

## **Using Nonfinancial Measures to Assess Fraud Risk**

Joseph F. Brazel  
North Carolina State University  
Department of Accounting  
College of Management  
Campus Box 8113  
Nelson Hall  
Raleigh, NC 27695  
919-513-1772  
joe\_brazel@ncsu.edu

Keith Jones  
George Mason University  
Department of Accounting  
Enterprise Hall, MSN 5F4  
Fairfax, VA 22030-4444  
703-993-4819  
kjonesm@gmu.edu

Mark F. Zimbelman  
Brigham Young University  
School of Accountancy  
540 Tanner Building  
Provo, UT 84602  
801-422-1227  
mz@byu.edu

December 2006

# Using Nonfinancial Measures to Assess Fraud Risk

## ABSTRACT

The purpose of this study is to examine whether auditors can effectively use nonfinancial measures to detect financial statement fraud. Given that auditors can identify nonfinancial measures (e.g., facilities growth) that are positively correlated with financial measures (e.g., revenue growth) and that are less easily manipulated by fraud perpetrators than financial measures, inconsistencies between nonfinancial measures and financial performance indicate high fraud risk. We find that the difference between nonfinancial measures and financial performance is significantly greater for fraud firms than for their non-fraud competitors. In short, the fraud-firms' nonfinancial measures were not consistent with their financial growth. We also find these inconsistencies between nonfinancial and financial measures appear to be a significant fraud indicator when included in a model containing financial measures that have previously been linked to fraudulent reporting. Overall, our results provide evidence suggesting that nonfinancial measures can be effectively used to assess the likelihood of fraud.

## ***1. Introduction***

During former HealthSouth CEO Richard Scrushy's trial, federal prosecutors argued that Scrushy must have known something was amiss with HealthSouth's financial statements since there was a discrepancy between the company's financial and non-financial performance. The prosecutor noted that twice during the seven-year fraud, revenues and assets increased even though the number of HealthSouth facilities decreased. "And that's not a red flag to you?" asked prosecutor Colleen Conry during the trial (WSJ 2005). Conry's question implied the following: Because HealthSouth's financial statement data was inconsistent with its nonfinancial measures the risk of financial statement fraud (hereafter fraud) at HealthSouth was obviously high. The defense witness responded that the inconsistency was not apparent at the time and—importantly—HealthSouth's external auditors also failed to take note of the inconsistency between the firm's financial and nonfinancial measures.

This paper investigates whether publicly available nonfinancial measures (NFM) can be used to assess the likelihood of fraud. Auditors are not currently required to consider NFM (e.g., facilities growth, number of retail outlets) although audit practice does recognize that NFM may be valuable for performing analytical procedures (see Messier et al. 2006, 188 and Bell et al. 2005, 29). SAS 56 (AICPA 1988) and SAS 99 (AICPA 2002) require auditors to perform analytical procedures during the planning and final stages of an audit and to consider the results of these procedures when assessing fraud risk. However, academic research shows that auditors fail to recognize unusual trends and ratios within the financial statements because they do not have a sufficient understanding of the client's business or they rely too much on management's explanations (Erickson et al. 2000). In addition, both field and experimental research show that auditors generally do not self-generate explanations for unusual trends and ratios uncovered in

the financial statements and they tend to rely on management explanations without adequately testing the validity of their explanations (Anderson and Koonce 1995; Hirst and Koonce 1996; Bierstaker et al. 1999). NFMs may provide one avenue for auditors to both generate reliable expectations for their analytical procedures and test the validity of management's explanations to their inquiries.

Prior archival research has provided evidence of a link between fraud and financial statement variables (Summers and Sweeney 1998; Lee et al. 1999; Dechow et al. 1996; Beneish 1997), corporate governance variables (Beasley 1996; Dechow et al. 1996; Abbott et al. 2000; Beasley et al. 2000; Farber 2005), and other indicators of fraud such as weak internal controls (Bell and Carcello 2000). However, no prior study has examined whether comparing financial statement data to NFMs can distinguish fraud firms from non-fraud firms. Given claims that NFMs are valuable for measuring the economic performance of a firm (e.g., Amir and Lev 1996; Kaplan and Norton 1996; Ittner and Larcker 1998), we believe it is important to empirically test whether fraud firms are more likely to show a discrepancy between their financial and operating performance relative to non-fraud firms. Thus, assuming a fraud firm fails to manipulate its NFMs and that some NFMs are correlated with financial results (e.g., revenue growth and plant closings), fraud firms should be more likely than non-fraud firms to report financial results that are inconsistent with their NFMs (Bell et al. 2005). Consequently, the aforementioned inconsistency may be a valuable tool for auditors and regulators attempting to identify fraud.

This paper provides evidence that the comparison of financial measures to NFMs does provide incremental explanatory power for discriminating fraud from non-fraud firms. Using a matched-pair sample of fraud firms and competitors, we show that fraud firms are more likely to report inconsistent revenue growth relative to their growth in various NFMs that should be

positively correlated with revenue. We analyze this result from the year prior to the initial fraud year to the first year of the fraud for each matched-pair. When including the difference between a firm's financial measures and its NFMs in a model including financial factors that have been found to be indicative of fraud, we find the difference to be a significant discriminator between fraud and non-fraud firms. Thus, we provide evidence showing that comparisons between financial measures and NFMs can be used to assess the likelihood of fraud.

This paper is organized as follows. Section II develops our hypotheses. Section III explains our sample selection and research method. Section IV provides the results. Section V concludes the paper.

## ***2. Development of Hypotheses***

### **2.1 PRIOR RESEARCH**

The use of NFMs in the evaluation of firm performance has garnered much attention since Kaplan and Norton (1996) published the "The Balanced Scorecard." Proponents of NFMs claim they are not subject to the limitations of traditional financial measures (i.e., short-term focus, emphasis on narrow groups of stakeholders, and limited guidance for future actions; see Langfield-Smith 2003). In auditing, SAS no. 56 (AICPA 1988) suggests that auditors may want to consider NFMs when determining the reasonableness of their clients' financial statements. The effectiveness of using NFMs to help assess fraud risk is dependent on whether NFMs are correlated with financial performance. Thus, if NFMs are correlated with financial performance and auditors can detect fluctuations in NFMs that appear unusual given reported financial performance, NFMs may be an effective tool in determining fraud risk.

While several prior studies investigate the use of NFMs in compensation plans (e.g., Banker et al. 2000; Said et al. 2003), little published research has investigated the relationship

between financial measures and NFMs (Ittner and Larcker 1998). Amir and Lev (1996) and Riley et al. (2003) studied the cell-phone and airline industries, respectively, and conclude that the value-relevance of nonfinancial information overwhelms that of traditional, financial statement variables for investors. The former study also stresses the importance of significantly expanding the use of nonfinancial information in both practice and research. Ittner and Larcker (1998) find one form of NFMs, customer satisfaction measures, to be significantly related to future accounting performance and partially reflected in current accounting book values. Two studies investigate the relationship between NFMs and financial statement data in the airline industry. Liedtka (2002) employs factor analyses that suggest that the growing reliance on NFMs is justified. Specifically, this study shows that the nineteen NFMs disclosed by the airline industry represent seven constructs not measured by eighteen common financial measures. Behn and Riley (1999) find that NFMs are useful in predicting quarterly revenue, expense, and net income numbers. Lastly, audit guidance suggests that NFMs such as production capacity should be consistent with revenue reported on the income statement (AICPA 2002).

In addition to the research noted above, anecdotal evidence suggests that considering NFMs in conjunction with financial results should help auditors accurately assess the reasonableness of their clients' financial statements. For example, Delphi Corporation appears to have boosted net income through sham sales of assets during a period when Delphi and its competitors were laying off workers and experiencing production cuts (Lundegaard 2005). Similar to the HealthSouth prosecutor's comments noted previously, it appears that Delphi's auditors might have detected this fraud if they had noted the inconsistency between the firm's reported performance and its NFMs. In addition, both short-sellers and fraud examiners appear to

consider NFMs when evaluating the reasonableness of firms' sales growth that substantially exceeds expectations (Eisinger 2005).

