Using Nonfinancial Measures to Assess Fraud Risk

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ABSTRACT

This study examines whether auditors can effectively use nonfinancial measures to assess the reasonableness of financial performance and, thereby, help detect financial statement fraud (hereafter, fraud). If auditors or other interested parties (e.g., directors, lenders, investors, or regulators) can identify nonfinancial measures (e.g., facilities growth) that are correlated with financial measures (e.g., revenue growth), inconsistent patterns between the nonfinancial and financial measures can be used to detect firms with high fraud risk. We find that the *difference* between financial and nonfinancial performance is significantly greater for firms that committed fraud than for their non-fraud competitors. We also find that this difference is a significant fraud indicator when included in a model containing variables that have previously been linked to the likelihood of fraud. Overall, our results provide empirical evidence suggesting that nonfinancial measures can be effectively used to assess the likelihood of fraud.

Keywords: *analytical procedures, fraud, nonfinancial measures*

Data Availability: *Data are available from public sources.*

I. INTRODUCTION

This paper investigates whether publicly available nonfinancial measures (NFMs), such as the number of retail outlets, warehouse space, or employee headcounts, can be used to assess the likelihood of fraud. During the trial of former HealthSouth CEO Richard Scrushy, 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 prosecution 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 2005a]. Conry's question implied that HealthSouth's financial information was inconsistent with its nonfinancial information and thus, the risk of financial statement fraud (hereafter, fraud) at HealthSouth should have been a concern. The defense witness responded that the inconsistency was not apparent at the time and that HealthSouth's external auditors also failed to note the inconsistency.

We frame our discussion of using NFMs to detect fraud from the perspective of the external auditor who is charged with the responsibility to detect material fraud in Statement on Auditing Standards (SAS) No. 99 (AICPA [2002]).[1] Audit standards (e.g., AICPA [1988] and [2002]) require external auditors to perform analytical procedures (such as ratio analysis) and to consider the results when assessing fraud risk. Although audit guidance recognizes that NFMs may be valuable for performing analytical procedures and assessing fraud risk (AICPA [1988] and [2002]; Bell et al. [2005]; Messier et al. [2006]), auditors are not required to consider them. The Public Company Accounting Oversight Board (PCAOB) is considering whether auditors

[1] Many other parties, including internal auditors, boards of directors, investors, creditors, and regulators, have incentives for detecting fraud. Our discussion could be adapted to these parties as well.

should be required to use NFMs to help detect fraud (PCAOB [2004]; Hogan et al. [2008]). The PCAOB has concluded that analytical procedures using only financial data are likely to be ineffective for detecting fraud because management can make fictitious entries to financial data in order to create an expected pattern (PCAOB [2004]).

Importantly, management may attempt to conceal a fraud by manipulating their NFM data to make it consistent with their fraudulent financial data. For example, Royal Dutch Shell allegedly misled investors for years by overstating their oil and gas reserves (WSJ [2008]).[2] If such NFM manipulations are commonplace, then inconsistencies between financial and NFM data should be no more pronounced for fraud firms than for non-fraud firms. On the other hand, manipulating other NFMs can be difficult to conceal because (unlike oil and gas reserves) NFM verification is often straightforward. For example, auditors can effectively verify the number of facilities, retail outlets, or employees. Still, there are several examples, such as HealthSouth, where the reported financial performance was not supported by NFM data and the inconsistency was not noted by auditors or regulators. This study provides the first empirical test of whether inconsistencies between financial and NFM data can be used to detect fraud. By doing so, we also implicitly provide evidence on whether systematic NFM manipulation is occurring at fraud firms.

Although there is a vast amount of fraud research that looks at numerous explanatory variables (see Nieschweitz et al. [2000]), no prior study examines the potential for NFMs to help distinguish fraud firms from non-fraud firms. Prior archival research on detecting fraud provides

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[2] The evidence does not suggest that Royal Dutch Shell was manipulating reserves in order to conceal financial statement fraud. It is more likely that Royal Dutch Shell was simply overzealous in moving "probable" oil reserves to "proved" oil reserves, which reflected favorably on *future* financial performance (Carey et al. [2004]). However, this example does show that the manipulation of NFMs is possible. It also illustrates that empirical tests of the ability of NFMs to detect fraud are needed to test claims made by regulators and standard setters that NFMs can be used to effectively assess fraud risk.

evidence of a link between fraud and financial statement variables (Dechow et al. [1996]; Beneish [1997]; Summers and Sweeney [1998]; Lee et al. [1999]), corporate governance variables (Beasley [1996]; Dechow et al. [1996]; Abbott et al. [2000]; Beasley et al. [2000]; Farber [2005]), suspicious accounting (Marquardt and Wiedman [2004]; McVay [2006]), and other fraud indicators, such as weak internal controls (Bell and Carcello [2000]). We add to this literature by exploring whether a new category of variables—namely, NFMs—can add discriminatory power to fraud prediction models developed from prior research.

Our second research contribution is that we build on prior research that explores the relevance of NFMs for measuring firm performance (e.g., Amir and Lev [1996]; Kaplan and Norton [1996]; Ittner and Larcker [1998]). We extend this literature by empirically testing whether NFMs can be used to detect when a firm's reported financial performance does not accurately portray its economic performance. This study expands the NFM literature by providing an empirical test of their potential to *verify* current financial results, whereas the extant NFM research looks at the ability of NFMs to *predict* future firm performance. We believe both roles of NFMs are valuable—one to validate and the other to forecast.

We find that the relation between reported financial performance and NFMs can distinguish fraud from non-fraud firms. Using a matched-pair sample of fraud firms and non-fraud competitors, we document that fraud firms are more likely than non-fraud firms to report inconsistent revenue growth relative to their growth in NFMs. We analyze the growth from the year prior to the fraud to the first year of the fraud for each matched-pair. When we include a variable that measures the difference between a firm's financial performance and its NFM performance in a model that includes other factors that have been found to be indicative of fraud, we find the difference is a significant discriminator between fraud and non-fraud firms. Thus, we provide evidence showing that comparisons between financial measures and NFMs can be effectively used to assess fraud risk.

This paper is organized as follows: section II develops our hypotheses; section III explains our sample selection and research method; section IV presents the results; and section V concludes the paper.

II. DEVELOPMENT OF HYPOTHESES

Prior Research

Academic research suggests that auditors' analytical procedures are ineffective at detecting fraud for at least three reasons. First, auditors may not recognize unusual trends and ratios within the financial statements because they lack a sufficient understanding of their client's business (Erickson et al. [2000]). Second, auditors tend to rely on management's explanations without adequately testing their validity (Anderson and Koonce [1995]; Hirst and Koonce [1996]; Bierstaker et al. [1999]). Third, traditional analytical procedures using financial statement data lead to high rates of misclassification and, therefore, yield limited success in identifying fraud (Beneish [1999]; Kaminski and Wetzel [2004]; Hogan et al. [2008]). If NFMs can be used to detect fraud, requiring auditors to use them could help address these challenges. For example, NFMs could be used to help auditors understand a client's business by pointing them to the drivers of economic performance (Ittner and Larcker [1998]). Similarly, if NFMs exist that are easily verified and are not being manipulated by management (Bell et al. [2005]), then using them will provide an avenue for auditors to both generate reliable expectations for their analytical procedures and test the validity of management's explanations to their inquiries.

The ability to use NFMs to validate financial performance implies that a correlation exists between NFMs and underlying firm performance. The use of NFMs in evaluating underlying firm performance has garnered much attention since Kaplan and Norton [1996] published *The Balanced Scorecard*. NFM proponents claim that NFMs 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.

Prior research investigates the relations between NFMs and financial performance measures. Amir and Lev [1996] and Riley et al. [2003] study the cell-phone and airline industries, respectively, and conclude that investors overwhelmingly value nonfinancial information over traditional, financial statement variables. 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 NFM, customer satisfaction, is significantly related to future accounting performance and is partially reflected in current accounting book values.

Two additional studies investigate associations between NFMs and financial statement data in the airline industry. Liedtka [2002] uses factor analyses to show that nineteen NFMs disclosed by the airline industry represent seven constructs not measured by eighteen common financial measures. Behn and Riley [1999] find that airline industry NFMs are useful for predicting quarterly revenue, expense, and net income numbers. Last, in a study of the retail industry, Lundholm and McVay [2008] illustrate that growth in retail outlets and same-store sales data can be modeled to provide sales forecasts that rival IBES analysts' forecasts. Consistent with this research, audit guidance suggests that NFMs, such as production capacity, should be correlated with revenue reported on the income statement (AICPA [2002]).

