

What Can Nonfinancial Performance Measures Tell Us About the Likelihood of Fraud?

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ABSTRACT: For audit firms, failing to detect fraud at their clients is usually accompanied by substantial monetary penalties and/or negative publicity for the audit firm. Thus, the profession has re-evaluated its fraud assessment processes and has attempted to find new ways in which material misstatements due to fraud can be identified. A factor or an analysis which can improve auditors' fraud risk assessments could simultaneously enhance audit quality and reduce auditor liability substantially. The purpose of this study is to empirically examine whether auditors can effectively use nonfinancial performance measures (NFPMs) in their analyses of fraud. Given that auditors can identify NFPMs (e.g., facilities growth) that are positively correlated with financial measures (e.g., revenue growth) and NFPMs are less easily manipulated by fraud perpetrators than financial statements, inconsistencies between NFPMs and financial performance measures may be indicative of higher fraud risk. We find that the differences between NFPMs and financial measures are significantly greater for fraud firms than their competitors (non-fraud firms). In short, for fraud-firms, NFPMs did not support the growth communicated by their financial statements. We also find these inconsistencies between NFPMs and financial measures appear to be a significant fraud indicator when included in models containing financial measures that have been previously linked to the likelihood of fraud. Therefore, our results empirically show that auditors may benefit from considering factors outside of the financial statements and including NFPMs in their analyses of fraud.

Keywords: *analytical procedures; earnings management; fraud; nonfinancial performance measures*

Data Availability: *Data are available upon request.*

I. 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 could be rephrased as: HealthSouth's financial statement fraud (hereafter fraud) was obvious because the firm's financial statement data was inconsistent with its nonfinancial data. 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 inconsistent relationship between the firm's financial and non-financial performance.

This paper investigates whether nonfinancial performance measures (NFPMs) can be used to assess the likelihood of fraud. Auditors are not currently required to consider NFPMs (e.g., facilities growth, number of retail outlets), although audit practice does recognize that NFPMs may be valuable for performing analytical procedures (see Messier et al. 2006, 188). 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 analytical procedures when assessing fraud risk, respectively. 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 shows that auditors generally do not self-generate explanations for unusual trends and

ratios and they tend to rely on management explanations without performing sufficient work to test the validity of their explanations (Hirst and Koonce 1996; Anderson and Koonce 1995; Bierstaker et al. 1999). NFPMs may therefore provide one avenue for auditors to both generate reliable expectations as part of their analytical procedures and test 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; Jones 2005), corporate governance variables (Beasley 1996; Dechow et al. 1996; 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 NFPMs can distinguish fraud firms from non-fraud firms. Given claims that NFPMs 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 that they could be used to detect fraud firms by identifying discrepancies between a firm's financial and operational performance. Thus, for financial results and NFPMs that are positively correlated, we should find a more *inconsistent* relationship between these two performance measures (e.g., revenue growth coinciding with plant closings) for fraud firms than for non-fraud firms. Consequently, the aforementioned inconsistency may be a valuable tool for auditors and regulators attempting to identify fraudulent financial statement activity at their clients and publicly traded corporations, respectively.

This paper provides evidence that the comparison of financial measures to NFPMs does provide incremental explanatory power for discriminating fraud from non-fraud firms. Using a matched-pair sample of fraud firms and competitors, we find for fraud firms a greater gap between revenue growth (financial measure) and growth in various NFPMs (e.g., number of

acquisitions) that should be positively correlated with revenue. We analyze this gap from the year prior to the initial fraud year to the first year of the fraud for each matched-pair. Also, when including the aforementioned gap between financial measures and NFPMs in a model including financial factors that have been found to be indicative of fraud, we find the gap to be a significant discriminator between fraud and non-fraud firms. Thus, we empirically illustrate that auditors and regulators can use comparisons between financial measures and NFPMs as a powerful tool 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.

II. HYPOTHESES DEVELOPMENT

The use of NFPMs in the evaluation of firm performance has garnered much attention since Kaplan and Norton (1996) published the “The Balanced Scorecard.” Also, SAS no. 56 (AICPA 1988) suggests that auditors may want to consider NFPMs when determining the reasonableness of their clients’ financial statements. Proponents of NFPMs 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) (Langfield-Smith 2003). While several prior studies investigate the use of NFPMs in compensation plans (e.g., Banker et al. 2000; Said et al. 2003), little published research has investigated the relationship between financial performance and NFPMs (Ittner and Larcker 1998). Amir and Lev (1996) and Riley et al. (2003) studied the cell-phone and airline industries, respectively, and found that the value-relevance of nonfinancial information overwhelms that of traditional, financial statement variables for investors. The former study also stresses the importance of, in both practice and

research, significantly expanding the use of nonfinancial information. Ittner and Larcker (1998) find one form of NFPs, 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 NFPs and financial statement data in the airline industry. Specifically, Liedtka (2002) employs factor analyses to show the growing reliance on NFPs is justified because the nineteen NFPs disclosed by the airline industry represent seven additional underlying constructs not measured by eighteen common financial performance measures. Behn and Riley (1999) find that NFPs are useful in predicting quarterly revenue, expense, and net income numbers. Establishing that NFPs are correlated with financial performance is important since our goal is to identify fraud firms by looking at inconsistencies between their financial results and their NFPs.