We explore whether fraud firms' financial results are inconsistent with their NFMs such that the financial results suggest strong performance while the NFMs show weaker performance. For example, an airline that is consistently poor relative to its competitors in the number of on-time arrivals or percent of seats filled is not likely to achieve above average revenue growth. Thus, such an inconsistency suggests a higher likelihood of fraud.

We assume that fraud firms will be unable to conceal these inconsistent patterns between their financial and non-financial performance because NFMs are often less vulnerable to manipulation and/or are more easily verified than financial data (Bell et al. 2005, 28). Whereas controls over financial data can be overridden by management and financial statements are produced internally, NFMs are frequently produced and reported by independent sources (e.g., industry quality rankings). Also, when management reports an NFM it is often easily verified (e.g., number of production facilities) whereas financial results can be difficult to verify (e.g., the estimation of the allowance for doubtful accounts). Thus, when management engages in fraud it is likely that they will be unable to manipulate all their firm's NFMs consistently. In summary, if fraud firms do not manipulate their NFMs in a manner that is consistent with their financial performance and if NFMs can be identified that are normally positively correlated with financial performance, then unexpected differences between NFMs and financial performance should help discriminate fraud from non-fraud firms.

It is important to note that the purpose of our study is not to provide auditors or other interested parties with a specific model or variable that can be used to detect fraud. Instead, our purpose is to empirically test whether a relationship exists between NFMs and fraud such that

auditors could potentially design such NFM models to assess fraud risk. Such evidence would support the claims by auditing regulators (SAS 99) and educators (see Messier et al. 2006, 188) that NFMs provide valuable incremental information for assessing fraud risk. We assume that because auditors have access to a larger pool of firm-specific data than what is publicly available, empirical tests using publicly available NFM data will be no more (and probably less) likely to detect fraud than the pool of NFM data available to auditors. Thus, tests using publicly available data that suggest NFMs can be effectively used to detect fraud will provide strong evidence that auditors could effectively use NFMs to detect fraud. Potential reasons why auditors may not currently search for and use NFMs include budgetary pressures and/or over-reliance on prior year workpapers that do not include analyses of NFMs (cf., Wright 1988; Houston 1999; Brazel et al. 2004). Thus, our tests may be used by policymakers to determine whether benefits to the profession would accrue if auditors were required to use NFM data when assessing fraud risk. Several anecdotal examples suggest such benefits would accrue.

## 2.2 EXAMPLES

We provide two examples of fraud firms where their NFMs suggested fraud was occurring. Del Global Technologies makes electronic components, assemblies, and systems for medical, industrial, and defense uses. The Securities and Exchange Commission alleges that in fiscal years 1997-2000 Del Global Technologies Corp. engaged in improper revenue recognition when it held open quarters, prematurely shipped products to third-party warehouses, and recorded sales on products that Del had not yet manufactured (SEC 2004a). Del overstated pretax income in 1997 by at least \$3.7 million or 110%. Del's revenue increased 25 percent from \$43.7 million in 1996 to \$54.7 million in 1997. However, Del reported a decrease in the total number of employees over the same period. Employees decreased from 440 in 1996 to 412 in

1997. We believe that while a company could increase profits by cutting payroll, it is improbable that the company would double in profitability while laying-off employees and even less probable that employee layoffs would correspond with a significant increase in revenue. In addition, Del's total number of distribution dealers also decreased from 400 to 250 from 1996 to 1997. A decrease in distribution dealers would also seem unlikely to lead to a significant increase in revenue. This case illustrates how an unusual relationship between NFMs (i.e., total number of employees and total number of distribution dealers) and financial data (i.e., revenue) could help an auditor assess fraud risk. In contrast, one of Del Global's competitors, Fischer Imaging Corp., realized a 27 percent decrease in revenue over the same period accompanied by a 20 percent decrease in employees and a 24 percent decrease in distribution dealers.

Anicom, Inc. represents another case of unusual trends among NFMs and financial data. Prior to filing for bankruptcy in early 2001, the company was a leading distributor of industrial and multimedia wire, cable, and fiber-optic products. The SEC alleges that from January 1, 1998 through March 30, 2000, Anicom's management perpetrated a massive fraud in which it falsely reported millions of dollars of non-existent sales and used other fraudulent techniques to inflate net income by more than \$20 million (SEC 2004b). During the first year of the fraud, 1998, Anicom reported a substantial increase in employees (46 percent) and in the number of facilities (55 percent). However, the company's revenue growth was 93 percent over the same period. Anicom's revenue increased from \$244 million in 1997 to \$470 million in 1998. Anicom's growth in NFMs (i.e., employees and facilities), while robust, did not keep pace with its enormous revenue growth. In contrast, one of Anicom's closest competitors, Graybar Electric Company, Inc., reported more modest sales growth (11 percent) from 1997 to 1998. Graybar's growth in NFMs was consistent with its revenue growth. Total employees increased 10 percent

and total number of facilities increased three percent.<sup>1</sup> While we recognize that factors other than fraud could cause unusual relationships between NFMs and financial data, we argue that firms that are committing fraud are more likely to exhibit these relationships.

### 2.3 HYPOTHESES

One general challenge in studying fraud is a shortage of data; this study is no exception. Indeed, Levitt and Dubner (2005) posit that one reason academics know very little about the practicalities of fraud is the paucity of good data. Ideally, a study of NFMs would focus on common nonfinancial measures, which are industry specific. Compiling a reasonable database of fraud firms in one industry is problematic because publicized fraud cases are rare.

To overcome this limitation, we construct a measure that is consistent across firms in different industries with different NFMs. We do so by using NFMs with an expected positive correlation with revenue and determining whether inconsistencies in revenue and NFM growth discriminates between fraud and non-fraud firms. Revenues are utilized as the financial measure in our study due to the concentration of frauds and restatements related to improper revenue recognition (e.g., Beasley et al. 1999; AICPA 2002; Gullapalli 2005).<sup>2</sup> Also, SAS 99 (AICPA 2002) explicitly advises auditors to compare recorded revenue amounts with relevant NFMs. For example, we selected the number of retail outlet stores as an NFM for a firm in the retail industry. Then, we examine the difference between an identified fraud firm's percentage change in revenue and percentage change in retail outlets from the year prior to the fraud to the year of the fraud. We then compare this difference with that of an industry competitor with the expectation that the difference between revenue growth and the growth in the NFM will be larger for fraud firms than for their non-fraud competitors. Thus, we test the following hypothesis:

**H1:** Fraud firms will have greater differences between their percent change in revenue growth and percent change in NFMs than their non-fraud competitors.

We also consider whether differences between financial measures and NFMs can enhance fraud risk assessment models, which include other indicators of fraud. Because nonfinancial data is less subject to manipulation and is not derived from financial data contained within the financial statements, we expect that NFMs contain additional information not provided by financial statement variables shown previously to be associated with fraud.

When performing analytical procedures, auditors commonly rely on prior years' trends and ratios in financial data to develop expectations for the current year financial performance (Anderson and Koonce 1995; Hirst and Koonce 1996; Bierstaker et al. 1999; POB 2000). SAS 99 (AICPA 2002, ¶28) states,

In performing analytical procedures ... the auditor develops expectations about plausible relationships that are reasonably expected to exist, based on the auditor's understanding of the entity and its environment. When comparison of those expectations with recorded amounts yields unusual or unexpected relationships, the auditor should consider those results in identifying the risk of material misstatement due to fraud.

We argue that comparing financial data to nonfinancial data is more likely to help auditors detect fraud than performing analytical procedures based solely on financial data which has also been subject to manipulation or fraud. To test this expectation, we explore whether the consistency between financial measures and NFMs provides additional predictive power over other financial variables known to discriminate fraud from non-fraud firms.