In addition to this research, anecdotal evidence suggests that considering NFMs in conjunction with financial results may, in some cases, help auditors identify fraudulent financial statements. For example, Delphi Corporation appears to have boosted net income through sham sales 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 Delphi's reported financial performance and its NFMs. In addition, both short-sellers and fraud examiners appear to consider NFMs when evaluating the reasonableness of sales growth that exceeds expectations [WSJ 2005b].

Interestingly, internal and external stakeholders are pressuring businesses to report more NFMs (Ballou et al. [2006]; Holder-Webb et al. [2008] and [2009]). As businesses respond to this pressure, it may become more difficult to conceal inconsistencies between financial performance and NFMs. We explore whether fraud firms' financial results are inconsistent with publicly available NFMs such that the financial results suggest significantly stronger performance than the NFMs. For example, a retailer that is closing outlets is not likely to achieve substantial revenue growth. Such an inconsistency suggests a higher likelihood of fraud.

The PCAOB recognizes the potential for NFMs to be a powerful, independent benchmark for evaluating the validity of financial statement data, and recently endorsed their usage to improve fraud detection (PCAOB [2007]). In addition, Bell et al. [2005] claim that NFMs are less vulnerable to manipulation and are often more easily verified than financial data.[3] However, cases do exist where fraud firms have manipulated NFMs. For example, the *New York Times* [2002] reports that WorldCom inflated their internet traffic growth while committing fraud. The

[3] Bell et al. [2005] recognize that some NFMs are more easily manipulated than others. For example, it may be easier for management to distort (and conceal) spoilage rates than to distort square footage of operations or number of retail outlets.

article explains that when investors discovered that WorldCom's internet data strategy was not profitable, they were shocked because they "had come to believe the boasts of (WorldCom) executives that internet traffic was doubling about every three months." Regarding WorldCom's NFM fraud, Scott Cleland, CEO of Precursor Group (a Washington DC research firm), stated: "The $4 billion accounting fraud is baby stuff compared to the fraud of data traffic growth, which allowed WorldCom's stock to appreciate tenfold" [NYT 2002].

Despite the cases where NFMs have been misstated, several factors suggest that many NFMs are difficult to manipulate, or at least that such manipulations may be difficult to conceal. First, while financial controls can be overridden by management and while financial statements are produced internally, some NFMs are produced and reported by independent sources (e.g., customer satisfaction ratings produced by J. D. Power and Associates). Second, many NFMs are not difficult for auditors to verify (e.g., number of acquisitions, production facilities, or employees), whereas many financial results are difficult to verify (e.g., the estimation of the allowance for doubtful accounts). Third, if management attempts to manipulate their NFMs to conceal a fraud, they will need to expand the perpetrator pool in order to conceal the misstated NFM (e.g., involve human resource employees to manipulate headcounts). Thus, a fraud involving both misstated financial data and NFMs will require a greater degree of collusion to conceal. Finally, the manipulation of NFMs involves another set of data that management will need to falsify, which adds complexity to the act of fraud. To summarize, NFM manipulations may not be commonplace for fraud firms. We do not test whether NFMs are more difficult to manipulate than financial data. We believe such a test would be difficult, if not impossible, to perform. However, if fraud firms have manipulated NFMs to be consistent with their fraudulent financial statements, our empirical tests will likely not detect differences between fraud and non-fraud firms with respect to inconsistencies between financial data and NFMs.

Our goal is to explore whether NFMs can be used to detect fraud. Importantly, our study does not provide auditors or other interested parties with a specific model or variable for detecting fraud. We use publicly available empirical data to test the validity of claims by regulators (AICPA [2002]; PCAOB [2004]) and educators (Messier et al. [2006]) 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 NFM data available to auditors. Thus, tests using publicly available data that suggest NFMs can detect fraud will provide strong evidence that auditors can effectively use NFMs as part of their forensic procedures.[4] Our findings can be used by policymakers to determine whether benefits to the audit profession would accrue if auditors were required to use NFM data when assessing fraud risk. We offer two anecdotal examples suggesting that such benefits would accrue.

Examples

The following examples illustrate how NFMs may be used to detect fraud. Del Global Technologies makes electronic components, assemblies, and systems for medical, industrial, and defense uses. The Securities and Exchange Commission (SEC) alleges that in fiscal years 1997–2000, Del Global Technologies Corp. (Del) engaged in improper revenue recognition when it held open quarters, prematurely shipped products to third-party warehouses, and recorded sales

[4] Potential reasons why auditors may not currently search for and use NFMs include budget pressures, over-reliance on prior-year workpapers that do not include analyses of NFMs, and hesitancy among auditors to adjust the nature of their fraud testing (cf., Wright [1988]; Zimbelman [1997]; Houston [1999]; Glover et al. [2003]; Brazel et al. [2004]).

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% 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 it is even less probable that employee layoffs would correspond with a significant increase in revenue. In addition, Del's total number of distributors also decreased from 400 to 250 from 1996 to 1997. A decrease in distributors would also seem unlikely to correspond with a significant increase in revenue. This case illustrates how an unusual relationship between NFMs (i.e., total number of employees and 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% decrease in revenue over the same period, accompanied by a 20% decrease in employees and a 7% decrease in distributors.

Anicom, Inc. represents another case of unusual trends among NFMs and financial data. Prior to filing for bankruptcy in 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 they 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%), in the number of facilities (55%), and in square feet of operations (29%). However, the company's revenue growth was 93% 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%) from 1997 to 1998. Graybar's growth in NFMs was consistent with its revenue growth: total employees increased 10%, total number of facilities increased 3%, and square feet of operations increased 6%. While we recognize that factors other than fraud can cause unusual relationships between NFMs and financial data, we test whether firms that are committing fraud are more likely to exhibit these relationships.

Hypotheses

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, industry-specific NFMs. 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 determine whether inconsistencies between revenue growth and NFM growth discriminate between fraud and non-fraud firms.[5] For example, we select 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 the 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

[5] We concentrate our analyses on revenues due to the concentration of frauds and restatements related to improper revenue recognition. SAS No. 99 explicitly advises auditors that revenue recognition should be considered a high-fraud-risk area, and, consequently, auditors should compare recorded revenue amounts with relevant NFMs. In addition, any future PCAOB guidance on fraud is likely to include required procedures related to revenue recognition (e.g., Beasley et al. [1999]; AICPA [2002]; PCAOB [2004]; WSJ [2005c]).

competitor with the expectation that the difference between revenue growth and NFM growth will be larger for fraud firms than for their non-fraud competitors. Thus, we test the following hypothesis:

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

When performing analytical procedures, auditors commonly rely on trends in prior-year financial data to develop expectations for the current-year's financial performance (Anderson and Koonce [1995]; Hirst and Koonce [1996]; Bierstaker et al. [1999]; POB [2000]). As mentioned previously, audit guidance suggests that auditors should incorporate the results of analytical procedures into their fraud risk assessments. SAS No. 99 (AICPA [2002], ¶28) specifically 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.

The PCAOB [2004] contends that comparing financial data to NFMs is more likely to help auditors detect fraud than performing analytical procedures based solely on financial data that has also been subject to manipulation or fraud. To test this claim, we explore whether the consistency between financial measures and NFMs is associated with fraudulent financial reporting when controlling for other financial variables (e.g., leverage) known to discriminate fraud from non-fraud firms. We also control for nonoperational / nonfinancial data (e.g., corporate governance variables, auditor type, age of the firm, etc.) that have been linked to fraud. In a fraudulent financial reporting model, the explanatory power of these nonoperational / nonfinancial factors should be complemented by including NFMs that serve as a reliable benchmark for financial reporting accuracy.

Prior research and audit guidance identifies three factors—collectively known as the *fraud triangle*—that lead to fraud: incentive, opportunity, and attitude (Loebbecke et al. [1989]; Albrecht et al. [1995]; AICPA [2002]). Incentive factors include inducement from capital markets and compensation schemes that result in a perceived benefit from committing fraud. Opportunity factors include weak corporate governance and other working conditions that result in circumstances that allow management to commit fraud. Attitude factors are items that reveal management's propensity to rationalize fraudulent behavior. Archival research shows that factors related to both incentive and opportunity are related to fraud (e.g., Beasley [1996]). However, we are not aware of prior archival research that measures and controls for management's attitude, a finding confirmed by Hogan et al. [2008] in their review of the fraud literature.[6]

Prior archival studies and educators identify variables related to suspicious accounting (e.g., special items) that are useful in detecting fraud or earnings management (Albrecht et al. [2008]; Marquardt and Wiedman [2004]; McVay [2006]). Thus, three categories of factors found in prior archival research to be associated with fraud are: incentive, opportunity, and suspicious accounting. To determine if inconsistencies between financial measures and NFMs discriminate fraud firms from non-fraud firms, we incorporate our variable of interest into a model containing financial and nonoperational proxies for incentive, opportunity, and suspicious accounting and measure its effects. Our expectation is formalized as follows:

H2: An independent variable that compares change in revenue growth and change in NFMs is positively associated with fraudulent financial reporting after controlling for variables that have been previously linked to fraudulent financial reporting.

