

An Historical Perspective on Fraud Detection: From Bankruptcy Models to Most Effective Indicators of Fraud in Recent Incidents

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Why are auditors unable to detect fraudulent financial reporting in some audits? Should auditors be able to first anticipate and then detect fraud? Even if fraud cases are relatively few among the number of audits performed each year, they certainly get the most attention. Fraudulent financial reporting (FFR) arises because the top managers reporting accounting numbers intentionally misrepresent underlying economic conditions to advance their own economic interest. The auditing profession over the years has developed its own set of tools to unravel such misrepresentations and to ensure that financial statements are in accordance with generally accepted accounting principles. However, when major fraudulent events have escaped detection by auditors, these standards have often been supplemented with additional rules by the SEC and by the U.S. Congress (Baker et al., 2006). In addition, accounting practitioners and researchers have formulated various decision models to aid in the detection of fraud.

Various studies have shown the use of these decision models, and expert systems, for fraud detection and the study of internal controls (Lenard and Alam, 2004; Lenard, 2003; Bell and Carcello, 2000; Whitecotton and Butler, 1998; Eining, Jones, and Loebbecke, 1997; Bonner, Libby, and Nelson, 1996; Hansen et al., 1996; Persons, 1995; Bell, Szykowny, and Willingham, 1993; Pincus, 1989). There are also a number of closely related studies that use decision models to predict bankruptcy, or financial stress. Notable studies are by Altman (1968), Ohlson (1980) and Beaver (2005). These models for detecting financial stress are important in the development of fraud detection models for two reasons. First, bankruptcy is sometimes a result when companies commit fraud. Second, companies that have filed for bankruptcy protection are more likely to be prosecuted for fraud since the temptation to commit fraud

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is higher at a financially troubled firm (Johnson, 2008). In recent years, studies by Persons (1995) and Lenard and Alam (2004) described models that were developed specifically to detect fraud.

The purpose of this paper is to examine the development of fraud examination and detection models over the years, and determine their relative usefulness. We first examine regulation regarding fraud and the evolution of statistical models in the accounting and auditing literature designed to measure financial difficulties and fraudulent financial reporting. Next, we test the usefulness and present a comparison of several specific models using company data from two different time periods representing recent incidents of fraudulent financial reporting. Finally, we present our conclusion and make suggestions for future action.

BACKGROUND

Following the recommendation of the *Committee of Sponsoring Organizations*, consideration of internal control has become part of the audit with the issuance of the *Statement of Auditing Standard (SAS) No. 78* (Auditing Standards Board, 1995). In addition, the Sarbanes-Oxley Act of 2002 (SOX) mandates the evaluation of internal controls and an opinion by external auditors. Since SOX established the Public Company Accounting Oversight Board (PCAOB), recent papers have focused on the interaction between the accounting profession, the SEC, and the U.S. Congress. A study by Baker et al. (2006) examined SOX from an institutional perspective. The authors reviewed how historical events led to various institutional developments that led in turn to changes in accounting and auditing practices. The authors concluded that this process, which involves the interaction of U.S. politics with the development of accounting rules, indicates a legitimate need for regulation of the accounting profession by the SEC and the U.S. Congress. In contrast, Lenard et al. (2005) surveyed accountants for their perceptions of the role of the SEC, the FASB, and the U.S. Congress regarding the regulation of the accounting profession. The results showed that those surveyed believed that the SEC should take a more active role in standard-setting when there is earnings manipulation or when the FASB's standards are not adequate or timely.

However, the respondents in the survey felt that the U.S. Congress should only get involved if external auditors are not independent (Lenard et al., 2005).

The study by Baker et al. (2006) investigated three major events: the McKesson scandal in 1938, the Savings and Loan (S&L) failures in the 1980's, and the failure of Enron in 2001. In response to the McKesson scandal, the accounting profession issued revised standards for observation of inventory and confirmation of receivables. Following the S&L failures, the government held hearings chaired by Moss, Metcalf, and Dingle, and a new series of accounting standards were issued that attempted to cover the "expectations gap" between public perception and the audit of financial statements. Finally, the response to the Enron failure was the 2002 Sarbanes-Oxley legislation. Our paper examines the fraud detection models that have been developed in response to these events.

Following the events mentioned above, the success of any fraud detection model used by accountants would indicate that regulation efforts played a part in the improvement of the fraud detection process and led to a successful response by the accounting profession to re-establish itself in the public interest, whether in response to the increased government regulation or by self-motivation. Success of improved fraud detection models would also reinforce the stability of the U.S. accounting framework and the proper functioning of specific entities within the U.S. economy.

LITERATURE REVIEW

Literature and accounting practice through the 1960's and Altman's model

While there was a "royal auditor" position in Britain even in the 1400's, and while the British investors sending colonists to America used accountants, auditing became more formal in the U.S. and Britain with the revision of the British Companies Clauses Consolidated Act in 1845. The provisions of this act authorized outside expert auditors to assist in audits by shareholders (Flesher, Previts, and Samson, 2005). The focus of accounting and auditing in the early 1900's was on eliminating fraud and defalcation from financial statements. In 1906, the editor of the *Journal of Accountancy* called for public

accountants to contribute the results of their professional experience (Johnson, 1906). He noted that these experiences would bring up points of practice, which would be of value to the members of the profession.