In addition to the academic studies noted above, anecdotal evidence suggests that considering NFPs 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 of time 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 NFPs.

The Treadway Commission (National Commission on Fraudulent Financial Reporting 1987) concluded that the intent of most frauds is to improve earnings and financial position to meet the market's expectations. We explore whether fraud firms have an inconsistent pattern between their financial performance and their NFPs such that the financial performance is

strong while the NFPMs show weak operating 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 would not likely 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 NFPMs are often less vulnerable to manipulation and/or are more easily verified than financial data. Whereas controls over financial data can be overridden by management and financial statements are produced internally, NFPMs are sometimes produced and reported by independent sources (e.g., industry quality rankings). Also, when an NFPM is reported by management 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 management will be unable to manipulate all their firm's NFPMs in a consistent manner. In summary, if fraud firms do not manipulate their NFPMs in a manner that is consistent with their financial performance and if NFPMs can be identified that are positively correlated with financial performance, then unexpected differences between NFPMs and financial performance should help to discriminate fraud from non-fraud firms.

Two Examples

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. It is possible that a company could increase profits by cutting payroll; however, it is improbable that a 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. The Del Global case illustrates how an unusual relationship between NFPMs (i.e., total number of employees and total number of distribution dealers) and financial data (i.e., revenue) could raise red flags when assessing 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 NFPMs and financial data. Prior to filing 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, including sales to a fictitious customer, 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 NFPMs (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 NFPMs (i.e., increase in employees and facilities) was consistent with its revenue growth. Total employees increased 10 percent and total number of facilities increased three percent.¹ Certainly, factors other than fraud could cause unusual relationships between NFPMs and financial data; however, firms that are committing fraud would seemingly be more likely to exhibit such unusual trends.

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 NFPMs would focus on common nonfinancial measures which are industry specific. Compiling a reasonable data set 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 NFPMs. To do so, we identify NFPMs that should have a positive correlation with growth in revenue and determine whether inconsistencies between revenue and NFPM growth can discriminate 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; Jones 2005).² For example, we selected the number of retail outlet stores as an NFPM for firms 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 NFPM will be larger for fraud firms than 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 NFPMs than their non-fraud competitors.

We also consider whether differences between financial measures and NFPMs can enhance fraud risk assessment models, which include other indicators of fraud. Because nonfinancial data is less subject to manipulation, we expect that NFPMs contain additional information not provided by financial statement indicators previously associated with fraud.

SAS 99 (AICPA 2002, ¶28) states,

In performing analytical procedures in planning the audit, 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.

If an auditor is concerned specifically with fraudulent reporting, the auditor would be better served by comparing financial data (i.e., fraudulent data) to nonfinancial data (i.e., non-manipulated data). Creating expectations of data based on other manipulated financial data would be less likely to uncover financial shenanigans. For example, HealthSouth is a provider of rehabilitative health care, ambulatory surgery, and diagnostic services. The Company had to restate its financial statements from 1999-2002 due to fraudulent reporting. If HealthSouth's auditors had developed an expectation of HealthSouth's revenue for 1999 on discussions with management and prior year trends then a slight increase from 1998 (as was reported) would have been expected. Auditors commonly rely on management explanations and prior years' trends and ratios to develop expectations for current year analytical procedures (Anderson and Koonce

1995; Hirst and Koonce 1996; Bierstaker et al. 1999; POB 2000). However, if the auditors had considered the number of outpatient visits and the number of patient days in hospitals, then the auditors would have expected a decrease in revenue as was actually the case.

Potential reasons why auditors may not search for and use NFPMs include budgetary pressures and/or over-reliance on prior year workpapers that do not include analyses of NFPMs (cf., Wright 1988; Houston 1999; Brazel et al. 2004). Given the recent efforts to improve auditors' detection of fraud, we believe audit firms could more efficiently and effectively assess fraud risk if NFPMs (or specifically the comparison of NFPMs to related financial measures) are good predictors of fraud.