[6] As noted earlier, several parties are calling on businesses to report more NFM information. Some of these NFMs may be useful for measuring managements' attitude toward fraud. For example, NFMs that measure a firm's social and environmental performance may be correlated with managements' attitude. We believe that future research exploring this relationship may be fruitful.

III. SAMPLE SELECTION AND RESEARCH METHOD

Sample

Our fraud sample includes firms charged by the SEC with having fraudulently reported revenue in 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/As, 8-Ks, 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 find 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 also appears that Compustat does not change the data they originally entered when a restatement occurs at a later time. We therefore compare Compustat data with the original 10-K filing to verify that the data reported in Compustat is the fraudulently reported numbers and not restated data. We find that Compustat reports restated data for nine of the fraud firms in our fraud sample. We hand-collect the fraudulent data from the original 10-K filing for those nine firms. SEC filings are available on EDGAR from 1994 onward and on Lexis/Nexis for selected companies for years prior to 1994.

We identify our fraud sample from three sources. First, the Committee of Sponsoring Organizations of the Treadway Commission (COSO) published a report, "Fraudulent Financial Reporting: 1987–1997, An Analysis of U.S. Public Companies" (Beasley et al. [1999]), that investigates frauds identified in SEC Accounting and Auditing Enforcement Releases (AAERs) issued during the period of 1987–1997.[7] Second, we perform our own search for AAERs issued during the years 1998–2007. Finally, we search the popular press (e.g., the *Wall Street Journal*) for reports about fraud cases.

We exclude firms from our sample for one or more of the following reasons: firms had missing or incomplete data (largely due to missing Compustat data required to measure many of our control variables), firms did not misreport at least one 10-K (e.g., fraudulent reported quarterly data), firms were in the financial services or insurance industries,[8] firms perpetrated frauds that did not involve fraudulent financial reporting (e.g., omitted disclosures, insider trading, options backdating), firms did not manipulate revenues (e.g., inventory/expense frauds), firms committed fraud prior to 1993 (i.e., no 10-K or proxy statement available on EDGAR to verify fraudulent revenue data), or firms did not have similar NFMs for the firm and a competitor (non-fraud firm) that we could hand-collect. Our initial fraud sample consists of 50 fraud firms that, according to the SEC, intentionally manipulated revenues. This sample size is comparable to the sample sizes of previous fraud studies (e.g., Beasley [1996]; Erickson et al. [2006]). For our analysis of only one NFM available on Compustat, number of employees, our sample size expands to 110 fraud firms. Panel A of table 1 reports our sample selection method.

Insert table 1 here

Several of our fraud firms misreported revenues for 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., the year prior to the fraud) to a year that was manipulated (i.e., the first

[7] Prior studies (Pincus et al. [1987]; Feroz et al. [1991]; Dechow et al. [1996]) provide more detail on AAERs and the SEC's process in investigating firms.
[8] We exclude firms in these industries because they generally lack the control variables (e.g., financing) used in our models and to be consistent with prior fraud research (e.g., Lee et al. [1999]; Erickson et al. [2006])

year of the fraud). For our initial sample of 50 fraud firms, panels B and C of table 1 present the number of frauds by industry and year, respectively. The 50 firms accused of fraud reside in 22 different two-digit SIC codes. The 7300–7399 Business Services classification code has the largest percentage (24%) of fraud firms. The frauds in our sample occurred during a nine-year period between 1994 and 2002, with 82% of the alleged frauds in the sample taking place in the years 1997–2000.

Table 2 presents the types of alleged accounting fraud in our sample firms as obtained from the AAERs. We were also able to hand-collect information on the size of the restatement for 39 of the 50 firms in our sample. For each fraud firm, we searched the AAER and subsequent 10-Ks, 10-K/As, and 8-Ks to find the restated earnings number. The average earnings restatement for all firms was 11% of total revenue.

Insert table 2 here

Methodology for Collecting NFM Data

Students enrolled in undergraduate and graduate auditing courses at three universities selected the non-fraud competitors and collected NFM data for our sample of fraud firms. Emulating audit practice, we asked the students to assume the role of staff assistant, with each student assigned to a different auditee (i.e., fraud firm). They were informed that their audit task involved 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). The students were not aware of the study's hypotheses, they did not collect revenue data, and they were not evaluated on whether the data was consistent with the hypotheses. They were evaluated solely on their ability to collect NFM data.

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 require identical NFMs for both the fraud firm and its competitor. We conclude 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 competitors. More importantly, discussions with practicing auditors reveal that our matching procedure was more likely to be performed by independent auditors rather than a simple SIC code match.[9]

Students were instructed to collect up to four quantitative NFMs that were identical for both the client and one competitor of their choosing for the initial fraud year and the prior fiscal year-end (noting source references). We told 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, Lexis/Nexis, Standard and Poor's Market Insight, and Google for NFMs for each fraud firm and one competitor of their choosing. The students were told to be creative in finding new sources of NFM data and to share information about possible new data sources with other students. Students reported that collecting the NFM data took between two to five hours for each firm-competitor combination.

[9] Some prior fraud research matches on SIC code, year, and size (e.g., Beasley [1996]; Summers and Sweeney [1998]; Erickson et al. [2006]). Our matching process differs but yields similar results, since only 18 of our 50 fraud firms were matched with competitors in a different two-digit SIC code. However, we find some competitors were in entirely different SIC codes than the fraud firms. For example, Genesco allegedly committed fraud in 2001 (SEC [2003]). Compustat lists Genesco's SIC code as 5661 (Apparel and Accessory Stores: Shoe Stores). Hoover's lists Stride Rite as one of Genesco's closest competitors, but Stride Rite's SIC code is 3140 (Leather and Leather Products: Footwear). We had similar experiences matching other fraud firms with their competitors and conclude that matching on SIC code does not necessarily include the firm's competitors as listed by Hoover's Online.

Our sample includes NFMs that are quantitative, non-financial, non-employee related, and relate to firm capacity.[10] For example, several NFMs involve the capacity of the firm's operational space, including square feet of operations, manufacturing space, floor space, and warehousing space. Other measures involve the number of facilities available to the firm, such as the number of retail outlets, number of facilities, and number of stores. Some measures were explicitly given the label of capacity by the firm, including annual capacity in tons and energy-producing capacity. Others were deemed to reflect capacity, such as gas reserves, distribution dealers, and number of product lines. From the NFMs submitted by students, we identify a total of 115 common NFMs for 50 fraud firms and their competitors.

Some NFMs collected by the students do not fit our requirements as quantitative, non-financial, non-employee-related measures of capacity; therefore, we exclude those NFMs from our sample. Examples of data that we exclude are bond ratings and number of litigation cases. We include NFMs in our analysis only if we could make a relatively strong argument for their correlation with capacity. Importantly, 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 for assessing fraud risk. Because we believe auditors have access to client NFMs that are not publicly available (and perhaps more predictive of financial data), we view our tests as lacking strong power to reject the null. Therefore, finding statistical support for our hypotheses using this methodology suggests that NFMs have significant potential for assessing fraud risk.

[10] As an alternative test of H1 and H2, we separately examine whether our hypotheses are supported using one type of NFM—total number of employees (Compustat data #29).