In the late 1930's, Himmelblau (1933), Tirrell (1936), Brady (1938) and Greeley (1938) all discussed the responsibility of auditors to third parties. Tirrell (1936) explained the SEC rules, issued in 1935, that required financial reports to contain full disclosure of elements included in the income accounts. Brady (1938) noted that after the Ultramares vs. Touche fraud case in 1931, untrue certification of fact was a sufficient basis for determining liability for fraud. At the end of the decade, there was another case of fraud when McKesson & Robbins falsified their financial statements. Following the McKesson scandal, Seidman (1939) declared that the only way to prevent fraud was through internal controls and by employing outside auditors.

By the 1950's, there were explanations of the development and use of statistical techniques for auditing (Vance, 1951). Moving on to the 1960's, a number of authors (Fess, 1963; Chaps, 1966; Blake, 1967; Simon, 1965) discussed fraud in the balance sheet. Employing financial variables developed through analysis of the balance sheet, Altman (1968) was one of the first to publish a study that used a statistical model (specifically, discriminant analysis) to predict bankruptcy. As mentioned previously, detection of bankruptcy is closely related to fraud detection because analysis of the financial statements to detect potential bankruptcy can also detect fraud. The theme of Altman's paper was to bridge the gap "between traditional ratio analysis and the more rigorous statistical techniques which have become popular among academicians" (Altman, 1968, p. 589). He used financial ratios as variables in his discriminant model. The ratios were those intended to analyze liquidity, profitability, leverage, solvency, and activity. Altman's overall prediction accuracy for his sample was 95 percent. The success of his paper reflects the robustness of multiple discriminant analysis in financial applications.

Literature, accounting practice and regulation in the 1980's and Ohlson's model

In 1980, Ohlson (1980) published his study that used a decision model to detect bankruptcy, this time using logistic regression as opposed to Altman's discriminant model. As with Altman's model, the

prediction accuracy for each of the three models tested in Ohlson's study was greater than 90 percent (Ohlson, 1980). Instead of a "score", as in Altman's model, Ohlson promoted his model as one which developed a probabilistic estimate of failure. He also used financial ratios as his variables, and these ratios fell into the categories of liquidity, leverage and profitability. He did, however, have several "qualitative" variables, where the variable was coded as a zero or a one based on a particular condition. These variables were intended to provide more explanatory power to the model.

Following Ohlson's study, the late 1980's were a time of the failure of many savings and loan institutions, which led to the Moss, Metcalf, and Dingle Congressional hearings and the passage of additional accounting standards and regulations to manage the "expectations gap," in an attempt to align the interest of the investing public with that of the performance of accounting firms. Following these events, Booth et al. (1989) used a robust multivariate procedure aimed specifically at savings and loan institutions. The model was intended as an "early warning" model, and was able to identify problem savings and loan institutions as "outliers" in their sample. The authors used two profitability measures and a leverage measure in their model, selected because consistent losses and high leverage often lead a firm into bankruptcy.

Literature, regulation and fraud detection models in the 1990's and beyond

The 1990's was a decade when decision models were often developed to specifically examine fraud, not just bankruptcy. Beasley (1996) completed an empirical analysis of the relationship between the board of directors' composition and financial statement fraud. Persons (1995) used a logistic regression model to successfully identify factors associated with fraudulent financial reporting. Persons' model was developed using publicly available financial information, so it was similar to what Altman (1968) and Ohlson (1980) had done for their bankruptcy studies. Persons used ratios for financial leverage, profitability, liquidity, capital turnover, and size – similar to those used in bankruptcy studies. She also used the Z-score from Altman's model. In addition, she used ratios that reflect asset composition – current assets divided by total assets; receivables divided by total assets, and inventory

divided by total assets. These ratios reflect the fact that fraud firms' financial statements often report current assets that consist mostly of receivables and inventories, which are likely overstated (Persons 1995). Success rates in terms of prediction accuracy for Persons' study were as high as 97 percent.

In the *Journal of Accountancy*, Hall (1996) discussed how to spot fraud and Herman-Hoffman, Morgan, and Patton (1996) discussed the warning signs of fraudulent financial reporting. Bell and Carcello (2000) also developed a decision aid for assessing the likelihood of fraudulent financial reporting. The effect of accounting standards was evidenced by the release of Statement on Auditing Standards No. 82, *Consideration of Fraud in a Financial Statement Audit* (AICPA 1997). Later that year, Zimbleman (1997) and the *Journal of Accountancy* (Anonymous, 1997) discussed the effects of SAS No. 82, which focused auditors' attention on fraud risk factors and audit planning decisions.

The trend of articles on computer models for fraud detection and internal control continued into the 21st century. Lampe (2002) suggested data mining as an audit tool, and Lenard and Alam (2004) described a model based on data mining that could be used to detect fraud. Financial variables for leverage, profitability and liquidity were included, along with a cash flow variable and a variable designed specifically to represent a company's risk of fraud. The variable was developed using fuzzy logic to quantify fraud risk factors identified by the guidelines in SAS No. 82 (1997). The model had an overall prediction accuracy of 86.7 percent. While additional articles were written describing how to detect fraud and the effects of fraudulent financial reporting (Beaulieu, 2001; Church, 2001; Church, McMillan, and Schneider, 2001; Newman, Patterson, and Smith, 2001; Montgomery, 2002; Rezaee, 2002; Thomas, 2002; Verschoor, 2002), Beaver et al. (2005) published a study emphasizing the ability of several robust financial ratios to predict bankruptcy. The authors used a model based on just three financial variables and were able to predict bankruptcy with significant results for companies over a 40-year time period.