Prior research has identified several financial statement variables that are correlated with fraud. Summers and Sweeney (1998) investigate a link between fraud and insider trading. In doing so, they find a significant correlation between fraud and two financial statement variables: return on assets and change in inventory. Lee et al. (1999) find that the difference between earnings and cash flow from operations is a significant fraud indicator; furthermore, adding this variable, which is a measure of total accruals, to a model of control variables increases their

model's predictive power. Beneish (1997) attempts to distinguish firms that violate GAAP from firms that have not violated GAAP but have large discretionary accruals. His sample includes 64 GAAP violators of which 47 had allegations of fraud. He finds that GAAP violators have larger total accruals and are more likely to have consecutive positive accruals in years prior to and including the year of the GAAP violations. Finally, Dechow, Sloan and Sweeney (1996) find that firms subject to enforcement actions by the SEC are likely to have greater total accruals, a greater market value of equity, and more debt than a control group. While some of the aforementioned financial statement variables may likely be included in auditors' analytical procedures related to fraud, it is an empirical question as to whether the comparison of financial data to NFMs can improve these procedures.

If inconsistencies between financial measures and NFMs discriminate fraud firms from non-fraud firms, we expect an independent variable that compares changes in revenue and changes in NFMs will add to the predictive ability of fraud risk assessment models that include the aforementioned financial statement variables. This expectation is formalized as follows:

**H2:** Including an independent variable that compares change in revenue growth and change in NFMs adds to the power of a fraud risk assessment model comprised of financial variables that have previously been associated with fraudulent financial reporting.

The evidence provided in this study should not only assist auditors but anyone (i.e., investors, lenders, and others) in their assessment of fraud risk. However, given the enormous cost of an audit failure and SAS 99's (AICPA 2002) requirement that auditors document their assessment of fraud risk for each audit, there is a premium for information that can aid auditors in their detection of fraud.

### ***3. Sample Selection and Research Method***

#### **3.1 SAMPLE**

Our fraud sample includes firms charged by the SEC with having fraudulently reported financial data on at least one 10-K filing. We do not include frauds that involve quarterly data for several reasons: prior studies restrict their samples to annual data, quarterly disclosures provide little nonfinancial data, quarterly financial statements are not audited, and discrepancies between financial and nonfinancial data would be less likely in a shorter time frame. We also limit our sample to firms for which we were able to access the original 10-K filing and subsequent filings of restated data (i.e., 10-K/A's, 8-K's, etc.). We do this for two reasons. First, 10-K filings are valuable sources of information to help identify NFMs. Second, Compustat is our primary financial data source. We found that Compustat does not consistently report restated data. It appears that if the restated data is available when Compustat personnel enter the data in their database, the restated data is entered and the fraudulent numbers are discarded. It does not appear that Compustat changes data upon restatements several years after the original data is entered in the database. We therefore compare Compustat data with the original 10-K filing to verify the data reported in Compustat is the fraudulently reported numbers and not restated data. We find that Compustat reported restated data for 15 of the 77 firms in our fraud sample so we hand-collect the fraudulent data from the original 10-K filing for those 15 firms. SEC filings are available on EDGAR from 1994 and for selected companies on Lexis/Nexis for years prior to 1994. The majority of the frauds in our sample occurred after 1994.

We identified our fraud sample from two sources. First, COSO published a report "Fraudulent Financial Reporting: 1987-1997 - An Analysis of U.S. Public Companies" (Beasley et al. 1999). The COSO study investigated frauds that were identified in SEC Accounting and

Auditing Enforcement Releases (AAERs) issued during the period of 1987-1997.<sup>3</sup> The frauds weren't necessarily committed during that time frame. In fact, only six frauds in the COSO study occurred in 1994 and beyond. We were able to include three firms (nonduplicates of our own search) from the COSO study in our sample. Second, we performed our own AAER search for AAERs issued during the years 1998-2004. We used "fraud" as a search term and identified 245 firms. We excluded firms from our sample for one or more of the following reasons: 46 firms didn't misreport at least one 10-K (e.g., fraudulent reported quarterly data), 21 were non-financial frauds (e.g., insider trading, omitted disclosures), for 64 firms we were unable to locate company data (e.g., small firms, foreign companies, frauds prior to 1992) and for 40 firms we could not find similar nonfinancial information about the firm and its competitor. Our final fraud sample consists of 77 fraud firms, which is comparable to or greater than the sample sizes of previous fraud studies (e.g., Beasley 1996; Erickson et al. 2006). Panel A of Table 1 reports the sample selection method.

Several of the firms misreported more than one year. Our sample includes only the first year of manipulation because we want to compare a year that was accurately reported (i.e., year prior to the fraud) to a year that was manipulated (i.e., first year of the fraud). Panels B and C of Table 1 present the number of frauds by industry and year respectively. The 77 firms accused of fraud reside in 22 different two digit-SIC codes. The 7300-7999 Business Services classification code has the largest percentage (26%) of fraud firms. The frauds occurred during a 12-year period between 1991 and 2002. Seventy-four percent of the alleged frauds in the sample began in the years 1996-2000.

Insert Table 1 here

Table 2 presents the types of alleged accounting fraud in our sample firms as obtained from the AAERs. Seventy-five percent of our study group allegedly committed fraudulent financial reporting via material misstatements of revenue. We were able to hand-collect information on the size of the restatement for 63 of the 77 firms in our sample. For each fraud firm, we searched subsequent 10-K's, 10-K/A's, and 8-K's to find the restated earnings number.<sup>4</sup> The average earnings restatement for all firms equaled 11 percent of total revenue.

Insert Table 2 here

### 3.2 METHODOLOGY FOR COLLECTING NFM DATA

Students enrolled in undergraduate auditing courses at two large state universities performed the duties of selecting the competitors and recording the NFM data. Emulating practice, we asked the students to assume the role of staff assistant with each student assigned to a different client audit (i.e., fraud firm) and informed them that their audit task would concern NFM collection for the client and a competitor of their choice. The students were also told the current fiscal year-end under audit (initial fraud year) and the prior fiscal year-end (pre-fraud year). We also provided the students with three of the client's closest competitors (non-fraud firms) as identified by Hoover's Online database. We did not perform a simple match based on SIC code and size because we required identical NFMs for both the fraud firm and its competitor. We concluded that simply matching by SIC code and size would be less likely to yield corresponding NFM data for both the fraud firm and the matched pair and that we were more likely to find corresponding NFM data by matching fraud firms with their true competitors. More importantly, discussions with practicing auditors revealed that our matching procedure was more likely to be performed by independent auditors rather than a simple SIC code match.

Students were then instructed to collect up to four quantitative NFMs (along with the source references) which were identical for both the client and one competitor of their choosing for the initial fraud year and the prior fiscal year-end. We instructed the students to target NFMs that have positive contemporaneous correlations with revenue. The students were asked to perform an exhaustive search of 10-Ks, Hoover's Online, Proquest, ABI-Inform, LexisNexis, Standard and Poor's Market Insight, and Google for NFMs for each fraud firm and one competitor of their own choosing. The students were informed that they should be creative in finding new sources of NFM information and to share information about possible new data sources with other students. Students reported that collecting the NFM data took between two and five hours for each firm - competitor combination.