Statistical Models

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

$$\text{CAPACITY DIFF}_t = \text{REVENUE GROWTH}_t - \text{NFM GROWTH}_t$$

where,

REVENUE GROWTH	$= (\text{Revenue}_t - \text{Revenue}_{t-1}) / \text{Revenue}_{t-1}$
NFM GROWTH	$= (\text{NFM}_t - \text{NFM}_{t-1}) / \text{NFM}_{t-1}$
REVENUE	= Total Revenue
NFM	= Nonfinancial Measure
t	= Initial Year of the Fraud

H1 posits that fraud firms will have, on average, a greater value for CAPACITY DIFF than non-fraud firms (i.e., competitors).[11] When we have multiple NFMs for a matched-pair, we use the *average* change in NFMs to calculate CAPACITY DIFF. For example, as noted previously, Anicom reported a substantial increase in square feet of operations (29%) and in the number of facilities (55%) during the year of the fraud. In Anicom's case, the average change in NFM is 42%. During the same period, Anicom's sales grew 93% for a CAPACITY DIFF of 51%. As an alternative test of H1 and H2, we examine whether our hypotheses are supported using one

[11] We winsorize both our DIFF measures at 1 and -1, which means the difference between revenue growth and NFM growth could not be greater than 100% or less than -100%. We did this because the majority of our sample had values for DIFF between 100% and -100%. However, some firms had extreme values of DIFF, which are primarily driven by years of extreme revenue growth. For example, M&A West allegedly committed fraud in 2000 (SEC [2001]). M&A's revenues increased from $602 thousand in 1999 to $7.5 million in 2000 for an increase of 1,145 percent. M&A's NFM growth was still substantial (491%); however, M&A's DIFF value is 654%. Financial ratios often "blow up" at the tails, and the problems with using accounting-based financial ratios are well documented (Kane and Meade [1998]). Both our measures of DIFF are especially sensitive to these problems because they are the difference of two ratios. In the case of M&A West, it is unlikely that an auditor attempting to assess fraud risk would attach six and a half times more weight to M&A's difference in revenue and NFM growth than a firm that has a 100% difference. The differences for both are simply very high and abnormal. Therefore, we cap the value of our DIFF measures at 100% and -100%. As a sensitivity test, we also replace both DIFF measures with a dummy variable that equals 1 if NFM GROWTH is greater than REVENUE GROWTH and generate qualitatively similar results (see the Robustness Tests section). Finally, deleting firms (and their corresponding matched pair) with DIFFs in excess of 100% and -100% generates qualitatively similar results, as does ranking the DIFFs and using the ranking as our dependent variable (Cheng et al. [1992]; Ireland and Lennox [2002]).

NFM, total number of employees (Compustat data #29).[12] We refer to this variable as EMPLOYEE DIFF. We calculate EMPLOYEE DIFF for 110 matched-pairs (220 observations) as opposed to the 50 matched-pairs (100 observations) for CAPACITY DIFF.

We test whether EMPLOYEE GROWTH is typically correlated with REVENUE GROWTH by performing the following regression on all firms in Compustat during our sample period (1993–2002):

$$\text{REVENUE GROWTH}_t = \beta_0 + \beta_1\text{EMPLOYEE GROWTH}_t$$

where, REVENUE GROWTH equals ($\text{Revenue}_t - \text{Revenue}_{t-1}$) / Revenue_{t-1} and EMPLOYEE GROWTH equals ($\text{Employees}_t - \text{Employees}_{t-1}$) / Employees_{t-1}. In non-tabulated results, the coefficient on EMPLOYEE GROWTH is positive (.597) and highly significant ($p < 0.01$). The R^2 is high (.28), suggesting a strong correlation between employee growth and revenue growth reported by companies. Thus, at least for non-fraud firms, one would expect a relatively low EMPLOYEE DIFF.

To test H2, we examine CAPACITY DIFF and EMPLOYEE DIFF in multivariate regressions with control variables for incentive, opportunity, and suspicious accounting, and an indicator for fraud as the dependent variable. We examine the effects of our variables of interest in these regressions to determine whether they are positively associated with fraudulent financial reporting. Our selection and measurement of control variables is reflective of variables that have been examined in prior studies of fraud, earnings management, and accounting restatements (e.g., Erickson et al. [2006]; McVay [2006]; Richardson et al. [2007]). Our models are as follows:

[12] See Berenson [2003] for a description of how substantial discrepancies between revenue growth and employee growth were present at Computer Associates while the company was committing fraud. Also, using two variables to test for our hypotheses provides a robustness test to ensure some systematic variation in a business practice, such as employee outsourcing, is not driving our results. Outsourcing is also addressed in the Robustness Tests section later in the paper.

$P(FRAUD_t) = \beta_0 + \beta_1 \text{Capacity Diff}_t + \beta_i \text{Control Variables}$

$P(FRAUD_t) = \beta_0 + \beta_1 \text{Employee Diff}_t + \beta_i \text{Control Variables}$

$P(FRAUD_t)$ = A dummy variable coded 1 for fraud firms and 0 for non-fraud firms

t = year of the fraud

We define the control variables as follows:

<u>*INCENTIVE FACTORS*</u>

FINANCING	= An indicator variable coded 1 if $FREECASH_t$ is less than -0.5, and coded 0 otherwise.
FREECASH	= (Cash Flow from Operations_t - Average Capital $\text{Expenditures}_{t\text{-3 to }t\text{-1}}$) / Current $\text{Assets}_{t\text{-1}}$
LEVERAGE	= (Short-Term Debt_t + Long-Term Debt_t) / Total Assets_t
ALTMAN'S Z SCORE	= $1.2X_1 + 1.4X_2 + 3.3X_3 + .6X_4 + 1.0X_5$ X_1 = (Current Assets_t – Current Liabilities_t) / Total Assets_t X_2 = Retained Earnings_t / Total Assets_t X_3 = Earnings Before Interest and Taxes_t / Total Assets_t X_4 = Market Value of Equity_t / Book Value of Total Liabilities_t X_5 = Revenue_t / Total Assets_t
MARKET VALUE OF EQUITY	= End-of-Year Share Price_t x Total Common Shares Outstanding_t
BOOK TO MARKET	= (Total Assets_t – Total Liabilities_t) / Market Value of Equity_t
EARNINGS TO PRICE	= Net Income (Compustat data #18) per Share / End-of-Year Share Price_t
RETURN ON ASSETS	= Net Income Before Extraordinary Items_t / Total $\text{Assets}_{t\text{-}1}$
AGE OF FIRM	= The length of time in years the firm has been publicly traded (from the Center for Research in Security Prices).
M&A IN YEAR OF FRAUD	= An indicator variable set equal to 1 if the firm had an acquisition that contributed to sales in the prior year (acquisition in the first year of fraud for fraud firms). (Variable set equal to 1 if Compustat data #249 > 0. Otherwise, variable is set to 0.)

<u>*OPPORTUNITY FACTORS*</u>

BIG FOUR	= An indicator variable set equal to 1 if the firm

	had a Big Four Auditor at t, and set to 0 otherwise.
INSIDERS ON THE BOARD	= The percentage of insiders (company employees) on the Board of Directors.
CEO=COB	= An indicator variable coded 1 if the firm's CEO was also Chairman of the Board, and coded 0 otherwise.
<u>*SUSPICIOUS ACCOUNTING FACTORS*</u>	
TOTAL ACCRUALS	= (Net Income Before Extraordinary Items$_t$ + Depreciation$_t$ – Cash Flow from Operations$_t$) / Total Assets$_t$
SPECIAL ITEMS	= An indicator variable set equal to 1 if the firm reported a special item (Compustat #17). Otherwise, variable is set to 0.
REVENUE GROWTH	= (Revenue$_t$ – Revenue$_{t-1}$) / Revenue $_{t-1}$
<u>*OTHER CONTROLS*</u>	
TOTAL ASSETS	= Total Assets$_t$
NEGATIVE CHANGE IN NFM	= An indicator variable set equal to 1 if the firm had a negative change in NFM. Otherwise, variable is set to 0.

FINANCING captures the extent to which the firm may need external financing. Consistent with Dechow et al. [1996], we create an indicator variable set equal to 1 if the firm will likely need external financing in the next two years. Firms closer to exhausting their internal funds may have incentives to manipulate revenues in anticipation of accessing the capital markets. Following Erickson et al. [2006], if FREECASH is less than or equal to -0.5, then FINANCING is set equal to 1; otherwise, FINANCING is set to equal 0. This cutoff implies that if a firm will need external financing in the coming years it will need to start raising the desired funds now.

Both LEVERAGE and ALTMAN'S Z SCORE control for financial distress. Financially distressed firms may have a greater incentive to commit fraud than those that are not distressed (Begley et al. [1996]). We also include several variables that measure market and financial performance. Above average financial or stock performance may indicate that the firm is achieving abnormally high performance through fraudulent reporting, or that the firm may have incentives to commit fraud in order to sustain their performance. We use MARKET VALUE OF EQUITY, BOOK TO MARKET, EARNINGS TO PRICE, and RETURN ON ASSETS to control for stock and financial performance and to be consistent with prior fraud studies (e.g., Dechow et al. [1996]; Beneish [1997]; Summers and Sweeney [1998]; Lee et al. [1999]; Erickson et al. [2006]). AGE OF THE FIRM controls for the fact that fraud firms tend to be younger (Beneish [1997]), which may be due to a greater incentive to commit fraud as a result of an initial public offering or other newly issued stock. M&A IN YEAR OF FRAUD is an indicator variable set equal to 1 if a portion of firm revenues are from an acquisition. Firms have incentives to manage earnings prior to an acquisition in order to raise their stock price (Erickson and Wang [1999]; Louis [2004]).[13]

BIG FOUR is a measure of audit quality and opportunity. We use the term *Big Four* to represent the four largest international accounting firms, their predecessor firms, and Arthur Andersen. Teoh and Wong [1993] find evidence consistent with the hypothesis that larger auditors generate more precise earnings. Palmrose [1988] concludes that Big Four auditors experience less litigation than non-Big Four auditors, despite having deeper pockets. Based on this research, employing a Big Four auditor may lead to higher audit quality and reduce a firm's opportunity to engage in fraud.