Our goal is therefore to determine whether the level of consistency between financial measures and NFPMs provides additional predictive power over other 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. Finally, Jones (2005) finds that the most powerful fraud-risk indicators among a comprehensive list of financial statement variables are total accruals and market value of equity. Firms committing fraud are more likely to have a higher market value of equity and more total accruals than a sample of non-fraud firms. In addition, Jones finds that return on assets, revenue growth and total debt are also positively correlated with fraud. 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 NFPMs can improve these procedures.

If inconsistencies between financial measures and NFPMs discriminate fraud firms from non-fraud firms, we expect an independent variable that compares changes in revenue and changes in NFPMs 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 NFPMs adds to the power of fraud risk assessment models comprised of financial variables that have previously been associated with fraudulent financial reporting.

The evidence provided in this study should assist auditors in their assessment of fraud risk. 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 on any information that can aid auditors in their detection of fraud.

III. SAMPLE SELECTION AND RESEARCH METHOD

Our sample of fraud firms was derived 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 Commission identified 294 companies that were cited by the SEC from 1987-1997 for alleged fraud violations. The firms were identified through a search of the SEC's Accounting and Auditing Enforcement Releases (AAER's). We performed a similar AAER search for the years 1998-2003. We used "fraud" as a search term and identified another 252 firms for a total of 546 fraud firms for the years 1987-2003. However, we excluded firms from our sample that didn't restate at least one 10-K, were non-earnings management frauds (such as omitted disclosures), or did not have data available on Compustat. We were left with 95 fraud firms. From Hoover's Online database, we identified each fraud firm's closest competitors. We

then underwent an exhaustive search of 10-Ks, Hoover’s Online, Proquest, ABI-Inform, LexisNexis, Standard and Poor’s Market Insight, and Google for NFPMs for each fraud firm and one of its competitors. From the 95 firms, we were able to identify NFPMs for 32 different fraud firms and 32 matched competitor firms. We identified multiple NFPMs for several of the matched pairs. Thus, for several of our matched pairs we have multiple observations. Our final sample consisted of 93 fraud and 93 non-fraud observations. The Del Global Technologies and Anicom examples above illustrate a few of the specific NFPMs (i.e., employees, facilities, distribution dealers) we included in our sample. Table 1 provides a consolidated list of the

Insert Table 1 here

NFPMs used in our analyses.

Because our fraud firms are in several industries and because NFPMs are generally industry specific, we were unable to identify any one single NFPM that we could analyze across all firms. Instead, we purposely identified NFPMs that we expect to have a positive correlation with firm growth in revenue. We created a variable that measures the difference between the percent change in revenue growth and the percent change in each NFPM for each fraud firm and their competitor separately. The difference for each firm was measured from the year prior to the fraud to the year of the fraud. The variable is measured as follows:

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

where,

Rev = total revenue

NFPM = nonfinancial performance 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).³

As noted in the previous section, prior research has identified various financial statement variables that are significant at discriminating fraud from non-fraud firms. Those variables include return on assets (ROA), total accruals (ACC), market value of equity (MVE), and debt (Debt).⁴ 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:

$$P(\text{FRAUD}_t) = \beta_0 + \beta_1 \text{Diff}_t + \beta_2 \text{Control Variable}_t \quad (2)$$

$P(\text{FRAUD}_t)$ = 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:

$$\begin{aligned} \text{ACC}_t &= ((\Delta \text{CA}_t - \Delta \text{Cash}_t) - (\Delta \text{CL}_t - \Delta \text{STD}_t - \Delta \text{TP}_t) - \text{Dep}_t) / \text{total assets}_{t-1} \\ \Delta \text{CA}_t &= \text{current assets}_t - \text{current assets}_{t-1} \\ \Delta \text{Cash}_t &= \text{cash}_t - \text{cash}_{t-1} \\ \Delta \text{CL}_t &= \text{current liabilities}_t - \text{current liabilities}_{t-1} \\ \Delta \text{STD}_t &= \text{debt included in current liabilities}_t - \text{debt included in current liabilities}_{t-1} \\ \Delta \text{TP}_t &= \text{income taxes payable}_t - \text{income taxes payable}_{t-1} \\ \text{Dep}_t &= \text{depreciation}_t + \text{amortization expense}_t \\ \text{Debt}_t &= \text{current liabilities}_t + \text{long-term debt}_t / \text{total assets}_{t-1} \\ \text{ROA}_t &= \text{Net income before extraordinary items} / \text{total assets}_{t-1} \\ \text{MVE}_t &= \text{end-of-year share price}_t \times \text{total common shares outstanding}_t / \text{total assets}_{t-1} \end{aligned}$$