We included in our sample all NFMs which were quantitative, non-financial and appeared to have a contemporaneous correlation with revenue. Some NFMs collected by the students did not fit these requirements and, therefore, were not included in our sample. Some common examples of data that we excluded are bond ratings because they were non-quantitative, percent spending on research and development because it was financial in nature and number of litigation cases because it failed to have a contemporaneous correlation with revenue. As evidenced by a low  $R^2$  (12 percent) when we regressed change in NFM on change in revenue (see Panel A of Table 6), we erred on the side of including NFMs in our analysis even if we could only make a weak argument for their correlation with revenue. We reasoned that allowing some noise in the association between NFMs and revenue would reduce the subjectivity of the data collection process and would bias against finding results. In addition, our objective is not to find the best methodology for collecting NFM data. Rather, our goal is to test whether NFMs have the potential to be effectively utilized in auditors' fraud risk assessments. Because we

believe auditors have access to client NFM data that is not publicly available but more predictive of financial data, we view our test as lacking strong power to reject the null. Therefore finding support for our hypotheses using this methodology suggest that NFMs have significant potential to predict fraud risk.

From the NFMs submitted by students, we identified a total of 142 common NFMs for 77 fraud firms and their competitors (an average of almost two NFMs per firm). Thus, our sample consists of 284 observations. The Del Global Technologies and Anicom examples discussed previously illustrate a few of the specific NFMs (i.e., employees, facilities, distribution dealers) included in our sample. Table 3 provides a list of the NFMs included in our sample.

Insert Table 3 here

### 3.3 STATISTICAL MODELS

We create a variable that measures the difference between the percent change in revenue growth and the percent change in each NFM for each fraud firm and competitor. The difference for each firm is measured from the year prior to the fraud to the year of the fraud. The variable is measured as follows:

$$\text{Diff}_t = \text{ChgRev} - \text{ChgNFM}$$

where,

$$\text{ChgRev} = (\text{Rev}_t - \text{Rev}_{t-1}) / \text{Rev}_{t-1}$$

Rev = total revenue

$$\text{ChgNFM} = (\text{NFM}_t - \text{NFM}_{t-1}) / \text{NFM}_{t-1}$$

NFM = nonfinancial measure

$t$  = year of the fraud

H1 posits that the fraud sample will have, on average, a greater value for Diff than the competitor sample (i.e., control sample). To control for extreme values, we winsorized all variables at the 99<sup>th</sup> and 1<sup>st</sup> percentile.

As noted in the previous section, prior research has identified financial statement variables that have a significant correlation with fraud. Those variables include total accruals (ACC), return on assets (ROA), market value of equity (MVE), debt (Debt) and change in inventory (ChgInv). Table 4 presents a list of financial statement variables that prior research has shown to be significant. The variables are separated into categories (i.e., accruals, profitability, leverage, inventory and size). To reduce collinearity, we select one variable from each category to include in our list of control variables. We selected the variables employed in the most recent paper (Lee et al. 1999) except for change in inventory (which was not tested by Lee et al. 1999). Change in inventory was calculated consistent with Summers and Sweeney (1998).<sup>5</sup>

Insert Table 4 here

To test H2, we examine each of these control variables in a multivariate regression with Diff to determine whether Diff provides additional explanatory power when discriminating between the fraud and non-fraud firms in our sample. Our model appears as follows:

$$P(\text{FRAUD}_t) = \beta_0 + \beta_1 \text{Diff}_t + \beta_2 \text{ACC}_t + \beta_3 \text{MVE}_t + \beta_4 \text{ROA}_t + \beta_5 \text{Debt}_t + \beta_6 \text{ChgInv}_t \quad (2)$$

$P(\text{FRAUD}_t)$  = A dummy variable coded 1 for fraud firms and 0 for non-fraud firms  
 $t$  = year of the fraud

The control variables are defined as follows:

$$\begin{aligned} \text{ACC}_t &= (\text{net income before extraordinary items}_t + \text{depreciation}_t - \text{cash flow from operations}_t) / \text{total assets}_t \\ \text{MVE}_t &= (\text{end-of-year share price}_t \times \text{total common shares outstanding}_t) / \text{total assets}_t \\ \text{ROA}_t &= \text{net income before extraordinary items}_t / \text{total assets}_{t-1} \\ \text{Debt}_t &= (\text{current liabilities}_t + \text{long-term debt}_t) / \text{total assets}_t \\ \text{ChgInv}_t &= (\text{Inventory}_t / \text{Sales}_t) - (\text{Inventory}_{t-1} / \text{Sales}_{t-1}) \end{aligned}$$

Including the financial data for multiple NFM observations for a given firm causes repeated measurements of financial data. For example, the first year of the WorldCom fraud was 1999. WorldCom has three NFMs in our sample. Including all three NFMs in our sample causes

WorldCom's financial variables (ROA, MVE, etc.) to be in our sample under three separate observations. We control for repeated measures of financial data by estimating alternating logistic regression models (ALR) in addition to standard logistical regressions. Carey et al. (1993) derive and explain the use of ALRs. Controlling for repeated measures via ALR results in an increase in standard errors and a loss of significance among predictors in the ALR. However, the parameter estimates remain unchanged. We present the results for both the standard logistic regression and the ALR.<sup>6</sup>

#### **4. Results**

##### **4.1 DESCRIPTIVE STATISTICS**

Table 5 provides descriptive statistics for our study's variable (Diff), control variables, auditor type, and size of the fraud.<sup>7</sup> We include the percentage of firms that have a Big Four auditor to determine whether the fraud and control group differ in audit quality (Teoh and Wong 1993). We use the term "Big Four" to represent the four largest international accounting firms, their predecessor firms, and Arthur Andersen. For the fraud sample, we include a variable that measures fraud size (i.e., the size of the earning restatement as a percentage of revenue) to provide an estimate of the extent of the earnings manipulation.

Insert Table 5 here

On average, the fraud firms were smaller than the control group and had a lower return on assets; however, the differences in total assets, return on assets (ROA), market value of equity (MVE), debt to assets, and change in inventory are not statistically significant. Consistent with prior research, the fraud firms had greater total accruals than the competitors. The difference in means for accruals (ACC) is statistically significant at the .01 level. There was little variation in the type of auditor between the fraud and control sample as 94 percent of the fraud firms and 93

percent of the control group had a Big Four auditor. The average earnings manipulation for the fraud firms equaled 11 percent of total revenue.

#### 4.2 TESTS OF HYPOTHESES

H1 predicts a greater difference between percent change in revenue growth and percent change in NFM for the fraud sample than for the control sample (i.e., non-fraud competitors). The results support H1 as Diff is significantly ( $p < .01$ ) greater for the fraud sample. Thus, for fraud firms, the performance portrayed by their financial statements was inconsistent with that portrayed by their NFMs. For their competitors, we observe a mean Diff of .15, indicating that their revenue grew faster than their NFMs. However, for the fraud firms, we observe a much larger mean Diff of .33. The difference in means between the fraud and control group is .18, which, interestingly, is similar to the average earnings restatement (as a percentage of revenue) of .11 for the fraud firms. Thus, H1 is supported in that the extent to which financial measures are not aligned with related NFMs may be an indicator of greater fraud risk.

Table 6 presents the results of various regression models. Panel A presents the results of regressing change in NFM on change in revenue. We estimate both the OLS and the generalized estimating equations (GEE). GEE is the OLS equivalent of the alternating logistic regression (ALR) discussed above. Zeger and Liang (1986) derive and explain the use of GEEs. The results show a significant ( $p < .01$ ) relationship between NFMs and revenue, which provides support for the selection of NFMs that are positively correlated with revenue.

Insert Table 6 here

Panel B provides the results of performing both logistic regression and ALR for Diff individually on fraud (1, 0). The positive and significant ( $p < .01$ ) parameter estimate provides

additional support for H1. That is, the degree to which changes in revenue outpace changes in NFMs can signal a greater fraud risk.

Panel C reports the results of two multivariate regressions. One regresses a set of control variables on the probability of fraud and the other includes the control variables and Diff. The sample size decreased from 284 to 264 because several firms either had no inventory or no stock price information to calculate MVE. The results show that, consistent with prior research, total accruals (ACC) is the most significant financial fraud risk indicator. The addition of Diff to the equation provides support for H2. The addition of Diff improves the fit of the model (i.e., Max Rescaled  $R^2$  improves from .21 to .25 and the likelihood ratio test improves from 44.73 to 55.91).<sup>8</sup> The positive and significant parameter estimates for Diff in both regressions in Panel C indicate a positive relationship between the size of Diff and the likelihood of fraud. In other words, the likelihood of fraud appears to increase as inconsistencies between financial data and NFMs increase.