Weak corporate governance may lead to less monitoring of financial and non-financial information and greater opportunities to commit fraud (Beasley [1996]; Deloitte LLP [2004]). Dechow et al. [1996] show that several corporate governance variables are correlated with

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[13] We do not include a control variable for equity-based compensation in our model for two reasons. First, in their study of the link between executive equity incentives and accounting fraud, Erickson et al. [2006] do not find consistent evidence that equity-based compensation is associated with fraud. Second, for the majority of the firms in our sample, we were unable to obtain equity-based compensation data from ExecuComp.

fraudulent reporting. They classify 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 include INSIDERS ON BOARD, which is the percentage of company employees that sit on the board of directors. To control for the power of the CEO over the board, we select a dummy variable that is set to 1 if the CEO is also the chairman of the board (CEO=COB), and 0 otherwise. We hand-collect corporate governance data from proxy statements.

Our model controls for three specific forms of suspicious accounting. TOTAL ACCRUALS controls for the difference between earnings and cash flow from operations. Lee et al. [1999] find this difference to be an indicator of fraudulent financial reporting. If earnings are fraudulent, there will be no corresponding cash inflow. We include the existence of SPECIAL ITEMS as a control variable because prior research suggests that special items have been used as an earnings management tool (Marquardt and Wiedman [2004]; McVay [2006]). REVENUE GROWTH controls for the possibility that high growth firms may have high values for our two DIFF measures and that fraud firms are simply high growth firms needing to sustain their growth (Erickson et al. [2006]), rather than firms for which there are inconsistencies between their financial data and NFMs.

TOTAL ASSETS proxies for size; including this variable controls for the possibility that size is driving our results. Similarly, NEGATIVE CHANGE IN NFM controls for the possibility that our results are driven by firms in crisis. Firms with a negative change in their NFMs may be downsizing or in turmoil, causing a large value for our two DIFF measures. We include this variable to control for this possibility.

Methodology Related to Missing Data

In order to maximize the size of our sample (in terms of total sample size and total control variables) in our multivariate analyses (H2 testing), we employ Rubin's [1987] multiple imputation procedure to control for missing data. Our primary data constraint with respect to control variables was hand-collecting the corporate governance variables from proxy statements. We were able to collect INSIDERS ON BOARD and CEO=COB for only 42 fraud firms. The multiple imputation procedure replaces the missing values with a set of plausible values that represent the uncertainty about the correct value to impute. The imputed data sets are analyzed using standard procedures (e.g., standard logistic regression) and the results are combined (Yuan [2007]).[14]

IV. RESULTS

Descriptive Statistics

Table 3 provides descriptive statistics for our study's main variable of interest (CAPACITY DIFF), the alternative variable of interest (EMPLOYEE DIFF), and control variables. 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 3 here

On average, the fraud firms are smaller and have a smaller return on assets than non-fraud firms; however, the differences in means for TOTAL ASSETS and RETURN ON ASSETS were not significant. Several control variables are significantly different between the two groups

[14] Three methods have been used for imputing missing data. Our results use the Markov Chain Monte Carlo method developed by Schafer [1997], which assumes that the missing data follow an arbitrary pattern. Two other methods, the parametric regression method and the propensity scores method, are used when the missing data follow a monotone pattern (Yuan [2007]). We do not report results using these methods because we have no evidence to assume our missing data follow a monotone pattern. However, models using these two other methods produce results that are qualitatively similar.

including control variables from two of the three fraud factors; *incentive* (FINANCING, LEVERAGE, MARKET VALUE OF EQUITY, AGE OF FIRM, M&A IN YEAR OF FRAUD) and *suspicious accounting* (TOTAL ACCRUALS, REVENUE GROWTH). The average earnings manipulation for the fraud firms equals 11% of total revenue.

Tests of Hypotheses

H1 predicts a greater difference between revenue growth and NFM growth (CAPACITY DIFF) for the fraud sample than for the non-fraud sample. The results in table 3 support H1 as CAPACITY DIFF is significantly greater ($p < 0.05$) for the fraud sample relative to the sample of non-fraud competitor firms.[15] Thus, for fraud firms, there appears to be a greater inconsistency between the performance portrayed by their financial statements and that portrayed by their NFMs. For their competitors we observe a mean CAPACITY DIFF of 0.11. For non-fraud competitors, revenue appears to grow faster than their NFMs, but the percentage difference appears reasonable given the expected noise between financial statement data and NFMs. However, for the fraud firms, we observe a much larger mean CAPACITY DIFF of 0.30. A greater CAPACITY DIFF may therefore be indicative of greater fraud risk. For auditors, investors, regulators, or other parties examining CAPACITY DIFF in future applications, our descriptive results provide a benchmark for a reasonable CAPACITY DIFF (0.11) and what might be considered unreasonable (0.30), and would therefore require investigation.

The results are stronger for EMPLOYEE DIFF ($p < 0.01$), which provides slightly less variance than CAPACITY DIFF, as evidenced by smaller standard deviations. While CAPACITY DIFF represents the change in revenue less the average change of multiple, industry-specific NFMs, EMPLOYEE DIFF represents the change in revenue less the change in

[15] Our tests of hypotheses are one-tailed. All other tests are two-tailed.

one consistent NFM. It is interesting to note the close relationship between revenue growth and employee growth for non-fraud firms (mean EMPLOYEE DIFF = .04). As such, H1 is also supported with EMPLOYEE DIFF.

Table 4 provides a correlation matrix that shows NFM GROWTH and EMPLOYEE GROWTH are significantly correlated with REVENUE GROWTH (at 61% and 62%, respectively). This provides support for using NFMs as a benchmark for revenue growth. These correlations exist despite the fact that half of the firms in the sample committed revenue fraud (i.e., revenue growth is likely to be materially misstated for fraud firms). It is likely that the strong relation between NFMs and revenue for non-fraud firms is driving this correlation. Our tests of H1 support this premise. As expected, our variables of interest, CAPACITY DIFF and EMPLOYEE DIFF, are highly correlated with REVENUE GROWTH (at 56% and 59%, respectively). This correlation is expected because both DIFF variables are a function of REVENUE GROWTH (e.g., CAPACITY DIFF = REVENUE GROWTH – NFM GROWTH).[16]

Insert table 4 here

Table 5 presents the results of a multivariate logistic regression for CAPACITY DIFF and our control variables on P(FRAUD). H2 is supported by a positive and significant coefficient

[16] The high correlation between CAPACITY DIFF and REVENUE GROWTH raises the question of multicollinearity. However, when we perform the multivariate regressions in tables 5 and 6 with and without CAPACITY DIFF (and EMPLOYEE DIFF) we find (not tabulated) that the coefficient on REVENUE GROWTH is not significant ($p > 0.05$) in either case. This is not surprising because REVENUE GROWTH (or derivations thereon) has not traditionally been a significant variable in the multivariate settings of prior fraud research (e.g., Lee et al. [1999]; Summers and Sweeney [1998]; Beneish [1997]). One exception is one of the two multivariate regressions in Erickson et al. [2006]. We also perform our multivariate regressions with and without REVENUE GROWTH and find (not tabulated) that the coefficients on CAPACITY DIFF and EMPLOYEE DIFF are significant ($p < 0.05$) in both cases. Additionally, for analyses in tables 5 and 6, the variance inflation factors (VIFs) for both DIFF measures and REVENUE GROWTH are substantially below (VIFs < 3.0) the standard threshold of 10 (e.g., Neter et al. [1996]; Kennedy [1998]). Thus, multicollinearity with REVENUE GROWTH does not appear to be affecting the statistical significance of the coefficients on CAPACITY DIFF and EMPLOYEE DIFF. In addition, REVENUE GROWTH by itself does not appear to yield as much information as it does when anchored on NFM growth. As a practical matter, anchoring on NFM growth is useful to auditors (or others) because it provides auditors a frame of reference to assess when revenue growth (which may or may not be a fraud risk) appears *abnormally* high.