Also passed during this period was the Sarbanes-Oxley legislation (SOX 2002), and Statement on Auditing Standards (SAS) No. 99 was adopted as an update to SAS No. 82. The Sarbanes-Oxley Act went into effect to address widespread outrage and waning investor confidence resulting from a series of

financial disasters, earnings restatements, and other corporate and accounting abuses (Hein et al. 2002). The legislation requires reports on the sufficiency of a public company's internal control system. In addition, to restore trust of investors and the general public in the accounting profession, the Public Company Accounting Oversight Board (PCAOB) was established in conjunction with SOX. The PCAOB was established to police the accounting profession's audit of publicly traded companies (Tackett et al. 2006). The PCAOB is required to carry out audit inspections periodically and report on those inspections with respect to the professional standards and policies of the PCAOB and the Securities Exchange Commission (SEC). The PCAOB inspections are regarded as assessments of the accounting firm's audit quality and other related matters that are vital to the framework of the firm. The requirements of the SOX legislation were promoted to enhance the use of SAS No. 99 (2001), which instructs auditors to look for "red flags" in situations with a client that may indicate financial reporting fraud. Academic research continued, using these new guidelines as a basis for the investigation and development of fraud detection models. Lenard, Watkins, and Alam (2007) developed a model for detection of financial statement fraud that used a combination of financial statement data, readily available non-financial information, and a variable constructed by quantifying the statements of SAS No. 99 using fuzzy logic. The authors adapted the model from the Lenard and Alam (2004) study to include the guidelines for recognizing "red flags" in the financial statements as described by SAS No. 99 (2001). In addition to the variable that represented the risk of fraud, the authors found that the financial variables that most successfully distinguished between fraud and non-fraud companies were financial variables for cash flow, liquidity, the ratio of sales to assets, and an indicator of company size. The model had a prediction accuracy of 76.7 percent.

In additional literature that examined fraud, Grove and Basilico (2008) studied key ratios and found that ratios which examined days' sales in receivables, gross margin, asset quality, sales growth, and changes in accruals were more likely to detect situations of fraudulent financial reporting. Liou (2008) indicated that many financial variables are effective at detecting both bankruptcy and fraud, but ratios that examine capital turnover, accounts receivable, inventory, and other indicators of asset composition and

liabilities (fixed assets / total assets, total liabilities / total assets, and working capital / total assets) are more likely indicators of fraud. In terms of whether increased regulation is needed, de Mesa Graziano and Heffes (2008) have indicated that the current regulatory structure, which includes the United States Financial Accounting Standards, may still be needed for consistency and comparability purposes, as opposed to rushing too soon to implement International Financial Reporting Standards. These assessments of legislation and improvements in computer models continue to emphasize the CPA's original duty to search for defalcations, as spelled out in the early years of the accounting profession (Johnson, 1906).

DATA AND MODELS

Our research uses the models by Altman (1968), Ohlson (1980), Persons (1995), Beaver, McNichols, and Rhie (2005), Lenard and Alam (2004), and Lenard, Watkins, and Alam (2007) as the basis for our analysis. The models by Altman (1968), Ohlson (1980), and Beaver et al. (2005) were developed for bankruptcy prediction, and the models by Persons (1995), Lenard and Alam (2004), and Lenard et al. (2007) were developed specifically for fraud detection. Ohlson (1980), Persons (1995), Beaver et al. (2005), Lenard and Alam (2004), and Lenard et al. (2007) use logistic regression models, Altman (1968) uses discriminant analysis with a "Z" score. If we consider why these models are successful, we must consider the status of fraud research. Persons (1995), and Kinney and McDaniel (1989) noted that companies in weak financial condition were more likely to "window dress" in an attempt to disguise financial difficulties. The models that use a leverage ratio, such as total liabilities divided by total assets, do so because higher leverage is associated with higher potential for violations of loan agreements and lower ability to obtain additional capital through borrowing (Persons, 1995). As such, this is a financial ratio that indicates financial stress as well as possible susceptibility to fraud. Another ratio that is often examined in fraud detection models is one for asset composition, such as current assets divided by total assets. Often companies that commit fraud overstate receivables and

inventory (Persons, 1995). Also linked to assets is a capital turnover ratio, such as sales to total assets. Such a ratio represents the sales generating power of a company's assets. Since fraud firms may have smaller capital turnover than non-fraud firms, the sign of this variable in a regression analysis is expected to be negative for a fraudulent firm. The negative coefficient for this ratio would go along with a negative profitability ratio, or a negative *trend* in earnings, such as in Ohlson's (1980) model, which is also an indicator of financial stress.