These results provide evidence that NFMs can convey new information not previously contained in financial statement variables that have been found to be correlated with fraud. NFMs can act as an expectation or benchmark against which auditors can compare actual revenue to enhance the effectiveness of their analytical procedures during fraud risk assessment. These findings are consistent with Erickson et al.'s (2000, 168) statement that one of the major failures of the Lincoln Saving and Loan (LSL) audit was "the auditor's failure to obtain and use knowledge of LSL's business, the industry in which it operated, and the economic forces that influenced this industry/business."

### 4.3 ADDITIONAL ANALYSES

Loebbecke et al. (1989) suggest that rapid growth is a significant indicator of fraud. Because many fraud firms are also high growth firms, it is possible that high growth firms will have greater differences between their financial data and their NFMs due to differences in lag times for their financial and non-financial measures. For example, growth firms could experience higher revenue in a period by operating above capacity for a short time while they increase their capacity to meet demand. If so, our multivariate results for Diff may be driven by the tendency for fraud firms to be high growth firms as opposed to fraud firms manipulating their financial results without effectively manipulating their NFMs. To test this alternative explanation, we investigate whether revenue growth was a correlated omitted variable by including ChgRev  $[(Rev_t - Rev_{t-1}) / Rev_{t-1}]$  in our multivariate model. The results of this test show that ChgRev is not significant ( $p = .19$ , two-tailed) while Diff remains significant ( $p = .08$ ). This finding is consistent with prior research which tests similar measures of sales growth and does not find a significant relationship with fraud (e.g., Summers and Sweeney 1998, Lee et al. 1999, Dechow et al. 1996, and Beneish 1997).

We also test the significance of another proxy for growth. Goyal, Lehn, and Racic (2002) create a proxy for growth opportunities, where growth equals capital expenditures divided by total assets. We include this proxy in our multivariate model with insignificant results ( $p = .18$ , two-tailed), while Diff maintains significance ( $p = .006$ ). These results suggest that our result for Diff is not driven by different response times of financial and non-financial variables for growth firms but, rather, by an inconsistency between fraudulent financial results and non-fraudulent NFMs.

In addition to revenue growth, we consider whether weak corporate governance is the primary driver leading to financial statement fraud. Weak corporate governance may lead to less monitoring of financial and non-financial information and greater discrepancies between these two forms of data (Deloitte LLP 2004). Therefore, proxies of weak corporate governance may be better predictors of fraudulent reporting than Diff. Dechow et al. (1996) show that several corporate governance variables are correlated with fraudulent reporting. They break down the variables into two groups. One group measures low management oversight and the other measures the power of the CEO over the Board. To control for low management oversight, we measured the percentage of insiders on the Board. Insiders were defined as officers. To control for the power of the CEO over the Board, we selected a dummy variable that measures one if the CEO is also the Chairman of the Board (CEO=COB) and zero otherwise. We hand-collected corporate governance data from proxy statements and were able to collect insider information for 57 competitors and 58 fraud firms and CEO=COB data for our entire sample. Dechow et al. (1996) found both of these proxies to be significant in a univariate analysis. We found percentage of insiders (%Insider) on the board to be significant in a univariate analysis, but not CEO=COB. However, considering the small sample sizes of both studies and the fact the samples do not overlap, this finding is not inconsistent with prior research. When we include both corporate governance variables in our multivariate model, we find that Diff remains significant ( $p = .005$ ), while neither corporate governance variable is significant (%Insider  $p = .55$ ; CEO=COB  $p = .59$ ).

### ***5. Concluding Comments***

The current regulatory environment is placing increased scrutiny on auditors' ability to detect fraud. Additionally, SAS No. 99 (AICPA 2002) requires auditors to document a separate

fraud risk assessment for each engagement. The purpose of this paper is to investigate whether the relationship between financial data and nonfinancial measures (NFMs) can be used by auditors or regulators to assess fraud risk. We believe that firms that fraudulently misstate their financial statements will be unlikely or unable to concurrently misstate NFMs that are indicative of their true financial condition. We therefore predict that fraud firms will have greater differences in percent change in revenue growth and percent change in NFMs than their non-fraud competitors and that these differences will add to the power of fraud-risk-assessment models comprised of financial variables that have previously been associated with fraudulent financial reporting. We compare a matched sample of firms that committed fraud to a control sample of competitor firms to test these predictions. Our analyses incorporate NFMs that should correspond with growth in firm revenue and indicate that a variable that measures the difference between the percent change in revenue growth and NFMs can discriminate between fraud and non-fraud firms.

These findings have implications for future audit practice and research. Prior literature suggests that fraud goes undetected when auditors fail to understand the environments in which their clients operate (Erickson et al. 2000). We provide evidence suggesting that fraud risk assessment models that incorporate NFMs can help prevent these failures. Thus, understanding the various NFMs for the industries in which an audit client operates and comparing the NFMs to reported financial results has the potential to be a powerful fraud detection tool. Substantial differences between financial statement data and NFMs should serve as a red flag to auditors and lead them to ask pointed questions of client management, corroborate and test management's responses, and, if necessary, devote additional resources to identify fraud. Such an analysis could increase audit quality and decrease litigation costs associated with audit failures.

Future research could study whether our results, found with annual data, can be replicated with quarterly data (e.g., data from 3<sup>rd</sup> quarter 10Qs). Such research would show whether auditors could use the analysis contained herein to possibly detect fraudulent activity prior to performing fiscal year-end audit procedures. Alternatively, evaluating whether the discriminatory power of the analysis could be improved by using more than one competitor or determining whether “Diff” for non-fraud firms and their competitors is consistently low represent fruitful areas of research. Survey and experimental research could investigate if and how auditors use NFMs in practice. Specifically, future studies could examine the degree to which auditors choose to use NFMs in practice and what mechanisms might promote their usage (e.g., higher fraud risk assessments, more explicit guidance, greater industry expertise). Such research could also determine the extent to which NFM usage improves auditors’ performance in analytical and fraud-related procedures and the extent to which variations in audit planning decisions can be influenced by changes in NFMs.

We recognize that it is difficult to determine if the change in our NFMs should lead, lag or mirror changes in revenue. For example, does an increase in employees lead to an increase in revenue in the same year or in future years? Furthermore, does an increase in revenue lead to the hiring of more employees as the firm expands operations to meet demand? Importantly, if changes and revenue and changes in an NFM are not completely contemporaneous, this would bias against our finding results. We hope that future research in the area of NFMs will provide more insight into the time frame auditors should examine when considering specific NFMs.