($p = 0.04$) for CAPACITY DIFF. The addition of CAPACITY DIFF improves the fit of the model—the max rescaled R^2 improves from .36 to .39 and the likelihood ratio improves from 31.0 to 34.2. A likelihood ratio test shows this improvement is statistically significant ($p < 0.10$). Interestingly, CAPACITY DIFF is significant despite the inclusion of M&A IN YEAR OF FRAUD, TOTAL ACCRUALS, and REVENUE GROWTH in our regression model. All three of these control variables can be considered indicators of firm growth. Thus, the positive and significant coefficient for CAPACITY DIFF suggests that the large CAPACITY DIFF for fraud firms presented in table 4 is not simply a function of fraud firms being high-growth firms. Our results indicate that comparing revenue growth to NFM growth provides additional information about the likelihood of fraudulent reporting not contained in variables identified in prior research, which supports H2.

Insert table 5 here

Table 6 presents the results of a multivariate logistic regression for EMPLOYEE DIFF and our control variables on P(FRAUD). H2 is further supported by a positive and significant coefficient ($p < 0.01$) for EMPLOYEE DIFF. The addition of EMPLOYEE DIFF improves the fit of the model—the max rescaled R^2 improves from .35 to .40 and the likelihood ratio improves from 67.6 to 77.8. A likelihood ratio test shows this improvement is statistically significant ($p < 0.01$). These findings are consistent, and slightly better, than those presented in table 5. Using one NFM may provide greater discriminatory power because some of the student-collected, capacity-related NFM data may not have been ideally suited for a comparison with revenue. In practice, auditors, investors, and other interested parties would be much more familiar with specific industries and the NFMs that drive revenue. As such, these parties could determine whether they should use multiple NFMs or concentrate their efforts on one single NFM. In summary, these results provide evidence that using NFMs can improve fraud risk assessment.

Insert table 6 here

Robustness Tests

We provide a simple robustness test that considers a dummy variable version of CAPACITY DIFF such that CAPACITY DIFF is set to 1 if REVENUE GROWTH > MEAN NFM GROWTH; otherwise, it equals 0. This dummy variable has a positive (2.29) and significant ($p = 0.01$) coefficient in our multivariate model and the max rescaled R^2 is 42% (not tabulated). We also perform this analysis with a dummy variable version of EMPLOYEE DIFF (i.e., the dummy variable equals 1 if REVENUE GROWTH > EMPLOYEE GROWTH; otherwise, it equals 0) and find it is also positive (1.75) and significant ($p < 0.04$) and the max-rescaled R^2 is 37% (not tabulated).

We recognize the possibility that outsourcing may be more prevalent in the fraud sample than in the control sample and, therefore, may be driving our results related to EMPLOYEE DIFF. If fraud firms are more likely than their competitors to be outsourcing during the year of the fraud, then their larger-than-average EMPLOYEE DIFF could be driven by a decrease in the number of people directly employed by the company rather than by an unsubstantiated revenue increase. We take several measures to control for this possibility. For each fraud firm and competitor in the EMPLOYEE DIFF sample, we search its 10-K for evidence of outsourcing in the year prior to the fraud and the year of the fraud.[17] We find ten instances (six competitors and four fraud firms) where a firm appears to be outsourcing during the two-year period. None of the 10-Ks provide specific information about the *number* of jobs outsourced. As such, we are unable

[17] We used the following search terms: *outsource, outsourcing, layoff(s), service contract(s), subcontract(s), subcontracting,* and *offshore*.

to incorporate outsourced employee numbers into our analyses. However, when we delete those firms and their corresponding matched-pair from the sample, our multivariate results are qualitatively the same as those reported in table 6 (untabulated coefficient = 1.93; $p < 0.01$). In addition, we match our fraud firms with competitors in the same industry to ensure that industry-wide differences are most likely randomized between the fraud firms and control firms. Finally, our tests using CAPACITY DIFF (where outsourcing is not an issue) are consistent with the model using EMPLOYEE DIFF, making it less likely that outsourcing is driving the EMPLOYEE DIFF results.

V. CONCLUDING COMMENTS

The current regulatory environment places 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. In this study we investigate whether comparing financial data to nonfinancial measures (NFMs) can aid auditors and others in assessing fraud risk. We predict and find that fraud firms have greater differences in percent change in revenue growth and percent change in NFMs than their non-fraud competitors. These differences are positively associated with fraudulent financial reporting after controlling for variables that have been previously linked to fraud.

Our findings have implications for auditors, other parties interested in assessing fraud risk, and future research. First, the prior literature suggests that fraud goes undetected when auditors fail to understand the environments in which their clients operate (Erickson et al. [2000]). Fraud risk assessment models that incorporate NFMs should help prevent these failures. 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, serve as a tipping point for assigning forensic specialists to the engagement. Second, our study supplies empirical evidence to policy-makers who are currently considering requiring the use of NFMs in auditing (e.g., PCAOB [2004]). Third, our descriptive results provide auditors and other parties (e.g., investors, directors, regulators) with benchmarks for what might be reasonable and unreasonable inconsistencies between financial data and NFMs.

Future research questions include whether our results, using annual data, can be replicated with quarterly data. Such research would show whether auditors could use the analysis contained herein to detect fraud prior to performing fiscal year-end audit procedures. Other fruitful areas of research include evaluating whether the discriminatory power of our analyses could be improved by using more than one competitor or determining whether values for DIFF for non-fraud firms are consistently low. Future studies could also investigate if and how auditors and investors use NFMs in practice. For example, researchers could examine the degree to which auditors choose to use NFMs and what mechanisms might promote their usage (e.g., higher fraud risk assessments, more explicit guidance, and greater industry expertise). Such research could also determine the extent to which NFM usage improves auditors' performance. Researchers could also investigate whether investors (e.g., short-sellers) benefit from identifying inconsistencies between financial measures and NFMs. Finally, exploring the ability of specific NFMs to measure the fraud risk construct of attitude (e.g., NFMs that attempt to measure social or environmental performance) would also be interesting.

Several limitations of this study should be noted. First, it is possible that fraud perpetrators have manipulated NFMs in the past and will manipulate NFMs in the future to make them consistent with reported financial results. Although we provide reasons why NFM manipulation may be difficult to perpetrate or conceal, we are unable to conclude that this did not occur in our sample or will occur in the future. We are also unable to incorporate controls for potential NFM manipulations in our analyses. To the extent that perpetrators have manipulated NFMs in the past, such manipulations bias against our finding support for H1 and H2. Like any fraud research, perpetrators may change their methods in the future to avoid the latest forensic accounting tools. Future research could explicitly examine ways in which NFMs are manipulated and the likely forms of these manipulations.

Second, because of the issue of NFM manipulation, those who choose to use NFMs for fraud risk assessment would be wise to complement firm-provided NFMs in the 10-K with NFMs from independent sources (e.g., customer satisfaction and product quality ratings). In general, the students that collected the NFMs for this study did not collect NFMs from independent sources. This was primarily due to the fact that, from 2005–2007, these students were collecting NFMs for frauds that occurred mostly in the 1990s (see table 1, panel C). Thus, online access to older, independent NFM data was not readily available to the students. A question for future research is whether such contemporaneous, independent NFMs can be used by interested parties to perform the analyses described in this paper.

Third, because the availability of NFMs varies by firm, users of NFMs may need to develop different approaches for using NFMs to detect fraud. For example, if contemporaneous competitor NFM data is not available, an auditor or investor may need to analyze fluctuations in DIFF measures over time for a particular company. An audit firm could develop a database of contemporaneous NFM data from their portfolio of clients. Hoitash et al. [2006] find that audit firms do this with industry financial data. Websites that promote investor protection could automate the calculation of DIFF measures through the use of webscraping software. Also, those who combine or standardize different forms of NFMs to create one CAPACITY DIFF measure will need to make certain that each of the NFMs used is an accurate predictor of revenue growth and is measured on the same scale (e.g., levels, changes).

Fourth, 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? It should be noted that we find the highest R^2 when we regress current revenue on current employee levels (vs. prior year or next year employee levels). However, that may not be the case for all NFM measures. We hope that future research in this area will provide more insight into the time frame for effectively using NFMs to verify financial data. Finally, our findings are limited in that we examine only revenue frauds. Future studies could examine other fraud schemes (e.g. expense frauds) and determine specific NFMs that might be useful in their detection.