Model Descriptions

Altman's (1968) model used the following equation:

$$Z = 0.012 (X_1) + 0.014 (X_2) + 0.033 (X_3) + 0.006 (X_4) + 0.999 (X_5),$$

where X_1 = working capital divided by total assets, X_2 = retained earnings divided by total assets, X_3 = earnings before interest and taxes divided by total assets, X_4 = market value of equity divided by total debt, and X_5 = sales divided by total assets. Altman's model emphasized income and equity value variables, paying only scant attention to leverage, where X_1 (current assets minus current liabilities divided by total assets) was the only leverage variable used in the model. In comparison, the models by Ohlson (1980), Persons (1995), and Beaver et al. (2005) paid equal attention to income based, equity based, and leverage based variables. According to Altman's model, if the Z-score, or value of "Z" above, is below a value of 1.81, the company is predicted to go bankrupt. If the Z-score is above 2.99, the company is predicted to be healthy, and if the score is between those two numbers, a prediction cannot be made without further evaluation.

Ohlson's (1980) model used logistic regression, which is the form of: $1/(1 + e^{-Y})$, where the equation for Y was constructed as follows:

$$Y = - 1.32 - 0.407 (\text{LOGTA}) + 6.03 (\text{TLTA}) - 1.43 (\text{WCTA}) + 0.0757 (\text{CLCA}) \\ - 2.37 (\text{NITA}) - 1.83 (\text{FUTL}) + 0.285 (\text{INTWO}) - 1.72 (\text{OENEG}),$$

where LOGTA = log of total assets, TLTA = total liabilities divided by total assets, WCTA = working capital divided by total assets, CLCA = current liabilities divided by current assets, NITA = net income divided by total assets, FUTL = funds provided by operations divided by total liabilities, INTWO = 1 if net income is negative for the last 2 years (0 otherwise), and OENEG = 1 if total liabilities are greater than total assets (0 otherwise). Ohlson (1980) developed three models, with prediction accuracy of 92 percent to 96%. Ohlson also described an analysis of the cut-off point. For his model, the point which minimized the sum of errors was 0.038, suggesting that a score or value higher than that indicated a bankrupt company.

Persons (1995) also used logistic regression and performed an analysis of determining the best “cut-off” score for the model that minimized type I (accepting results as correct when they are actually incorrect) and type II (rejecting results as incorrect when they are actually correct) errors. She presented two models, one for the preceding year and one for the fraud year. In the model for the financial ratios in the fraud year, the most successful cut-off probability was 0.6018, meaning that a value equal to or greater than 0.6018 indicated a fraudulent company. The equation for Y in that model was as follows:

$$Y = 1.3935 + 2.7837 (TLTA) + 1.8746 (CATA) - 0.6807 (SATA) - 0.2418 (LOGTA),$$

where TLTA = total liabilities divided by total assets, CATA = current assets divided by total assets, SATA = sales divided by total assets, and LOGTA = log of total assets.

Beaver, McNichols, and Rhie (2005), while referring to Altman (1968) and Ohlson (1980), among others, developed their own logistic regression model, using company data from 1962 – 2002. They also had several models, starting with an all-inclusive model that used the full time period, along with two others that split the data into two time periods: 1962-1993 (Period 1) and 1994-2002 (Period 2). In our analysis, we referred to the model using the second time period. The equation for Y in that model appears below:

$$Y = -5.754 - 0.985 (ROA) + 1.802 (LTA) - 0.218 (ETL),$$

where ROA = return on assets, LTA = total liabilities divided by total assets, and ETL = earnings before interest, taxes, depreciation and amortization divided by total liabilities.

Sample Development

In order to examine the development and success of the bankruptcy and fraud models, we tested the success of the models for fraud detection with a sample of companies that committed fraud in the late 1990s, before the Sarbanes-Oxley legislation was issued. The companies in the sample fell into the computer and technology services category of Compustat (SIC Code 8040). This category was chosen because of recent issues in fraudulent financial reporting in this industry (Chen and Sennetti 2005). The sample consisted of companies in the computer and technology services industry that were subject to litigation for financial statement fraud according to the Lexis-Nexis database during the 1996-2000 time period. This resulted in a list of 13 companies. The sample was matched with a random selection of healthy companies from the Compustat SIC Code 8040 mentioned above, which resulted in a final sample of 26 companies. We referred to this sample in our testing as the “1990’s sample”. The matching procedure followed the approach adopted in previous studies using logistic regression (logit) models (Chen and Church, 1992; Hansen, McDonald, and Stice, 1992; Lenard, Alam, and Madey, 1995; Udo, 1993).

We continued our testing with a sample of companies that were most recently charged with fraud. We obtained the 2008 Report on Corporate Fraud from the website of the U.S. Department of Justice (<http://www.usdoj.gov/dag/cftf/corporate-fraud2008.pdf>). We included cases prosecuted by the DOJ’s Criminal division, as well as from the U.S. Attorney’s office, which pertained to accounting and financial reporting fraud. There were 31 companies that met this definition. Their cases were being prosecuted in 2008, even though they had often occurred in earlier years. In addition, this sample includes WorldCom, a company that committed a major fraud in 2001. We were able to find data listed on the SEC’s Edgar Database for 17 of these companies. The dates of their infractions ranged from 2001 to 2004. We matched these 17 companies with a random sample of 17 companies taken from the list of Fortune 1000

companies also included in the Edgar Database. This brings the total size of our sample to 34 companies. We referred to this sample in our testing as the “2000’s sample”.