## REFERENCES

- Abbott, L., Y. Park, S. Parker. 2000. The effects of audit committee activity and independence on corporate fraud. *Managerial Finance* 26: 55-67.
- American Institute of Certified Public Accountants (AICPA). 1988. *Statement on Auditing Standards No. 56: Analytical Procedures*. New York, NY: AICPA.
- AICPA. 2002. *Statement on Auditing Standards No. 99: Consideration of Fraud in a Financial Statement Audit*. New York, NY: AICPA.
- Amir, E. and B. Lev. 1996. Value-Relevance of nonfinancial information: The wireless communications industry. *Journal of Accounting and Economics* 22 (Supplement): 3-30.
- Anderson, U. and L. Koonce. 1995. Explanation as a method for evaluating client-suggested causes in analytical procedures. *Auditing, A Journal of Practice and Theory* 14 (Fall): 124-132.
- Banker, R., G. Potter and D. Srinivasan. 2000. An empirical investigation of an incentive plan that includes nonfinancial measures. *The Accounting Review* 75 (January): 65-92.
- Beasley, M. 1996. An empirical analysis of the relation between board of director composition and financial statement fraud. *The Accounting Review* 71 (October): 443-465.
- Beasley, M., J. Carcello, and D. Hermanson. 1999. *Fraudulent Financial Reporting: 1987-1997 An Analysis of U.S. Public Companies*. Committee of Sponsoring Organizations of the Treadway Commission.
- Beasley, M., J. Carcello, D. Hermanson, P. Lapides. 2000. Fraudulent financial reporting: Consideration of industry traits and corporate governance mechanisms. *Accounting Horizons* 14 (December): 441-454.
- Behn, B. and R. Riley. 1999. Using nonfinancial information to predict financial performance: The case of the U.S. airline industry. *Journal of Accounting, Auditing & Finance* 14 (Winter): 29-56.
- Bell, T. B. and J. V. Carcello. 2000. A decision aid for assessing the likelihood of fraudulent financial reporting. *Auditing: A Journal of Practice & Theory* 19 (Spring): 169-184.
- \_\_\_\_\_, Peecher, M., Solomon, I. 2005. *The 21st century public-company audit: Conceptual elements of KPMG's global audit methodology*. Montvale, New Jersey: KPMG.
- Beneish, M. 1997. Detecting GAAP violations: Implications for assessing earnings management among firms with extreme financial performance. *Journal of Accounting and Public Policy* 16 (Fall): 271-309.

- Bierstaker, J., J. Bedard, and S. Biggs. 1999. The role of problem representation shifts in auditor decision processes in analytical procedures. *Auditing: A Journal of Practice & Theory* 18 (Spring): 19-36.
- Brazel, J. F., C. P. Agoglia, and R. C. Hatfield. 2004. Electronic versus face-to-face review: The effects of alternative forms of review on auditors' performance. *The Accounting Review* 79 (October): 949-966.
- Carey, V., S. Zegler and P. Diggle. 1993. Modeling Multivariate Binary Data with Alternating Logistic Regressions. *Biometrika*, 517-526.
- Dechow, P.M., R.G. Sloan, and A.P. Sweeney. 1996. Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC. *Contemporary Accounting Research* 13 (Spring): 1-36.
- Deloitte LLP. 2004. In the dark: What boards and executives don't know about the health of their businesses. New York, NY: Deloitte LLP.
- Eisinger, J. Cerner's growth has been healthy, but its accounting could be ailing. *The Wall Street Journal* (December 14, 2005): C1.
- Erickson, M., B. Mayhew, and W. Felix. 2000. Why do audits fail? Evidence from Lincoln Savings and Loan. *Journal of Accounting Research* 38 (Spring): 165-194.
- Erickson, M., M. Hanlon, and E.L. Maydew. 2006. Is there a link between executive equity incentives and accounting fraud? *Journal of Accounting Research* 44 (Spring): 113-143.
- Farber, D. 2005. Restoring trust after fraud: Does corporate governance matter? *The Accounting Review* 80. (April): 539-561.
- Feroz, E. H., K. Park and V.S. Pastena. 1991. The financial and market effects of the SEC's Accounting and Enforcement Releases. *Journal of Accounting Research* 29 (Supplement): 107-142.
- Goyal, V., K. Lehn, and S. Racic, 2002, "Growth opportunities and corporate debt policy: the case of the U.S. defense industry." *Journal of Financial Economics* 64: 35-59.
- Gullapalli, D. To err is human, to restate financials, divine: Companies redo reports in record numbers, partly due to Sarbanes-Oxley. *The Wall Street Journal* (January 20, 2005): C3.
- Hirst, D.E. and L. Koonce. 1996. Audit analytical procedures: A field investigation. *Contemporary Accounting Research* 13 (Fall): 457-486.
- Houston, R. W. 1999. The effects of fee pressure and client risk on audit seniors' time budget decisions. *Auditing: A Journal of Practice and Theory* 18: 70-86.

- Ittner, C. and D. Larcker, 1998. Are nonfinancial measures leading indicators of financial performance? An analysis of customer satisfaction. *Journal of Accounting Research* 36 (Supplement): 1-35.
- Kaplan, R. and D. Norton. 1996. *The balanced scorecard*. Boston, MA: Harvard Business School Press
- Langfield-Smith, K., 2003, *Management accounting*, 3<sup>rd</sup> edition, McGraw-Hill.
- Lee, T.A., R.W. Ingram, and T.P. Howard. 1999. The difference between earnings and operating cash flow as an indicator of financial reporting fraud. *Contemporary Accounting Research* 16 (Winter): 749-786.
- Levitt, S. D. and S. J. Dubner. 2005. *Freakonomics: A rogue economist explores the hidden side of everything*. New York, NY: HarperCollins.
- Liedtka, S. 2002. The information content of nonfinancial measures in the airline industry. *Journal of Business Finance & Accounting* 29 (September/October): 1105-1121.
- Loebbecke, J.K., M.M. Eining, and J.J. Willingham. 1989. Auditors' experience with material irregularities: Frequency, nature, and detectability. *Auditing: A Journal of Practice and Theory* 9 (Fall): 1-28.
- Lundegaard, K. 2005. Delphi discloses accounting problems. *Wall Street Journal* (March 7, 2005): A3.
- Messier, W., S. Glover, and D. Prawitt. 2006. *Auditing and assurance services: A systematic approach*, 4<sup>th</sup> edition. New York, NY: McGraw-Hill Irwin.
- Pincus, K., W. Holder, and T. Mock. 1998. *Reducing the incidence of fraudulent financial reporting: The role of the Securities and Exchange Commission*. Los Angeles, CA: SEC Financial Reporting Institute of the University of California.
- Public Oversight Board (POB) 2000. *The Panel on Audit Effectiveness: Report and Recommendations*. Stamford, CT: POB.
- Riley, R. A., T. Preason, and G. Trompeter. 2003. The value relevance of non-financial performance variables: The case of the airline industry. *Journal of Accounting and Public Policy* 22 (May/June): 231-254.
- Said, A., R. HassabElnaby, B. Wier. 2003. An empirical investigation of the performance consequences of nonfinancial measures. *Journal of Management Accounting Research*. 15: 193-223

Security and Exchange Commission (SEC) 2004a. Accounting and Auditing Enforcement Release No. 2027.

SEC 2004b. Accounting and Auditing Enforcement Release No. 1741.

Summers, S.L. and J.T. Sweeney. 1998. Fraudulent misstated financial statements and insider trading: An empirical analysis. *The Accounting Review* 73 (January): 131-146.

Teoh, S.H. and T.J. Wong. 1993. Perceived auditor quality and the earnings response Coefficient. *The Accounting Review* 68 (April): 346-366.

Wall Street Journal (WSJ), 2005. Defense expert: HealthSouth fraud too complex for detection. May 6.

Wright, A. M. 1988. The impact of prior year workpapers on auditor evidential planning judgments. *Accounting, Organizations, and Society* 13: 595-606.

Zeger, S. and K.Y. Liang, 1986. Longitudinal data analysis for discrete and continuous outcome. *Biometric* 42 (March): 121-130.