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Table 1

Sample Information

Selection Method

Panel A

Frauds from COSO's Report on Fraudulent Financial Reporting from 1987–1997 (Beasley et al. 1999).	204
Total Accounting and Auditing Enforcement Releases (AAERs) attributable to alleged or actual accounting fraud from January 1998–September 2007 (non-duplicates of the COSO report).	268
Additional frauds identified through other sources (e.g., popular press search and AAA monograph on litigation involving Big Four auditors).	6
Firms with missing or incomplete data on Compustat, Edgar, or Lexis/Nexis (including missing data from prior year).	(162)
Frauds related to quarterly (10-Qs), but not annual data (10-Ks).	(75)
Frauds dropped for other reasons (i.e., financial services or insurance firm or fraud was nonfinancial in nature (e.g., omitted disclosure, insider trading)).	(70)
Frauds unrelated to revenue (e.g., inventory and expense frauds).	(54)
Frauds prior to 1993 (no proxy or 10-K available on Edgar).	(44)
Frauds that we could not find similar capacity-related NFM data for the fraud firm and competitor for the year before the fraud and the first year of the fraud.	(23)
Total sample	50

Our sample of frauds with employee data includes 110 firms. Employee data is generally available on Compustat. The employee fraud sample consists of the 50 frauds in the sample above, plus the 23 for which we otherwise could not find capacity-related NFM data, plus the 44 frauds prior to 1993 (less 7 frauds for which employee data was not available on Compustat and we were not able to find it through any other source).

Table 1 (continued)

Frequency of Observations across Industries

Panel B:

SIC Code	Industry	Number	Percent
1300-1399	Oil & Gas Extraction	1	2%
1600-1699	Heavy Construction	1	2%
2000-2099	Food & Kindred Products	1	2%
2300-2399	Apparel & Other Finished Products	3	6%
2600-2699	Paper & Allied Products	1	2%
2800-2899	Chemicals & Allied Products	1	2%
3100-3199	Leather & Leather Products	1	2%
3300-3399	Primary Metal Industries	1	2%
3400-3499	Fabricated Metal Products	1	2%
3500-3599	Industrial & Commercial Machinery & Computer Equipment	5	10%
3600-3699	Electronic & Other Electrical Equipment & Components	4	8%
3800-3899	Measuring, Analyzing, & Controlling Instruments	5	10%
4800-4899	Communications	1	2%
4900-4999	Electric, Gas, & Sanitary Services	3	6%
5000-5099	Wholesale Trade—durable goods	2	4%
5100-5199	Wholesale Trade—non-durable goods	1	2%
5300-5399	General Merchandise Stores	1	2%
5600-5699	Apparel & Accessory Stores	1	2%
5900-5999	Miscellaneous Retail	2	4%
7300-7399	Business Services	12	24%
7900-7999	Amusement & Recreation Services	1	2%
8000-8099	Health Services	1	2%
		50	100%

Table 1 (continued)

Frequency of Observations across Years

Panel C:

Year	Number	Percent
1994	2	4%
1995	1	2%
1996	1	2%
1997	12	24%
1998	11	22%
1999	7	14%
2000	11	22%
2001	4	8%
2002	1	2%
	50	100%

Table 2

Type of Alleged Accounting Fraud

Accounts and Other Factors Involved in Fraud	Number of Firms	% of Fraud Sample
Revenues	50	100%
Accounts Receivable/Allowance for Doubtful Accounts	33	66%
Expenses	17	34%
Other Assets	16	32%
Inventory	9	18%
Debt	6	12%
Cost of Sales	5	10%
Accounts Payable and Other Accrued Expenses	5	10%
Related Parties	2	4%
Acquisitions and Mergers	2	4%
Other Gains/Losses	1	2%
Total	146 *	

* 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 a fraudulent credit to revenue and a debit to accounts receivable) and because several firms are accused of engaging in multiple types of fraudulent behavior (e.g., manipulation of revenue and expenses).

Table 3

Descriptive Statistics and Comparison of Means for Fraud and Control Samples (H1 Testing)

Variable		Mean	Difference		Median	Std Dev
CAPACITY DIFF	Fraud = F	0.30			0.28	0.48
	No Fraud = NF	0.11	0.19	**	0.09	0.41
EMPLOYEE DIFF	F	0.20			0.14	0.40
	NF	0.04	0.16	***	0.03	0.29
FINANCING	F	0.12			0.00	0.33
	NF	0.02	0.10	*	0.00	0.14
LEVERAGE	F	0.43			0.33	0.48
	NF	0.28	0.16	**	0.22	0.25
ALTMAN'S Z SCORE	F	4.60			3.30	3.79
	NF	7.09	-2.49		4.22	9.69
MARKET VALUE	F	4,131.55			561.18	6,445.41
OF EQUITY (000s)	NF	7,535.91	-3,404.36	**	2,907.94	8,250.87
BOOK TO MARKET	F	0.50			0.42	0.44
	NF	0.50	0.00		0.38	0.44
EARNINGS TO PRICE	F	0.001			0.03	0.13
	NF	0.002	-0.001		0.04	0.20
RETURN ON ASSETS	F	0.03			0.05	0.18
	NF	0.07	-0.04		0.06	0.09
AGE OF FIRM	F	13.46			7.50	13.79
	NF	22.02	-8.56	***	15.50	17.82
M&A IN YEAR	F	0.28			0.00	0.45
OF FRAUD	NF	0.12	0.16	**	0.00	0.33
BIG FOUR	F	0.90			1.00	0.30
	NF	0.90	0.00		1.00	0.30
INSIDERS ON BOARD	F	0.36			0.35	0.16
	NF	0.30	0.06		0.00	0.24
CEO=COB	F	0.74			1.00	0.44
	NF	0.70	0.04		0.00	0.47
TOTAL ACCRUALS	F	0.07			0.04	0.22
	NF	0.00	0.07	*	0.00	0.11
SPECIAL ITEMS	F	0.54			1.00	0.50
	NF	0.48	0.06		0.00	0.50
REVENUE GROWTH	F	0.55			0.35	0.92
	NF	0.27	0.28	*	0.12	0.55

TOTAL ASSETS (000s)	F	5,247.90		426.14	12,577.53
	NF	13,844.89	-8,596.99	1,650.05	35,970.57
NEGATIVE CHANGE IN NFM	F	0.24		0.00	0.43
	NF	0.34	-0.10	0.00	0.48
FRAUD SIZE / REVENUE	F	0.11		0.05	0.18

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

All variables are defined as follows: t = year of the fraud. The statistics are derived from the sample of 50 fraud firms and 50 control firms, except for the statistics on EMPLOYEEE DIFF, which are derived from a larger sample of 110 fraud firms and 110 control firms. See panel A of table 1 for a description of the two samples. CAPACITY DIFF_t = REVENUE GROWTH – NFM GROWTH. REVENUE GROWTH = $((\text{Revenue}_t - \text{Revenue}_{t-1}) / \text{Revenue}_{t-1})$ and NFM GROWTH = $((\text{NFM}_t - \text{NFM}_{t-1}) / \text{NFM}_{t-1})$. NFM is Nonfinancial Measure. If a firm has more than one capacity NFM, then we use the average NFM GROWTH to calculate CAPACITY DIFF. EMPLOYEE DIFF = REVENUE GROWTH – EMPLOYEE GROWTH. EMPLOYEE GROWTH = $(\text{Employees}_t - \text{Employees}_{t-1}) / \text{Employees}_{t-1}$. FINANCING = An indicator variable coded 1 if the firm's FREECASH is less than -0.5 and coded 0 otherwise. FREECASH_t = (Cash Flow from Operations_t – Average Capital $\text{Expenditures}_{t-3 \text{ to } t-1}$) / Current Assets_{t-1}. LEVERAGE = (Short-Term Debt_t + Long-Term Debt_t) / Total Assets_t. ALTMAN'S Z SCORE = $1.2X_1 + 1.4X_2 + 3.3X_3 + .6X_4 + 1.0X_5$. X_1 = (Current Assets_t – Current Liabilities_t) / Total Assets_t. X_2 = Retained Earnings_t / Total Assets_t. X_3 = Earnings before interest and taxes_t / Total Assets_t. X_4 = Market Value of Equity_t / Book Value of Total Liabilities_t. X_5 = Revenue_t / Total Assets_t. MARKET VALUE OF EQUITY = End-of-Year Share Price_t x Total Common Shares Outstanding_t. BOOK TO MARKET = (Total Assets_t – Total Liabilities_t) / Market Value of Equity_t. EARNINGS TO PRICE = Net income (Compustat #18) per share / End-of-Year Share Price_t. RETURN ON ASSETS = Net Income before extraordinary items_t / Total Assets_{t-1}. AGE OF FIRM = The length of time in years the firm has been publicly traded (from the Center for Research in Security Prices). M&A IN YEAR OF FRAUD = An indicator variable set equal to 1 if the firm had an acquisition that contributed to sales in the prior year (acquisition in the first year of fraud for fraud firms). (Variable set equal to 1 if Compustat data #249 > 0, otherwise variable is set to 0.) BIG FOUR= An indicator variable set equal to 1 if the firm had a Big Four auditor during the year of the fraud and set to 0 otherwise. INSIDERS ON BOARD = The percentage of insiders (company employees) on the Board of Directors. CEO=COB = An indicator variable coded 1 if the firm's CEO was also Chairman of the Board and coded 0 otherwise. TOTAL ASSETS = Total Assets_t. ACCRUALS = (Net Income before extraordinary items_t + Depreciation_t – Cash Flow from Operations_t) / Total Assets_t. SPECIAL ITEMS = An indicator variable set equal to 1 if the firm reported a special item (Compustat #17) and set equal to 0 otherwise. REVENUE GROWTH = $(\text{Sales}_t - \text{Sales}_{t-1}) / \text{Sales}_{t-1}$. NEGATIVE CHANGE IN NFM = An indicator variable set equal to 1 if the firm had a negative change in NFM, otherwise variable is set to 0. FRAUD SIZE / REVENUE = the size of the earnings restatement as a percentage of revenue after the fraud was discovered. All control variables are winzorized at the 99th and 1st percentile.