Fraud Variable

The fraud variable was originally developed by Lenard and Alam (2004). It was designed to include an assessment of qualitative information, based on the rules provided by *Statement on Auditing Standards No. 82* (AICPA 1997). In addition to the fraud variable, the fraud detection model developed by Lenard and Alam (2004) also included four financial variables. Total liabilities divided by Total assets (TLTA) was used to examine the percentage of debt. Cash flow provided by Operations divided by Total liabilities (CFOTL) was used to examine each company’s cash position. Current assets divided by Current liabilities (CACL) was a measure of liquidity, and Net income divided by Total Assets (NITA) was used to measure profitability.

The fraud variable was again used by Lenard, Watkins, and Alam (2007). It was updated with the rules provided by *Statement on Auditing Standards No. 99* (AICPA 2001) in order to detect fraud using the sample of firms in the computer and technology services industry. It is difficult to distinguish fraudulent companies from healthy companies in this industry. These companies have a small asset base and often rely on equity investment, so their financial ratios of liabilities to assets will be high, causing a model to possibly designate a healthy company in this industry as fraudulent. The model by Lenard et al. (2007) also used financial variables, which were similar to the variables used in the Persons (1995) study. Sales divided by Total assets (SATA) was used to examine capital turnover. The log of Total assets (LOGTA) was used to measure size. Current assets divided by Total assets (CATA) was used to measure asset composition. Cash flow provided by Operations divided by Total liabilities (CFOTL) was used to examine each company’s cash position. We tested our sample data with each of the bankruptcy models,

and Persons' model, described above, then in separate testing added the fraud variable developed by Lenard et al. (2007).¹

RESULTS

Descriptive statistics for the companies in the 1990's sample appear in Table 1. The results show that there is a significant difference in the ratios for Sales to Total Assets (SATA), Earnings before Interest and Taxes to Total Assets (EBITTA), Net Income to Total Assets (NITA), and the fraud variable (FR_1). The difference in SATA indicates that the fraud firms actually have a higher ratio for this

¹ The fraud variable in this study was implemented using fuzzy logic and was compiled based on statements that were posed in SAS No. 99 as "red flag" indicators that the auditor should examine to detect fraud. SAS No. 99 instructs auditors to look at three risk categories: 1) incentives or pressures, 2) opportunities; and, 3) attitudes or rationalizations. Lenard, Watkins, and Alam (2007) added additional categories: management risk/fiduciary responsibility, organization risk/opportunities, earnings risk/financial stability pressures, and control risk/attitudes. This last category combined questions from SAS No. 99's guideline for examining internal control components. The variable created using fuzzy logic captured responses to questions that pertained to the aforementioned categories and provided a "score" that was used as the fraud variable. When the value of the fuzzy fraud variable was 0.16 or above, the company typically had higher control risk and higher organization risk. This was the case for many of the fraud companies in the sample of computer and technology service firms. A value of the fuzzy fraud variable that was below 0.16 indicated higher management risk. Higher management risk occurs when management has significant financial interests in the company. While this certainly involves some risk, it does not necessarily indicate that fraud has been or will be committed. Higher management risk also occurs if there are difficulties with financing arrangements, which may necessitate refinancing, but again does not necessarily indicate fraudulent activity. Both of these situations were more common among the computer and technology service firms in the sample, and the distinction between these two risks was more clearly identified using the fuzzy fraud variable.

variable than the non-fraud firms. This result reflects the fact that during the time period of 1987 – 1997, companies committing fraud were usually quite small, according to the Committee on Sponsoring Organizations (COSO). In addition, the ratios for EBITTA and NITA are also higher for fraud firms. Because many of the companies in this industry experience difficulty in earnings, fraud firms could show higher earnings than non-fraud firms. The significantly higher mean value for fraud firms could also indicate that the fraudulent companies are arbitrarily or artificially supporting their income. The fraud variable (FR_1) is also significantly lower for the non-fraud firms. This is as expected for the fraud variable. The mean value of FR_1 was 0.1408 for healthy companies and 0.3117 for fraud companies. According to Lenard, Watkins, and Alam (2007), a value below 0.1600 indicates higher management risk, which does not necessarily indicate fraudulent activity. However, a value of FR_1 above 0.1600 indicates higher control risk, and is more likely to indicate fraud. (See Appendix A, Table 1).

When comparing the results of the financial models (Table 2, Panel A), the results using Persons' (1995) model indicate that all of the fraud companies are successfully identified. However, this is at the expense of the healthy companies, of which only one (7.7 percent) is identified correctly. The overall results of Persons' model for our sample, then, are that 14 of the 26 companies were correctly predicted, which represents a total accuracy of 53.8 percent.

Altman's (1968) model uses the "Z-score", which indicates a bankrupt firm if the score is less than 1.81, and a "suspect" firm if the score is above 1.81 and less than 2.99. Thus, the results for the Altman model show that while 61.5 percent of the fraud companies are correctly predicted, none of the healthy companies are correct, giving an overall prediction accuracy of only 30.8 percent. The cut-off point for Ohlson's (1980) model is 0.038, with a score higher than that indicating a bankrupt firm, and a score lower than that indicating a healthy company. The performance of Ohlson's model is similar to that of Person's model, predicting all companies to be fraudulent. This gives Ohlson's model a total prediction accuracy of 50.0 percent. Although Ohlson's model and Altman's model were not designed specifically to measure fraud, they do measure financial stress, which may certainly be present in a

fraudulent firm. However, their models, along with Person's model, are not able to distinguish between the specific financial stress that may be present in a fraudulent firm as compared to a healthy firm.

