnings with improper revenue recognition, the following indices are important: DSRI, GMI, SGI, SGAI and TATA.

The eight variables were calculated for the 93 companies that had available information on Research Insight for a three-year period (t-1, t, and t+2, where t is the year of earnings manipulation). Beneish (1999) calculated the M-score for two probit models: one with 5 coefficients (the first five indices) and the other with 8 coefficients (with all eight indices). The M-score is calculated using the coefficients in Beneish’s models. The eight variables and M-score for each company were compared with benchmarks set by Beneish (1999). These benchmarks identified whether a company was a “manipulator” or “non-manipulator”. (See Barksy, Catanach and Rhoades-Catanach 2003 and Wiedman 1999).

The coefficients for the 5 and 8 variables are the benchmarks listed on the table of results in the next section. An M-Score of less than -2.22 suggests that the company will not be a manipulator. An M-Score of greater than -2.22 signals that the company is likely to be a manipulator.[1]

RESULTS OF ANALYSIS

The following table summarizes the percentage of companies identified as manipulators by each of the indices and the M- score.

TABLE 1
SUMMARY OF EARNINGS INDICATORS AND M SCORES FROM BENEISH (1999) AS A PERCENTAGE OF TOTAL COMPANIES*

									M-Score	
	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA	5	8
Benchmarks	>1.031	>1.014	>1.039	>1.134	>1	>1	<1	>0.018	>-2.76	>-2.22
Percentage of manipulators identified in										
t+1	28	53	44	43	33	51	25	15	44	24
T	42	44	52	63	42	45	54	28	62	46
t-1	48	37	48	63	45	20	45	32	47	43
Percentage of manipulators identified in t+1 and t-1 and not t	34	36	34	23	24	35	25	23	25	22
Percentage of manipulators identified in t+1 and not t	18	31	24	12	18	30	12	6	16	6
Percentage of identified in t-1 and not t	26	13	25	14	22	13	18	20	15	14
Percentage of manipulators identified in all three years	4	10	4	30	6	4	5	6	15	11
Percentage identified as non-manipulators in all three years	21	20	18	13	20	12	17	48	5	14

*Some do not add to 100% because of rounding and incomplete financial data for some companies.

The 5-coefficient M-score identified more companies as manipulators than the 8-coefficient M-score for year t, 62% compared with 46%. If the 5-coefficient M-score for year t-1 is included the percentage increases to 77%, if year t+1 is included the percentage increases to 78% and if all three of the years is included it increases to 87%. Beneish (1999) tested his model with a holdout sample and found that it misclassified 26% of the manipulators and 13.8% of the non-manipulators in his study The 5-coefficient M-score did a better job of classifying manipulators than the individual indices.

Beneish (1999) found the following indices as significant: DSRI, GMI, AQI, SGI and TATA. Earnings manipulation through improper revenue recognition should be detected by DSRI, GMI, SGI, SGAI and TATA. Taking into account the indices calculated for all three years, the indices identified correctly around 76 to 86% of the manipulators with the exception of DEPI (66%) and TATA (51%). If you take into account the indices calculated just for year t, the percentage of classifying manipulators accurately drops to between 42 to 63%.

The 5-coefficient M-score identified correctly a greater number of manipulators than the individual indices. This M-score combines the five indices: DSRI, GMI, AQI, SGI, and DEPI. However, the individual indices will give the auditor a valuable starting point when they conduct their analysis to determine the nature of the earnings manipulation.

The contribution of this study to Beneish (1999) is the use of indices in years t+1 and t-1 because it decreases Type 1 errors of classifying manipulators as non-manipulators. For the companies examined in this study, the inclusion of 5-coefficient M-score for year t-1 increased the classification of manipulators by 15%. Although an auditor who is examining a company's financial statements for year t would not have access to data in year t+1, the auditor could still calculate the indices and M-scores for several years prior to the fraud. This could still give them a greater indication whether a company is an earnings manipulator and which areas to examine and analyze.

DIGITAL ANALYSIS USING BENFORD'S LAW

In the 1930s, Benford studied a collection of numbers and observed that lower digits (beginning with 1) appear more often than the higher digits in the leftmost digit of a number. Benford's Law contends that the number 1 appears in the leftmost digit of a collection of numbers 30.1% of the time, number 2 appears 17.6%, while the probability of the appearance of a digit decreases to 4.6% for the number 9. He also calculated the probabilities of each number appearing as the second leftmost digit. Benford's Law could be used to detect fraudulent manipulation of a set of numbers when digital analysis indicates they do not conform to Benford's predetermined probabilities. Johnson (2005) compiled a list of characteristics of data that must conform to Benford's Law. These characteristics exclude data that have: built-in or assigned numbers, maximum or minimum values, the numbers that are assigned, and the numbers that have free or artificial limits. He also reviewed several studies that tested various data to see if they conform to Benford's law. The types of data included tax return data, and various financial statement information data including: revenue, income, and earnings per share quarterly data.