## ENDNOTES

1. Both examples (Del Global and Fischer Imaging; and Anicom and Graybar Electric) came from data in our sample.
2. In fact, seventy-five percent of the frauds in our sample manipulated revenue. The inclusion of fraud firms in our sample that didn't manipulate revenue (e.g., manipulated expenses or other gains and losses) to manage earnings, biases against our hypotheses while positively contributing to the generalizability of our results (i.e., auditors do not perform fraud related procedures with a knowledge, ex-ante, of the method used by a fraud client to manage earnings). We ran the analyses without the firms that did not manipulate revenue and the results are unchanged.
3. Prior studies (Pincus, Holder and Mock 1988; Feroz, Park and Pastena 1991; Dechow, Sloan and Sweeney 1996) provide more detail on AAERS and the SEC's process in investigating firms.
4. We compared earnings before extraordinary items (Data 18 on Compustat) before and after the restatement to estimate the size of the fraud. Restated earnings figures are not available for 14 of the 77 fraud firms. Six firms did not restate because they went out of business or were acquired. Two other firms choose not to restate because the fraud was uncovered several years after the first year of the fraud and the company simply explained the non-restated years were not to be relied on. Three firms paid a fine but didn't appear to restate. One firm managed revenue without managing earnings. We could not find restatement information for two other firms.
5. Table 4 illustrates that we could have employed numerous variables in our multivariate regression. Ultimately we used variables employed in the most recent paper (Lee et al. 1999). However, we also considered whether other variables would have been better proxies for various controls by first regressing all variables in Table 4 individually on Fraud to determine which variables were individually significant. We then included those that were individually significant into a multivariate model in which we regressed these control variables and Diff on Fraud. Using this alternative multivariate approach, Diff remained significant and appears robust to different measures of control variables.
6. SAS can estimate ALR's using the Proc Genmod procedure. You must specify link=logit, dist=bin and repeated subject="name of repeated variable." SAS will then produce a standard logistic regression and the ALR.
7. Due to the directional nature of our expectations, our hypotheses tests are one-tailed while all other tests are two-tailed.
8. The fact that Debt and ChgInv are not significant would seem to contradict previous research. However, due to the small sample size of various fraud studies (including our own), we do not suggest that our results contradict the findings of prior research with respect to these variables.

**TABLE 1**  
**Sample Selection**

---

*Panel A*

Frauds from COSO's Report on Fraudulent Financial Reporting from 1987-1997 with sufficient data to include in sample (i.e. frauds post 1992 and non-duplicates of analysis below)	3
Total Accounting and Auditing Enforcement Releases (AAERs) attributable to alleged or actual accounting fraud (non-duplicates) issued since COSO's 1987-1997 Report on Fraudulent Financial reporting until June 2005	245
Firms that reported fraudulent quarterly data but not annual data	(46)
Nonfinancial frauds (e.g., insider trading, omitted disclosures)	(21)
Frauds where we could not locate company data (e.g., small firms, foreign companies, frauds prior to 1992)	(64)
Frauds where we could not find similar NFMs for both the fraud firm and a competitor.	(40)
Total sample	<hr style="width: 100%; border: 0.5px solid black;"/> 77
Frauds that did not restate (e.g., filed for bankruptcy prior to restating)	(14)
Sample of frauds that restated earnings	<hr style="width: 100%; border: 0.5px solid black;"/> 63

---

**Table 1 (continued)****Frequency of Observations across Industries and Years***Panel B:*

SIC Code	Industry	Number	Percent
1300-1399	Oil and Gas Extraction	1	1%
1600-1699	Heavy Construction	1	1%
2000-2099	Food and Kindred Products	1	1%
2300-2399	Apparel and other Finished Products	3	4%
2700-2799	Printing, Publishing and Allied Industries	1	1%
2800-2899	Chemicals and Allied Products	4	5%
3100-3199	Leather and Leather Products	1	1%
3300-3399	Primary Metal Industries	1	1%
3400-3499	Fabricated Metal Products	2	3%
3500-3599	Industrial and Commercial Machinery and Computer Equipment	5	6%
3600-3699	Electronic and other Electrical Equipment and Components	4	5%
3700-3799	Transportation Equipment	1	1%
3800-3899	Measuring, Analyzing, and Controlling Instruments	11	14%
4800-4899	Communications	4	5%
4900-4999	Electric, Gas, and Sanitary Services	4	5%
5000-5099	Wholesale Trade - durable goods	3	4%
5100-5199	Wholesale Trade - non-durable goods	2	3%
5600-5699	Apparel and Accessory Stores	1	1%
5900-5999	Miscellaneous Retail	4	5%
6700-6799	Holding and Other Investment Offices	1	1%
7300-7399	Business Services	20	26%
8000-8099	Health Services	1	1%
9900-9999	Other	1	1%
		<b>Rounding</b>	<b>4%</b>
		<b>77</b>	<b>100%</b>

**Table 1 (continued)**

---

*Panel C:*

<u>Year</u>	<u>Number</u>	<u>Percent</u>
1991	1	1%
1992	3	4%
1993	2	3%
1994	5	6%
1995	2	3%
1996	7	9%
1997	12	16%
1998	16	21%
1999	9	12%
2000	13	17%
2001	5	6%
2002	2	3%
	<u>Rounding</u>	<u>(1%)</u>
	77	100%

---

**Table 2****Type of alleged accounting fraud (Source: SEC Accounting and Auditing Enforcement Releases)**

Accounts and Other Factors Involved in Fraud	Number of Firms	% of Fraud Sample
Revenues	58	75%
Expenses	29	38%
Cost of Sales	10	13%
Accounts Receivable	43	56%
Inventory	15	19%
Other Assets	19	25%
Accounts Payable and Other Accrued Expenses	11	14%
Debt	8	10%
Other Gains/Losses	8	10%
Related Parties	4	5%
Acquisitions and Mergers	4	5%
Total	209	*

\* Does not sum to the number of firms in the sample because of the dual-entry nature of accounting (i.e., early revenue recognition generates fraudulent credit to revenue and debit to accounts receivable) and several firms are accused of engaging in multiple types of fraudulent behavior.

**Table 3**

**Types of Nonfinancial Measure**

<b>Nonfinancial measure</b>	<b>Observations</b>
Human Resources	76
Products & Services	14
Facilities	12
Capacity (other than facilities)	7
Patents & Trademarks	6
Mergers & Acquisitions	3
Subsidiaries	3
Web Influence	2
Miscellaneous	<u>19</u>
Total	142

**Table 4**

**Financial Ratios used in Prior Literature**

<b>Variable</b>	<b>Computation</b>	<b>Used by</b>	<b>p-value</b>
<b><u>Accruals</u></b>			
Total accruals	Total Accruals <sub>t</sub> / Assets <sub>t</sub>	Beneish (1997)	0.002 <sup>δ</sup> , 0.01 <sup>φ</sup>
Positive accruals	1 if Total Accruals > 0 in t-1	Beneish (1997)	0.02 <sup>φ</sup>
Declining cash sales	1 if Cash Sales <sub>t</sub> < Cash Sales <sub>t-1</sub>	Beneish (1997)	0.01 <sup>φ</sup>
Earnings Less CFO	Net income before Extraordinary Items <sub>t</sub> + Depreciation <sub>t</sub> – Cash flow <sub>t</sub> / Assets <sub>t</sub>	Lee et al. (1999)	0.000 <sup>θ</sup>
<b><u>Leverage</u></b>			
Leverage index	[(Long-Term Debt <sub>t</sub> +Curr.Liab <sub>t</sub> )/Asset <sub>t</sub> ] / [(LTD <sub>t-1</sub> +CL <sub>t-1</sub> )/Assets <sub>t-1</sub> ]	Beneish (1997)	0.044 <sup>δ</sup> , 0.12 <sup>φ</sup>
Leverage	Curr.Liab <sub>t</sub> + Long-Term Debt <sub>t</sub> / Assets <sub>t</sub>	Lee et al. (1999) Dechow et al. (1996)	<0.05 <sup>θ</sup> .01*
<b><u>Profitability</u></b>			
Return on assets	Earnings before Extraordinary Items <sub>t-1</sub> / Assets <sub>t-1</sub>	Summers and Sweeney (1998)	0.01 <sup>#</sup>
	Earnings before Extraordinary Items <sub>t</sub> / Assets <sub>t-1</sub>	Lee et al. (1999)	<0.10 <sup>θ</sup> , <0.05 <sup>θ</sup>
<b><u>Inventory</u></b>			
Days in inventory index	(Inventory <sub>t</sub> /Sales <sub>t</sub> )/(Inventory <sub>t-1</sub> /Sales <sub>t-1</sub> )	Beneish (1997)	0.046 <sup>δ</sup>
Inventory change	(Inventory <sub>t</sub> / Sales <sub>t</sub> ) – (Inventory <sub>t-1</sub> / Sales <sub>t-1</sub> )	Summers and Sweeney (1998)	0.05 <sup>#</sup>
<b><u>Market Value</u></b>			
Market value	Market Value <sub>t</sub> / Assets <sub>t</sub>	Lee et al. (1999) Dechow et al. (1996)	<0.05 <sup>θ</sup> , >0.10 <sup>θ</sup> .02*

**Table 4 (continued)****Notes**

\* *t*-tests of differences of means.