Beaver, McNichols, and Rhie (2005) do not give a specific cut-off value or "score" for their model. However, when we use a "standard" cut-off of 0.5 and above for a fraudulent company, their model correctly predicts 92.3 percent of the healthy companies, but recognizes none of the fraudulent firms. The overall prediction accuracy for their model is 46.2 percent. (See Appendix A, Table 2).

We then tested each of the above models by including the fraud variable (FR_1). To do this, we ran a logistic regression (or, in the case of Altman's model, a discriminant analysis) using the variables in the specific model, along with FR_1, and used the results to classify the companies in our sample as either fraud or non-fraud firms. We also tested our sample of companies with the variables used in the Lenard and Alam (2004) and Lenard et al. (2007) models. The results (Table 2, Panel B) show that each model was more accurate in distinguishing fraud companies from non-fraud companies. The models that performed best were the Beaver model, correctly classifying 88.5 percent of the companies, and the Lenard and Alam and Lenard et al. models, which had the same classification accuracy of 92.3 percent. The Altman model correctly classified 84.6 percent of the companies, the Persons model correctly classified 80.8 percent of the companies, and the Ohlson model did not converge on our small dataset. The use of the fraud variable improves the performance of all the models. This improved accuracy is an indication of the nature of the fraud variable, which allows for qualitative evaluation of the company's financial situation, given consideration of the various "red flags" that have been identified in the most recent accounting practice and literature as pertaining to accounting or financial reporting fraud.

We then tested the 2000's dataset. The descriptive statistics for this sample (see Table 3) indicate that the variables for Sales to Total Assets (SATA), Cash Flows to Total Liabilities (CFOTA), and the fraud variable (FR_1) are significant. For this sample, however, there is a combination of companies from different industries. As a result, the SATA ratio is significantly higher for the non-fraud companies, as is the CFOTL ratio. Again, the mean of the FR_1 ratio is below .1600 for the healthy companies, and

higher than that for the fraud companies, indicating that there is higher control risk for the fraud companies. (See Appendix A, Table 3).

Table 4, Panel A, shows the results of the financial models without the fraud variable. Persons' model and Ohlson's (1980) model have the same results, where all companies are classified as fraud companies, resulting in an overall prediction accuracy of 50.0 percent for each of those models. The Altman model correctly classifies 15 of the 17 fraud firms, but misclassifies all of the non-fraud firms, for an overall prediction accuracy of 44.1 percent. The model by Beaver et al. (2005) has the opposite result, predicting all of the non-fraud firms correctly, but none of the fraud firms. This also results in an overall accuracy of 50.0 percent, similar to the Persons (1995) and Ohlson (1980) models. (See Appendix A, Table 4).

When we evaluated the classification accuracy of the models using the fraud (FR_1) variable, the overall accuracy improves. The Lenard et al. (2007) model is the most accurate, with an overall classification accuracy of 85.3 percent. This is followed by the Lenard and Alam (2004) model, with a classification accuracy of 82.4 percent. Then Persons' (1995) model is next, with 79.4 percent accuracy. The bankruptcy models follow, with the Altman (1968) model at 76.5 percent accuracy, the Beaver et al. (2005) model at 73.5 percent accuracy, and the Ohlson (1980) model at 64.7 percent accuracy (Table 4, Panel B). The difference in accuracy again reflects the use of the fraud variable. In addition, the variables that indicate the risk of fraud in this decade are represented by a lower ratio of sales to total assets (SATA) and lower cash flows in relation to total debt (CFOTL).

SUMMARY AND CONCLUSIONS

This study first examines the literature to gain an understanding of various bankruptcy and fraud detection models that have been developed by academics in the wake of both the accounting profession's and the U.S. political system's response to major fraudulent events and company failures. We postulate that models that detect bankruptcy can also indicate fraud. Accordingly, we select three bankruptcy

detection models developed over a span of four decades (1968-2005), and a fraud detection model developed in 1995, to examine if they could correctly predict fraud using data samples from two recent and distinct time periods which were subject to incidents of fraudulent financial reporting. We then expand our examination by using these models and adding a fraud variable that was designed based on specific indicators of fraud identified by the accounting profession over time.

Our study is important because the accounting profession has reached a point where the auditor's "critical intent" in evaluating the financial statement now includes rules and expectations to detect fraud developed by both the public and private sector (Arrington and Watkins, 2002). We believe that a combination of accounting rules, regulation, and government enforcement have contributed to the development of fraud detection models. It is clear from our study that when the fraud variable is added to the bankruptcy prediction models (Beaver, McNichols, and Rhie [2005], Ohlson [1980], and Altman [1968]), the performance of bankruptcy models is enhanced. The model by Persons (1995), which is a fraud model, also performs better with the addition of the fraud variable and its ability to provide qualitative information. However, the evaluation of fraud risk factors that comprise the fraud variable must also be continually examined to reflect explicit "red flag" indicators.