Carslaw (1988) was the first researcher to test accounting data using Benford's Law. He found that New Zealand companies demonstrated earnings manipulation by having an unusually high number of second digit 0s and a lower number of second digit 9s or 8s in their reported net income. He hypothesized that companies rounded their net income figures up. Thomas (1989) had similar results for U.S. firms. He found the opposite phenomena for firms with negative earnings. The firms tended to round down their negative earnings. In addition, Thomas studied earnings per share (EPS) data for these companies. He found that companies tended to round up by observing an unusually high proportion of positive EPS data that were in multiples of 10s and 5s. He found the opposite for negative EPS. Craig (1992) reported the tendency of U.S. companies to round up their EPS rather than down. Nigrini (2005) found that earnings manipulation was more prevalent during 2002 than 2001 by examining revenues and EPS information.

Quick and Wolz (2005) examined the financial statements of German firms for 5 years. They tested whether financial statement data points as a whole, and balance sheet and profit and loss statements followed Benford's Law. They found that a couple of years' balance sheet data points indicate non conformity to Benford's Law. Skousen et al (2004) studied earnings of Japanese firms and found similar evidence of rounding up for positive earnings and rounding down for negative earning. They examined the first, second and third digits of the data. Guo (1995) studied reported earnings in Korea and found that the unusual earnings patterns were for the purpose of reducing taxes and the maintenance of the company reputation.

Other researchers took a look at other accounting data such as taxpayer data (Christian and Gupta, 1993). They found that there was a bias for taxpayers in a higher tax bracket would look for additional deductions to decrease their taxable net income to qualify for the lower tax bracket. Nigrini (1996) took a look at tax evasion with emphasis on reported interest income and interest expense. He found that the data followed Benford's Law with a bias for lowering first digit interest income and the opposite for interest expense.

Nigrini and MIttermaier (1997) examined accounts payable data of an oil company through the use of a six digital analysis tests. Although the data followed Benford's Law, the additional tests revealed an anomaly from one of the vendors. Using Benford's law, Reed and Pence (2005) compared 65 observable data points of the original financial information over a two-year period for a company that committed fraud with the corresponding data points for the restated financial information for the same two years. They performed a chi-square test to compare the original and restated data and found that digital analysis did not indicate the existence of fraud.

In this study financial data was analyzed of those companies identified as revenue manipulators. Unlike most of the previous studies this study will analyze a single financial data point for each company separately. All of the datasets examined consisted of revenue, earnings, and EPS data of companies for a given year. This study examines whether quarterly financial statement data (revenue, earnings and EPS) for a single company conforms to Benford's Law. Only companies with ten or more available quarterly financial information are examined. Similar to prior studies (Thomas 1998, Nigrini 2005), a second digit analysis is done on revenue and earnings (positive) to determine if there are more 0s and fewer 9s in the second digit (from the left). The incidence of EPS with multiples of 10s and 5s is also analyzed.

Results of Analysis

A second digit analysis was performed on the quarterly revenue numbers reported by fifty-seven companies to determine whether there was any evidence of rounding up indicated by the presence of more 0s than 9s in the second digit.

TABLE 2
RESULTS OF DIGITAL ANALYSIS: SECOND DIGIT REVENUES

Total number of companies analyzed	57	%
Number of companies with greater 0s than expected	21	37
Number of companies with greater 9s then expected	27	47
Number of companies with both greater 0s and 9s than expected	9	16

The second digits in the quarterly revenues reported by the fifty-seven revenue manipulator companies are examined. The results show that less than half of the companies show evidence of rounding-up or manipulating revenues as indicated by 37% of the companies with greater 0s than expected. On the other hand there, 47% of the companies showed results with greater than 9s than expected which does not indicate evidence of rounding.

In addition, the mean absolute deviation (MAD) was determined for each company. MAD is the summation of the absolute value of the difference between the actual value (or digit) and the expected value divided by the number of quarters in the sample. Drake and Nigrini (2000) used MAD to classify the conformity of the dataset to Benford's Law, as follows:

Rate of Mean Absolute Deviation (MAD)	Second digit
Close conformity	0.000-0.008
Acceptable conformity	0.008-0.012
Marginally acceptable conformity	0.012-0.016
Nonconformity	Greater than 0.016

All of the MADs calculated for each company' quarterly revenues were greater than 0.016. The average MAD for all fifty-seven companies was 0.046. The results of the digital analysis and the MAD calculation do not give a clear indication that revenues were manipulated.