δ - From median  $\chi^2$  test for estimation sample containing 43 GAAP violators and 1,763 nonviolators.

φ - From probit models using sample containing 43 GAAP violators and 1,764 nonviolators.

# - Inventory change and return on assets are significant in a logit model. Univariate significance levels are not reported.

θ - Probability from  $\chi^2$  test for estimation sample containing 56 fraud firm years and two control samples – one using deleted firms (those from the COMPUSTAT research file) and one using firms from the COMPUSTAT annual industrial file. Also, results were provided for two fraud samples. One fraud sample includes all prediscovery firm-years and the other includes only the maximum earnings-cash flow firm-year for each fraud firm. If one probability is given then all four models are below/above the stated probability. If two probabilities are given then the first probability relates to the models using deleted firms as the control group and the second probability relates to the models using industrial firms as the control group.

**Table 5**

**Descriptive Statistics and Comparison of Means for Fraud and Control Samples**

Variable		Mean	Difference		Median	Std Dev
Diff	Fraud=F	0.33			0.22	0.45
	No Fraud=NF	0.15	0.18	***	0.08	0.33
Total Assets (in thousands)	F	7,292			294.05	20,780.24
	NF	10,141	-2,849		1,248.50	27,965.98
Return on Assets (ROA)	F	0.05			0.06	0.29
	NF	0.06	-0.01		0.06	0.20
Market Value of Equity (MVE)	F	2.66			1.31	3.41
	NF	2.62	0.04		1.07	3.18
Debt to Assets (Debt)	F	0.44			0.43	0.19
	NF	0.44	0.00		0.46	0.18
Total Accruals (ACC)	F	0.09			0.05	0.24
	NF	0.00	0.09	***	0.01	0.15
Change in Inventory (ChgInv)	F	0.00			0.00	0.04
	NF	-0.01	0.01		0.00	0.03
Big Four Auditor	F	0.94			1.00	0.24
	NF	0.93	0.01		1.00	0.26
Fraud Size / Revenue	F	0.11			0.04	0.22

Significance Levels: \*\*\*<.01, \*\*<.05, \*<.1 using a t-test for test of differences.

- Diff<sub>t</sub> = ((Rev<sub>t</sub> - Rev<sub>t-1</sub>) / Rev<sub>t-1</sub>) - ((NFM<sub>t</sub> - NFM<sub>t-1</sub>) / NFM<sub>t-1</sub>)  
t = Year of the fraud  
Rev = Total Revenue  
Inc = Income before Extraordinary Item  
NFM = Non Financial Measure  
ACC = earnings before extraordinary items<sub>t</sub> + depreciation<sub>t</sub> - cash flow from operations<sub>t</sub> / total assets<sub>t</sub>  
MVE = end-of-year share price<sub>t</sub> x total common shares outstanding<sub>t</sub> / total assets<sub>t</sub>  
ROA = net income before extraordinary items / total assets<sub>t-1</sub>  
Debt<sub>t</sub> = current liabilities<sub>t</sub> + long-term debt<sub>t</sub> / total assets<sub>t</sub>  
ChgInv<sub>t</sub> = (Inventory<sub>t</sub> / Sales<sub>t</sub>) - (Inventory<sub>t-1</sub> / Sales<sub>t-1</sub>)  
Big Four = Coded 1 if Big Four auditor, 0 otherwise.  
Fraud Size = Amount of earnings restatement after fraud discovery

**TABLE 6**

**OLS and logistic regression comparing 77 fraud firms with 77 matched competitors**

<i>Panel A</i> - $\text{ChgRev} = \beta_0 + \beta_1 \text{ChgNFM}_t$						
Variables	Predicted Sign	Parameter Estimate	OLS		GEE	
			Standard Errors		Standard Errors	
ChgNFM	+	0.47	0.07	***	0.11	***
Intercept		0.32	0.03	***	0.03	***
R <sup>2</sup>			0.12			
Sample Size			284			

  

<i>Panel B</i> - $P(\text{FRAUD}_t) = \beta_0 + \beta_1 \text{Diff}_t$						
Variables	Predicted Sign	Parameter Estimate	Logistic		ALR	
			Standard Errors		Standard Errors	
Diff	+	1.16	0.33	***	0.42	***
Intercept		-0.27	0.14	*	0.22	
Likelihood Ratio Test			13.73	***		
Sample Size			284			

  

<i>Panel C</i> - $P(\text{FRAUD}_t) = \beta_0 + \beta_1 \text{Diff}_t + \beta_2 \text{ACC}_t + \beta_3 \text{MVE}_t + \beta_4 \text{ROA}_t + \beta_5 \text{Debt}_t + \beta_6 \text{ChgInv}_t$											
Variables	Predicted Sign	Parameter Estimate	Logistic		ALR		Logistic		ALR		
			Standard Errors		Standard Errors		Standard Errors		Standard Errors		
Diff	+					1.32	0.41	***	0.47	***	
ACC	+	8.38	1.57	***	2.45	***	8.36	1.63	***	2.68	***
MVE	+	0.15	0.05	***	0.07	**	0.13	0.05	**	0.08	*
ROA	+	-5.25	1.15	***	1.84	***	-5.33	1.24	***	1.72	***
Debt	+	0.01	0.82		1.38		-0.11	0.85		1.40	
ChgInv	+	-2.16	3.81		5.87		2.17	4.13		6.36	
Intercept		-0.38	0.43		0.72		-0.53	0.44		0.72	
Likelihood Ratio Test			44.73	***			55.91	***			
Max-Rescaled R <sup>2</sup>			0.21				0.25				
Sample Size			264				264				

Significance Levels: \*\*\*<.01, \*\*<.05, \*<.1.

**Table 6 (continued)**

P(FRAUD)	= Probability of sample Firm <sub><i>t</i></sub> being fraudulent.
<i>t</i>	= First year of the fraud
Rev	= Total Revenue
Inc	= Income before Extraordinary Item
NFM	= Non Financial Measure
ChgRev	= $(Rev_t - Rev_{t-1}) / Rev_{t-1}$
ChgNFM	= $(NFM_t - NFM_{t-1}) / NFM_{t-1}$
Diff <sub><i>t</i></sub>	= $((Rev_t - Rev_{t-1}) / Rev_{t-1}) - ((NFM_t - NFM_{t-1}) / NFM_{t-1})$
ACC	= Earnings before extraordinary items <sub><i>t</i></sub> + depreciation <sub><i>t</i></sub> – cash flow from operations <sub><i>t</i></sub> / total assets <sub><i>t</i></sub>
MVE	= End-of-year share price <sub><i>t</i></sub> x total common shares outstanding <sub><i>t</i></sub> / total assets <sub><i>t</i></sub>
ROA	= Net income before extraordinary items / total assets <sub><i>t-1</i></sub>
Debt <sub><i>t</i></sub>	= Current liabilities <sub><i>t</i></sub> + long-term debt <sub><i>t</i></sub> / total assets <sub><i>t</i></sub>
ChgInv <sub><i>t</i></sub>	= $(Inventory_t / Sales_t) - (Inventory_{t-1} / Sales_{t-1})$
Big Four	= Coded 1 if Big Four auditor, 0 otherwise.
Fraud Size	= Amount of earnings restatement after fraud discovery