SUGGESTIONS FOR FUTURE ACTION

In addition to highlighting recent frauds, we need to consider the method by which accounting students study fraud, and perhaps consider an approach whereby accounting students study fraud the way all students study history. How can we anticipate problems that might occur given various circumstances or political administrations if we do not study the history of fraud and fraud detection? If students study historical fraud cases and use fraud detection models and other methods of preventing and detecting fraud, they will be better equipped to anticipate fraud and become better auditors. If fraud does occur in cycles, then accountants can anticipate fraud through an analysis of the financial, economic, and political circumstances or recognize the environment in which a particular fraud is likely to occur. Much will be

written on this issue in the coming years and decades because the profession is committed to informing the public about fraud and deterring fraudsters. The challenge for researchers and practitioners will be to develop programs and research to help auditors decide how they can anticipate specific frauds before they happen.

We must also consider the nature of the audit process in the United States. The U.S. audit process is based on the combination of current accounting structure that informs us of the financial status of a company and the private/public creation and enforcement of rules and regulations. Further research can be done to see if this process is unique to the U.S. and if the U.S. method is the best way to respond to fraud. Since fraud is a global phenomenon, it is worthwhile to examine what has been done in other countries or other financial markets. Further research can pursue, given our quest for international standards, whether there is a better global approach or response.

We already know what fraud is and we have processes and rules in place to detect and prevent all manner of frauds. We have built and used computer models to detect fraud. We should now focus on how to combine these findings. Thus, future research could involve creating a global database of all frauds that have occurred. As suggested in the studies cited in this paper, we could then use data mining and statistical programs to sort through the data using a fraud check sheet. For example, a computer model could recognize fraud that could be committed by executives in an industry whose company has a stock price level counter-indicated by prevailing economic conditions. Future research could provide methods to determine solutions to particular questions, such as the personal and organizational characteristics that, in conjunction with a set of other particular business or economic conditions, could be a red flag for fraud. In this manner, researchers and practitioners could work together to strengthen the professional reputation of auditors. Since the cost is no longer prohibitive, we should work on continuing to build theoretical and practical research agendas and models to focus on developing a theory of fraudulent financial reporting, one that identifies the conditions and circumstances that lead to fraud and formulates methods to prevent fraud before it occurs.

Appendix A

Table 1
Descriptive Statistics for Healthy Companies vs. Fraud Companies
1990's Sample of 26 Companies (13 fraud, 13 non-fraud)

Variable	Mean – Healthy	Mean – Fraud	T-Test for Equality of Means
ETL	- 1.0112	- 0.1136	-2.713
CATA	0.4674	0.5448	-0.860
SATA	0.7892	1.3217	-2.477 **
LOGTA	3.6919	4.4109	-0.838
TLTA	0.6574	0.6659	-0.042
CFOTL	- 0.1091	- 0.2422	0.735
WKCAPTA	0.0024	0.1728	-1.020
RETA	0.3426	0.3341	0.042
EBITTA	- 0.6909	0.0054	-2.637**
MKT	1.6937	1.3533	0.427
CLCA	1.3406	0.8015	1.458
CACL	1.8763	2.1413	-0.350
FR_1	0.1408	0.3117	-2.337 **
NITA	- 0.7125	- 0.0077	-2.718 **

**p ≤ .05;

ETL = earnings before interest, taxes, depreciation and amortization divided by total liabilities; CATA = current assets divided by total assets; SATA = sales divided by total assets; LOGTA = log of total assets; TLTA = total liabilities divided by total assets; CFOTL = cash flow from operations divided by total liabilities; WKCAPTA = working capital divided by total assets; RETA = retained earnings divided by total assets; EBITTA = earnings before interest and taxes divided by total assets; MKT = market value of equity divided by total debt; CLCA = current liabilities divided by current assets; CACL = current assets divided by current liabilities; FR_1 = fraud variable; NITA = net income divided by total assets.

Table 2, Panel A
A Comparison of Fraud and Bankruptcy Models for Healthy Companies vs. Fraud Companies
1990's Sample of 26 Companies (13 fraud, 13 non-fraud)

	Persons ^a	Altman ^b	Ohlson ^c	Beaver ^d
Percent correct – fraud	100.0%	61.5%	100.0%	0.0%
Non-fraud	7.7%	0.0%	0.0%	92.3%
Total	53.8%	30.8%	50.0%	46.2%

^a Likelihood of fraud if score is $\geq .6018$. Accuracy of the sample is $14/26 = 53.8\%$.

^b “Z-score” indicates a likelihood of bankruptcy if score < 1.81 . Accuracy in the sample is $8/26 = 30.8\%$

^c Cut-off point = .038. If score $> .038$, indicates a bankrupt firm. Accuracy in the sample is $13/26 = 50.0\%$.

^d Using a cut-off score of .5 and above for a fraudulent company, accuracy is $12/26 = 46.2\%$.
 Dependent variable is coded 1 for fraudulent firm and 0 for all other firms.

Table 2, Panel B
A Comparison of Fraud and Bankruptcy Models for Healthy Companies vs. Fraud Companies
With a fraud variable
1990's Sample of 26 Companies (13 fraud, 13 non-fraud)

	Persons ^a w/ fraud	Altman ^b w/ fraud	Ohlson ^c w/ fraud	Beaver ^d w/ fraud	Lenard/ Alam ^e	Lenard et al. ^f
Percent correct – fraud	76.9%	92.3%	Did	84.6%	92.3%	92.3%
Non-fraud	84.6%	76.9%	not	92.3%	92.3%	92.3%
Total	80.8%	84.6%	converge	88.5%	92.3%	92.3%

^a Using a cut-off score of .5 and above for a fraudulent company, accuracy of the sample is $21/26 = 80.0\%$.