More than fifty percent of the companies experienced net losses. Companies were grouped into those with positive income and those with losses. We would expect the companies that have a positive net income to round up and those with losses to round down. Some companies experienced both income and losses and were put in a group depending on whether they had ten or more companies with income or losses. For example company 1 had 24 quarters of financial information and experienced 12 quarters of income and 12 quarters of losses. The losses were analyzed together with other companies that had losses and the quarters which showed income were analyzed together with other companies with income.

Table 3 shows that there were twenty companies that had ten or more quarters of positive EPS. Ten percent of the companies tended to round up income. The Mean Absolute Deviation (MAD) for all 20 companies showed nonconformity with Benford's Law.

TABLE 3
RESULTS OF DIGITAL ANALYSIS: SECOND DIGIT POSITIVE EARNINGS PER SHARE

Total number of companies analyzed	20	%
Number of companies with greater 0s and 5sthan expected	11	55
Number of companies with greater 9s then expected	5	25
Number of companies with both greater 0s and 9s than expected	3	15

A little over fifty percent of companies with a positive EPS for at least 10 quarters showed a tendency to round up EPS figures to a multiple of 10 or 5. One company's EPS figures were either a multiple of 10 or 5.

Table 4 shows the results of the analysis of 25 companies that experienced ten or more quarters of negative EPS. There were only 8 companies that exhibited the tendency to round down.

TABLE 4
RESULTS OF DIGITAL ANALYSIS: SECOND DIGIT NEGATIVE EARNINGS PER SHARE

Total number of companies analyzed	25	%
Number of companies with fewer 0s than expected	8	32
Number of companies with greater 4s or 9s then expected	8	32
Number of companies with both fewer 0s and 9s than expected	1	4

Almost fifty-five percent of the companies with a negative EPS for at least 10 quarters showed a tendency to round down EPS figures to a last digit of 4 or 9. Around 17% of the companies did not have a 4 or 9 as a last digit in any of the quarters in the data set.

A digital analysis of revenues did not reveal the tendency of "earnings manipulators to round up their reported quarterly revenues as evidenced by the number of 0s and 9s in the second digit. All second digits were examined without regard to the magnitude of the revenues. The examination of the second digit or the third digit depending on the magnitude might provide different results. For instance a company with revenue of $24,030,000 might be rounding the third digit to 24,100,00 while a company with revenue of $2,004,000 might be rounding the second digit.

A digital analysis of positive EPS figures showed that 55% of the companies tended to round-up their EPS figures. The opposite was not evident with an analysis of negative EPS. Companies with negative EPS did not show a tendency to round down losses. This study analyzed companies' revenues and EPS data with as little as 12 quarters. Better insight as to the efficacy of digital analysis could be done with more quarterly data or even monthly data, which would be available in an audit.

CONCLUSION

Although both methods of analysis did not identify all the earnings manipulators as "earnings manipulators", these two analytical tools are easy to use and interpret. It can quickly identify companies that might need further investigation. Knowledge of the company, its management/employees, internal control procedures and environment will also be necessary to determine whether financial statement fraud is present. One limitation of the study is that it does not determine whether "non-manipulators" are correctly determined as "non-manipulators."

Beneish's probit model did a better job of identifying 62% of the companies (using the 5 coefficient model) in the year of manipulation and an additional 15% of the companies could be identified when analyzing manipulation indicators in the year before the manipulation. Beneish's model's coefficients could be calculated periodically to recalibrate the benchmarks. Digital analysis or Benford's law should be further studied to see if it is an effective detector of earnings manipulation. One way is to look at more datasets or monthly data. Auditors can easily perform analysis with both of these analytical procedures. Analysis to see if data conforms to Benford's law is included in IDEA and ACL so it would be relatively easy to use.

Revenue recognition is an important issue to accounting professionals, FASB and the IASB. The new IFRS revenue recognition rules will impact US and international companies. International companies are allowed to use IFRS rules by the SEC without reconciliation to GAAP. This allows some revenues to be recognized earlier which would disadvantage U.S. firms. GAAP pronouncements covering the technology industry arose partly because of the revenue recognition problems and the complexity of the various revenue streams in this industry. Thirty percent of the companies identified as "earnings manipulators" by the SEC's Auditing and Accounting Enforcement Releases in the period under study are in the technology industry. Recent articles indicate that U.S. companies although they find GAAP more burdensome prefer to report using GAAP rules because they understand it. This might change with pressure for companies to show higher earnings especially in this economy.

ENDNOTES

1. (http://www.investopedia.com/ terms/b/beneishmodel.asp)

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