Because we have repeated measurements of financial data for the same firm in the same year (due to multiple observations of NFPMs for several of our matched pairs), we also estimate alternating logistic regression models (ALR) in addition to logistical regressions. Carey et al. (1993) derive and explain the use of ALRs. Generally, controlling for repeated measures results in an increase in standard errors and a loss of significance among predictors from the standard logistic regression; however, the parameter estimates remain unaffected. We present the results for both the standard logistic regression and the ALR.⁵

IV. RESULTS

H1 predicts a greater difference in percent change in revenue growth and percent change in NFPM for the fraud sample than for the control sample (i.e., non-fraud competitors). Table 2

Insert Table 2 here

provides descriptive statistics for our key variable, Diff, and shows a comparison of the means for the fraud and competitor samples. The results support H1 as Diff is significantly ($p < .01$) greater for the fraud sample. In short, for fraud firms, the financial picture portrayed by their financial statements was more positive than the depiction provided by their NFPMs. For their competitors, we observe a mean Diff of .003, indicating that their revenue growth was in line with growth in their NFPMs. Thus, H1 is supported in that the extent to which financial measures are not aligned with related NFPMs may be an indicator of fraud risk.

Table 3 presents the results of performing both logistic regression and ALR for Diff

Insert Table 3 here

individually on fraud (1, 0) for our sample and the results of performing both regressions for Diff and each of the financial variables previously associated with fraud. The multivariate regressions in Table 3 include Diff and only one control variable. We do not incorporate Diff and all control variables into one comprehensive model because of a high degree of correlation among the financial statement variables – particularly between ACC and ROA.⁶ The results show that Diff is significant ($p < .01$) when analyzing it individually, which provides additional support for H1. Diff maintains significance ($p < .05$ in all models) when adding each control variable, which supports H2. It should be noted that only Diff and Debt maintain significance in the ALR analyses. The positive and significant parameter estimates for Diff in all of the regressions in Table 3 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 measures and NFPMs increase.

These results provide evidence that NFPMs can convey new information not previously contained in financial statement variables that have been found to be correlated with fraud. NFPMs 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."

V. CONCLUSIONS

The purpose of this paper was to investigate whether examining the relationship between financial data and nonfinancial performance measures (NFPMs) can aid auditors in the assessment of fraud risk. The study of fraud detection has been elusive to researchers because of a lack of data and formal theory about how and why people commit financial statement fraud. However, the current regulatory environment is placing increased scrutiny on auditors' ability to detect fraud. SAS no. 99 (AICPA 2002) requires that auditors document a separate fraud risk assessment for each engagement. Consequently, auditors and regulators are placing a premium on methods auditors can use to detect fraud. The use of NFPMs in the evaluation of firm performance has garnered much attention since Kaplan and Norton (1996) published the "The Balanced Scorecard." For firms that fraudulently misstate their financial statements, it is unlikely that they will (or have the ability to) concurrently misstate NFPMs that are indicative of their true financial condition. We therefore hypothesized that (H1) fraud firms will have greater

differences in percent change in revenue growth and percent change in NFPMs than their non-fraud competitors and that (H2) these differences add to the power of fraud-risk-assessment models comprised of financial variables that have previously been associated with fraudulent financial reporting.

We specifically include NFPMs in our study that should correspond with growth in firm revenue. We matched a sample of firms that have committed fraud with a control sample of competitor firms. The results indicate that a variable that measures the difference between the percent change in revenue growth and NFPMs can discriminate between fraud and non-fraud firms and may aid auditors in their assessment of fraud risk.

This is a significant contribution to both auditors and regulator attempting to detect fraudulent financial reporting. Prior literature suggests that audits fail when auditors fail to understand the environments in which their clients operate (Erickson 2000). The results suggest that gaining insights into various NFPMs for the industries in which their clients operate and comparing those measures to reported financial results has the potential to be a powerful fraud detection tool.

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TABLE 1

Nonfinancial Performance Measures

Nonfinancial Performance Measure	Observations
Human Resources	29
Facilities	16
Capacity (other than facilities)	14
Patents and Trademarks	6
Mergers and Acquisitions	6
Subsidiaries	4
Products	3
Web Influence	2
Miscellaneous	<u>13</u>
Total	93

TABLE 2**Descriptive Statistics and Comparison of Means for Fraud and Control Samples**

Variable		N	Mean	Difference		Median	Std Dev
Diff	Fraud	93	0.182			0.186	0.447
	Competitor	93	0.003	0.179	***	0.028	0.379

Significance Levels: ***<.01, **<.05, *<.1 using a one-tailed t-test assuming unequal variances.