^b Used cut-off rule where a “score” > 0 indicates a fraud company, a “score” < 0 indicates a healthy company, accuracy of the sample is $22/26 = 84.6\%$.

^c Model did not converge due to small sample size.

^d Using a cut-off score of .5 and above for a fraudulent company, accuracy is $23/26 = 88.5\%$.

^e Using a cut-off score of .5 and above for a fraudulent company, accuracy is $24/26 = 92.3\%$.

^f Using a cut-off score of .5 and above for a fraudulent company, accuracy is $24/26 = 92.3\%$.
 Dependent variable is coded 1 for fraudulent firm and 0 for all other firms.

Table 3
Descriptive Statistics for Healthy Companies vs. Fraud Companies
2000's Sample of 34 Companies (17 fraud, 17 non-fraud)

Variable	Mean – Healthy	Mean – Fraud	T-Test for Equality of Means
ETL	0.0346	- 0.1033	0.936
CATA	0.3866	0.4622	-0.891
SATA	1.2638	0.7961	1.783 *
LOGTA	4.0028	5.0751	-1.398
TLTA	0.6371	0.6717	0.637
CFOTL	0.1033	- 0.0185	2.246 **
WKCAPTA	0.1003	0.1971	-1.314
RETA	0.3686	0.3282	0.740
EBITTA	0.0746	0.0192	1.051
MKT	0.6673	0.6155	0.291
CLCA	0.8643	0.9219	-0.315
CACL	1.3509	1.7867	-1.199
FR_1	0.1049	0.2049	-2.282 **
NITA	0.0197	- 0.0419	0.872

*p ≤ .10, **p ≤ .05;

ETL = earnings before interest, taxes, depreciation and amortization divided by total liabilities; CATA = current assets divided by total assets; SATA = sales divided by total assets; LOGTA = log of total assets; TLTA = total liabilities divided by total assets; CFOTL = cash flow from operations divided by total liabilities; WKCAPTA = working capital divided by total assets; RETA = retained earnings divided by total assets; EBITTA = earnings before interest and taxes divided by total assets; MKT = market value of equity divided by total debt; CLCA = current liabilities divided by current assets; CACL = current assets divided by current liabilities; FR_1 = fraud variable; NITA = net income divided by total assets.

Table 4, Panel A
A Comparison of Fraud and Bankruptcy Models for Healthy Companies vs. Fraud Companies
2000's Sample of 34 Companies (17 fraud, 17 non-fraud)

	Persons ^a	Altman ^b	Ohlson ^c	Beaver ^d
Percent correct – fraud	100.0%	88.2%	100.0%	0.0%
Non-fraud	0.0%	0.0%	0.0%	100.0%
Total	50.0%	44.1%	50.0%	50.0%

^a Likelihood of fraud if score is $\geq .6018$. Accuracy of the sample is $17/34 = 50.0\%$.

^b “Z-score” indicates a likelihood of bankruptcy if score < 1.81 . Accuracy in the sample is $15/34 = 44.1\%$

^c Cut-off point = $.038$. If score $> .038$, indicates a bankrupt firm. Accuracy in the sample is $17/34 = 50.0\%$.

^d Using a cut-off score of $.5$ and above for a fraudulent company, accuracy is $17/34 = 50.0\%$.
 Dependent variable is coded 1 for fraudulent firm and 0 for all other firms.

Table 4, Panel B
A Comparison of Fraud and Bankruptcy Models for Healthy Companies vs. Fraud Companies
With a fraud variable
2000's Sample of 34 Companies (17 fraud, 17 non-fraud)

	Persons ^a w/ fraud	Altman ^b w/ fraud	Ohlson ^c w/ fraud	Beaver ^d w/ fraud	Lenard/ Alam ^e	Lenard et al. ^f
Percent correct – fraud	70.6%	70.6%	58.8%	76.5%	82.4%	88.2%
Non-fraud	88.2%	82.4%	70.6%	70.6%	82.4%	82.4%
Total	79.4%	76.5%	64.7%	73.5%	82.4%	85.3%

^a Using a cut-off score of $.5$ and above for a fraudulent company, accuracy of the sample is $27/34 = 79.4\%$.

^b Used cut-off rule where a “score” > 0 indicates a fraud company, a “score” < 0 indicates a healthy company, accuracy of the sample is $26/34 = 76.5\%$.

^c Using a cut-off score of $.5$ and above for a fraudulent company, accuracy in the sample is $22/34 = 64.7\%$.

^d Using a cut-off score of $.5$ and above for a fraudulent company, accuracy is $25/34 = 73.5\%$.

^e Using a cut-off score of $.5$ and above for a fraudulent company, accuracy is $28/34 = 82.4\%$.

^f Using a cut-off score of $.5$ and above for a fraudulent company, accuracy is $29/34 = 85.3\%$.

Dependent variable is coded 1 for fraudulent firm and 0 for all other firms.

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