Table 4

Correlation Matrix

	1. CDIFF	2. EDIFF	3. FIN	4. LEV	5. ALTZ	6. MVE	7. BM	8. EP	9. ROA	10. AGE	11. M&A	12. BIG4	13. INSID	14. CEO	15. ACC	16. SPEC	17. REVG	18. ASST	19. NEGC	20. NFMG
1 CAPACITY DIFF	1																			
2 EMPLOYEE DIFF	0.50 ***	1																		
3 FINANCING	0.01	0.01	1																	
4 LEVERAGE	0.20 **	0.08	0.21 ***	1																
5 ALTMAN'S Z SCORE	0.04	0.03	-0.02	-0.21 ***	1															
6 MVE	-0.02	0.01	-0.15 **	-0.05	0.16 **	1														
7 BOOK TO MARKET	0.02	-0.05	-0.01	-0.12 *	-0.32 ***	-0.14 **	1													
8 EARNINGS TO PRICE	-0.04	0.06	-0.11	0.08	0.30 ***	0.29 ***	-0.56 ***	1												
9 RETURN ON ASSETS	0.14	0.13 **	-0.43 ***	-0.04	0.42 ***	0.12 *	-0.35 ***	0.48 ***	1											
10 AGE OF FIRM	-0.13	-0.02	-0.22 ***	0.00	-0.10	0.47 ***	0.00	0.21 ***	0.12 *	1										
11 M & A	0.30 ***	0.04	0.10	0.13 **	0.08	0.01	-0.05	-0.04	-0.08	-0.15 **	1									
12 BIG FOUR	-0.02	-0.13 **	-0.15 **	-0.15 **	0.05	0.20 ***	0.00	-0.01	-0.03	0.19 ***	0.00	1								
13 INSIDERS ON BOARD	0.06	0.06	0.05	0.11	0.00	-0.24 **	-0.09	-0.16	-0.06	-0.43 ***	0.09	-0.28 ***	1							
14 CEO=COB	-0.07	-0.07	0.01	-0.05	0.14	0.15	-0.16	0.27 ***	0.17 *	0.17 *	-0.03	-0.04	-0.09	1						
15 TOTAL ACCRUALS	0.09	0.23 ***	0.20 ***	0.22 ***	0.23 ***	-0.14 **	-0.35 ***	0.33 ***	0.44 ***	-0.09	-0.07	-0.20 ***	0.20 **	0.13	1					
16 SPECIAL ITEMS	0.10	-0.05	-0.14 **	-0.03	-0.09	0.06	0.06	-0.08	-0.14 **	0.08	0.16 **	0.11 *	-0.12	-0.04	-0.20 ***	1				
17 REVENUE GROWTH	0.56 ***	0.59 ***	0.12 *	0.22 ***	0.13 *	-0.09	-0.12 *	0.05	0.09	-0.13 **	0.17 ***	-0.25 ***	0.15	-0.16	0.34 ***	-0.01	1			
18 TOTAL ASSETS	-0.11	-0.03	-0.07	0.04	-0.01	0.54 ***	0.09	0.12 *	0.02	0.33 ***	-0.01	0.10	-0.17 *	-0.02	-0.06	0.07	-0.06	1		
19 NEG CHANGE IN NFM	0.16	-0.03	0.16	-0.01	0.04	0.02	0.08	-0.09	-0.04	0.04	-0.04	-0.01	-0.06	-0.01	-0.07	-0.08	-0.11	-0.04	1	
20 NFM GROWTH	-0.21 **	0.12	0.10	0.35 ***	-0.05	-0.12	-0.10	-0.02	-0.02	-0.01	-0.01	-0.23 **	0.14	-0.15	0.35 ***	-0.16 *	0.61 ***	-0.04	-0.24 **	1
21 EMPLOYEE GROWTH	0.37 ***	-0.05	0.22 ***	0.30 ***	0.33 ***	-0.09	-0.18 **	0.04	0.07	-0.19 ***	0.27 ***	-0.16 **	0.09	-0.14	0.24 ***	-0.04	0.62 ***	-0.09	-0.22 *	0.41 ***

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

Variables defined in table 3 except for NFM GROWTH and EMPLOYEE GROWTH. NFM GROWTH = (NFM_t – NFM_{t-1}) / NFM_{t-1}. EMPLOYEE GROWTH = ($Employees_t$ – $Employees_{t-1}$) / $Employees_{t-1}$

Table 5

Logistic Regression Comparing 50 Fraud Firms with 50 Matched Competitors
(H2 Testing for CAPACITY DIFF)

Variables	Predicted Sign	Parameter Estimate	*p-value*
INTERCEPT		-0.96	0.63
CAPACITY DIFF	+	1.43	0.04
FINANCING	+	0.09	0.96
LEVERAGE	+	1.58	0.18
ALTMAN'S Z SCORE	+	0.01	0.89
MARKET VALUE OF EQUITY	?	0.00	0.82
BOOK TO MARKET	?	0.01	0.99
EARNINGS TO PRICE	?	1.40	0.44
RETURN ON ASSETS	?	-5.58	0.08
AGE OF FIRM	-	-0.04	0.06
M&A IN YEAR OF FRAUD	+	0.76	0.35
BIG FOUR	-	1.37	0.16
INSIDERS ON BOARD	+	-1.10	0.64
CEO=COB	+	0.57	0.47
TOTAL ACCRUALS	+	6.00	0.07
SPECIAL ITEMS	+	0.19	0.75
REVENUE GROWTH	+	-0.36	0.60
TOTAL ASSETS	?	0.00	0.73
NEGATIVE CHANGE IN NFM	+	-0.86	0.18
Sample Size			100

This table presents the results of a logistic regression where the dependent variable is an indicator variable set equal to 1 for fraud firms accused of financial statement fraud and set equal to 0 otherwise. All variables are defined in table 3. Predicted signs are adopted from the prior literature on fraud (e.g., Erickson et al. [2006]) or posited in the paper (e.g., CAPACITY DIFF). Our tests of hypotheses are one-tailed. All other tests are two-tailed.

Table 6

Logistic Regression Comparing 110 Fraud Firms with 110 Matched Competitors
(H2 Testing for EMPLOYEE DIFF)

Variables	Predicted Sign	Parameter Estimate	*p-value*
INTERCEPT		-1.01	0.29
EMPLOYEE DIFF	+	1.92	<0.01
FINANCING	+	-0.14	0.89
LEVERAGE	+	2.20	<0.01
ALTMAN'S Z SCORE	+	0.02	0.68
MARKET VALUE OF EQUITY	?	0.00	0.51
BOOK TO MARKET	?	-0.38	0.27
EARNINGS TO PRICE	?	0.00	0.77
RETURN ON ASSETS	?	-0.94	0.55
AGE OF FIRM	-	-0.03	0.04
M&A IN YEAR OF FRAUD	+	1.20	0.02
BIG FOUR	-	-0.08	0.88
INSIDERS ON BOARD	+	0.65	0.61
CEO=COB	+	0.41	0.41
TOTAL ACCRUALS	+	5.20	<0.01
SPECIAL ITEMS	+	-0.13	0.71
REVENUE GROWTH	+	-0.47	0.06
TOTAL ASSETS	?	0.00	0.84
NEGATIVE CHANGE IN EMPLOYEES	+	0.53	0.28
Sample Size			220

This table presents the results of a logistic regression where the dependent variable is an indicator variable that is equal to 1 for fraud firms and equal to 0 otherwise. All variables are defined in table 3. Predicted signs are adopted from the prior literature on fraud (e.g., Erickson et al. [2006]) or posited in the paper (e.g., EMPLOYEE DIFF). Our tests of hypotheses are one-tailed. All other tests are two-tailed.