$Diff_t = ((Rev_t - Rev_{t-1}) / Rev_{t-1}) - ((NFPM_t - NFPM_{t-1}) / NFPM_{t-1})$
 Rev = Total Revenue
 Inc = Income before Extraordinary Item
 NFPM = Non Financial Performance Measure
 t = Year of the fraud

TABLE 3

Logistic regressions and Alternative Logistic Regression (ALR) modeling the probability of a firm being fraudulent

$$P(\text{FRAUD}_i) = \beta_0 + \beta_1 \text{Diff}_i + \beta_2 \text{Control Variable}$$

Variables	Predicted Sign	Logistic		ALR
		Parameter Estimate	Standard Errors	Standard Errors
Diff	+	1.06	0.38 ***	0.49 ***
Intercept		-0.10	0.15	0.30
Likelihood Ratio Test			8.57 ***	

Variables	Predicted Sign	Logistic		ALR
		Parameter Estimate	Standard Errors	Standard Errors
Diff	+	0.98	0.38 ***	0.50 ***
ACC	+	1.01	0.84	1.45
Intercept		-0.09	0.16	0.30
Likelihood Ratio Test			10.15 ***	

Variables	Predicted Sign	Logistic		ALR
		Parameter Estimate	Standard Errors	Standard Errors
Diff	+	0.89	0.39 **	0.51 **
Debt	+	1.66	0.48 ***	0.73 **
Intercept		-1.10	0.32 ***	0.56 **
Likelihood Ratio Test			22.89 ***	

Variables	Predicted Sign	Logistic		ALR
		Parameter Estimate	Standard Errors	Standard Errors
Diff	+	1.14	0.39 ***	0.52 **
ROA	+	-0.57	0.81	1.34
Intercept		-0.08	0.16	0.31
Likelihood Ratio Test			9.06 **	

TABLE 3 (continued)

Variables	Predicted Sign	Logistic		ALR
		Parameter Estimate	Standard Errors	Standard Errors
Diff	+	0.96	0.38 ***	0.51 **
MVE	+	0.03	0.02 *	0.02
Intercept		-0.24	0.17	0.33
Likelihood Ratio Test			12.36 ***	
Sample Size	Fraud	93		
(All Models)	Competitor	93		

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

FRAUD _{<i>t</i>}	= 1 for fraud firms and 0 for competitors,
Diff _{<i>t</i>}	= defined in Table 2
IncDiff _{<i>t</i>}	= defined in Table 2
ACC _{<i>t</i>}	= ((Δ CA _{<i>t</i>} - Δ Cash _{<i>t</i>})-(Δ CL _{<i>t</i>} - Δ STD _{<i>t</i>} - Δ TP _{<i>t</i>})-Dep _{<i>t</i>}) / total assets _{<i>t-1</i>}
Δ CA _{<i>t</i>}	= current assets _{<i>t</i>} - current assets _{<i>t-1</i>}
Δ CL _{<i>t</i>}	= current liabilities _{<i>t</i>} - current liabilities _{<i>t-1</i>}
Δ STD _{<i>t</i>}	= debt included in current liabilities _{<i>t</i>} - debt included in current liabilities _{<i>t-1</i>}
Δ TP _{<i>t</i>}	= income taxes payable _{<i>t</i>} - income taxes payable _{<i>t-1</i>}
Dep _{<i>t</i>}	= depreciation and amortization expense
Debt _{<i>t</i>}	= current liabilities _{<i>t</i>} + long-term debt _{<i>t</i>} / total tssets _{<i>t-1</i>}
ROA _{<i>t</i>}	= Net income before extraordinary items / total assets _{<i>t-1</i>}
MVE _{<i>t</i>}	= end-of-year share price _{<i>t</i>} x total common shares outstanding _{<i>t</i>} / total assets _{<i>t-1</i>}

FOOTNOTES

1. Both examples (Del Global and Fischer Imaging; and Anicom and Graybar Electric) came from data in our sample.
2. The possible inclusion of fraud firms in our sample that manipulated expenses (rather than revenues) to manage earnings, biases against our hypotheses while positively contributing to the generalizeability of our results.
3. To control for extreme values, we winsorized the values of Diff. Any value greater than 1 or less than -1 were set to 1 and -1 respectively.
4. Revenue growth and change in inventory have also been identified as potential fraud risk factors; however, we exclude revenue growth in our analyses because our test variable, Diff, is a function of revenue growth, and we exclude change in inventory because several firms in our study do not have inventory.
5. 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.
6. Results presented in the text are qualitatively similar to those obtained from a model containing all of the control variables examined in Table 3.